Modified FMEA Hazard Identification for Cross-Country Petroleum Pipeline using Fuzzy Rule Base and Approximate Reasoning

Shamsu Hassan[1], Jin Wang[2], Christos Kontovas[3], Musa Bashir[4]

Liverpool Logistics Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool, UK

Abstract

The pipeline industry's existing and new safety challenges require flexible and powerful techniques for performing a risk-based analysis of cross-country petroleum product pipeline systems. One of the traditional tools for the prediction of pipeline failure is the Failure Mode and Effects Analysis (FMEA) technique due to its ease of application. However, many limitations have been identified in its application especially for cross-country pipelines in developing countries. Firstly, failure data is often either unavailable or unreliable, therefore identification of the risk priority numbers for the three failure factors (*i.e.* probability of failure, severity and detection) relies on experts' elicitation. Secondly, domain experts often provide diverse opinions and knowledge, which could produce different assessment rankings and it is often difficult to harmonise due to the multidisciplinary nature of the FMEA team. Thirdly, there is a lack of a systematic way of accounting for the relative importance of individual failure factors, which carries the risk of the assessment results not representing the true risk picture of the assessed system. Consequently, this paper proposes a new approach, called the modified FMEA, by integrating the noted benefits of hybrid FMEA with Fuzzy Rule Base (FRB) and FMEA with Grey Relations Theory (GRT) in order to overcome the identified drawbacks. The study utilises both the fuzzy and the grey theory to include experts' diverse opinions and to assign a relative weighting to each assessment factor in the risk assessment. The results of the risk assessment are then used to determine the risk priority and rank the failure modes under different types of conditions. A case study of Nigeria's petroleum product pipeline system 2B is conducted to examine the applicability and validity of the new approach. The results show the practical application of the methodology in this new domain. The new approach offers a more effective method for identifying product pipeline system hazards and risk analysis in geographies with limited or unreliable data. The application of this new methodology in the oil and gas cross-country pipeline domain will aid decision making under uncertainty for pipeline inspection and maintenance.

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[1] S.I.Hassan@2017.ljmu.ac.uk
[2] J.Wang@ljmu.ac.uk
[3] C.Kontovas@ljmu.ac.uk
[4] M.B.Bashir@ljmu.ac.uk

Keywords: Hazard identification, FMEA, Fuzzy Rule Base, Grey Relations, Petroleum Pipeline, Risk Assessment

1 Introduction

Failure to detect, prevent and mitigate losses associated with pipeline systems can be attributed to an inadequate hazard identification process. Hazard identification is the first step of risk analysis and aims to determine proactively all sources, situations or acts, with a potential for harm, which can lead to fires, explosions or environmental damage. Inadequate hazard identification may be the result of applying wrong hazard identification tools or misuse of the correct tools (HSL, 2003). As a result, this may lead to a wrong diagnosis or non-identification of important hazards.

Lack of reliable data on the failure history, maintenance and management of pipelines makes the hazard identification and the risk analysis process more difficult (Shan *et al*., 2017). The use of a new approach, such as the proposed modified FMEA, is shown to be more appropriate under a scenario where data for a data-driven assessment is lacking (Iqbal, 2018).

Hazards associated with cross-country pipelines are varied and so are the resulting consequences, which include loss of life, damage to property and the environment, disruption to vital supplies, socio-economic setbacks and loss of revenue. The hazards of a pipeline system could be associated with the pipeline itself, pigging apparatus, pipeline manifold, pumps, metering package or utility equipment (Muhlbauer, 2004). Faults, failures, blockages, leakages or losses of supply are some of the main hazards that can affect the optimum operations of a pipeline system. The main contributors to pipeline failures in Nigeria include deliberate damage (third party interference), soil erosion and lack of maintenance (Achebe *et al.*, 2012).

Available data from literature (Onuoha, 2009; Rowland, 2010; Ekwo, 2011; Fadeyibi *et al.*, 2011; Omodanisi *et al.*, 2014) indicates that since the late 1980s thousands of fatalities, economic losses and environmental damage have occurred, linked to pipeline incidents in Nigeria. Incidents like Jesse in 1998, with more than 1,000 fatalities and Abule Egba in 2006, with circa 500 fatalities are among the worst globally. The direct product loss for the cross-country pipeline system in the country runs into hundreds of million dollars per annum. One pipeline system alone – system 2B - is estimated to be losing about fifty million dollars per annum due to direct product loss (Ekwo, 2011). When payments due to compensation, fines, and environmental clean-up are included, the annual loss to the economy is significantly higher.

Failures of oil and gas pipelines in developed economies have been extensively studied and addressed. The data required for analysing and assessing the risks is available and reliable, *e.g.*, EGIG (2018) and Concawe (2019) in Europe. This data-driven assessment results in a consistent downward trend in terms of pipeline failure since the 1970s in Europe (EGIG, 2015;

Haswell & McConnell, 2015; Cech *et al.*, 2018) and a flat-lining of the number of failures in the US in the past 20 years (PHMSA, 2017). In Nigeria and other developing countries, the absence of reliable failure data and effective maintenance and management procedures, amongst other factors, makes it difficult to conduct an effective assessment of pipeline risks. This lack of data makes the application of existing risk assessment tools ineffective and results in high pipeline loss incidents with devastating consequences.

A new and novel approach that aims to reduce the frequency and the consequence of the cross-country pipeline failure and extend the asset's life in Nigeria would be revolutionary, taking into account the limitation of the existing tools. The cross-country pipelines refer to pipelines that start outside the limits of a production site to the entry/fence line of the receiving terminal. Cross-country pipelines are not necessarily limited to pipelines that transcend international boundaries.

A number of research works have been carried out recently to identify oil and gas pipeline hazards and assess their failure. Dawotola *et al*. (2009; 2010) proposed a model to identify failure factors and calculate the failure likelihood for different causes of pipeline incidents by using a combination of Analytic Hierarchy Process (AHP) and Fault Tree Analysis (FTA). The model identified and then ranked the failure causes using expert elicitation and AHP weighting aggregation to evaluate the relative importance of each failure cause. On the other hand, Dey *et al*. (2004) and Al-Khalil *et al*. (2005) applied a similar approach but have used only the expert elicitation and the AHP to arrive at the ranking. Dey *et al*. (2004) used the expert input to identify the importance of different sources of pipeline failure and then use AHP to arrive at their relative ranking for maintenance prioritisation. Al-Khalil *et al*. (2005) used the assessment to obtain pipeline failure factor ranking, which informs the pipeline failure repair budget and prioritisation.

Shahriar *et al*. (2012) proposed a model to assess the risk of oil and gas pipelines failure applying Bowtie analysis. They combined Fault Tree Analysis with Event Tree Analysis to develop a Bowtie model. The Bowtie was developed to assess the risk of gas release from a pipeline, which is taken as the top event for the fault tree. The model identifies high-level failure events, including rupture, corrosion, geological hazards, incorrect operation and sabotage. It further identifies the low-level factors associated with each high-level event. For example, corrosion has low-level factors that include internal corrosion, external corrosion, stress corrosion cracking and corrosion fatigue. The ranking and assessment of the failure factors rely on expert opinion to assess the fuzzy likelihood of the low-level events.

Sadiq *et al*. (2004) used a fuzzy scale to determine the failure likelihood. The work uses triangular membership functions to develop the scale used for the evaluation. The scale translated the linguistic terms into fuzzy numbers for evaluating the likelihood of failure from a very low to a very high level. The occurrence likelihood of high-level events was arrived at by multiplying the attributes of the low-level events. Expert opinion was adopted to rank and weight the failure factors, which gives the likelihood of failure of the pipelines. The model was built with about 40 low-level events; clearly, asking experts to provide their opinion on such a large number of factors is difficult and time-consuming and therefore could limit their participation. To minimise this limitation, Shahriar *et al*. (2012) used historical data in combination with the elicitation of experts.

Li *et al*. (2020) proposed a novel methodology for risk management of ageing urban oil and gas pipelines by integrating an index-based risk evaluation system and a fuzzy TOPSIS model. The methodology identified pipeline hazard factors to establish an index based evaluation matrix. It subsequently employed the Fuzzy TOPSIS model to evaluate and rank the hazards for decision making. The work uses factors including Occurrence, Severity and Detectability, and introduces weighing using a combination weight method, based on AHP and Entropy Method (EM). Although the work identified and correctly assigned weighting to the failure factors, it did not attempt to assign a weighting to reflect the experts' experience and expertise.

Feng *et al*. (2020) proposed a method based on Noisy-OR gate Bayesian Network (BN) and FTA to assess the failure likelihood of the pipeline where there is insufficient data. The FTA has been used to model pipeline failures, which is mapped using the BN model. Noisy-OR gate is then used to determine the conditional probability of the related nodes of the BN and thus the failure probability. The data relies on literature and expert knowledge. The study shows that the combined methodology and the assessment provide a reasonable analysis of the pipeline's reliability.

Li *et al.* (2019) on the other hand, assessed gas pipelines risk of failure using a combination of three different approaches including Decision Making Trial and Evaluation Laboratory (DEMATEL), Interpretive Structure Modelling (ISM) and BN. The study uses a two-stage procedure; firstly, DEMATEL-ISM is used to develop a hierarchical network model for the cause-effect relationship identification. The model also identifies critical failure factors. BN is then used to map the hierarchical network model, transforming it into conditional probability distribution and helps quantify the strength of the coupling relationships among the accident-causing system.

The above literature shows that different researchers have attempted to address the inherent uncertainty and lack of reliable data in the conduct of hazards identification and ranking for pipelines using a variety of models. However, most of the work did not consider the uniqueness of the operation locations, diversity of the participating experts, uncertainty of the information obtained from such members and the different weight that each factor contributes towards the ranking of the risks. Also, some of the assessment grades employed by the researchers may be imprecise and vague.

To address these concerns, several studies have been undertaken that integrate other models into the FMEA hazard identification process, such as Fuzzy Rule Base (FRB) in FMEA (Şimşek & İç, 2020; Petrovskiy *et al.*, 2015; Dinmohammadi & Shafiee, 2013), Grey Relations

Theory (GRT) in FMEA (Liu *et al.*, 2019; Chang *et al.*, 2001), FRB and GRT in FMEA (Maniram Kumar *et al.*, 2018; Pillay & Wang, 2003; Chang *et al.*, 1999), FRB and BN in FMEA (Alyami *et al.*, 2014; Yang *et al.*, 2008) and BT (Bow-tie) and BN in FMEA (Zarei *et al.*, 2017). These studies largely focused on different domains such as LPG dispensing stations, concrete plants, fishing vessels, offshore wind turbines and tanker equipment. Although the precept of some of these studies could be applied to pipelines, none of it would be suitable to cross-country pipelines without substantially being modified. Extending the application of the modified studies to cross-country oil and gas pipelines will provide a useful tool for decision makers and address some of the weaknesses in the current models. In addition, it will also address one of the weaknesses of the FRB-FMEA, specifically the application of the 125 IF-THEN rules with different antecedents' combinations giving the same consequent risk. The rule base has been refined by extending the consequent risks to include a belief structure thus ensuring the precise and unique consequent risk estimate for each antecedent's combination in this study. Therefore, this study proposed new models that address the main problems of uncertainties and subjectivity in available variables. The main goal of the study is to develop a framework for the prediction of failure for cross-country pipelines through identification and assessment of the critical failure causes of oil pipelines.

The rest of this paper is organized as follows: Section 2 presents a background to theories relating to Failure Mode and Effects Analysis, Fuzzy Set Theory (FST) and GRT. Section 3 analyses the proposed modified FMEA methodology. Section 4 shows the application of the proposed methodology in the case of one of Nigeria's pipeline systems. Finally, Section 5 and 6 present the discussion and conclusions, respectively.

2 Background to Hazard Identification and Failure Mode Effects Analysis of Cross-country Pipelines.

Different models and approaches have been proposed to identify and analyse hazards that may lead to pipeline failure. A review of some typical approaches relating to the one proposed in this research is given below.

2.1 Failure Mode and Effects Analysis Background

FMEA is a risk analysis tool that has gained wide application in the oil and gas sector. This may include the examination of failure modes to perform a function within defined limits, the inadequate or poor performance of a function or the occurrence of an unintended or undesired function (Carlson, 2014). The "effects" analysis examines the consequence of such a failure on the system, the people or the environment. This may be an identification of the top-level effects or multi-levels effects. There can be more than one effect for each failure mode but usually the FMEA team concentrates on the effect with the most serious impact for the analysis. If the criticality of the component is to be considered, then the process becomes what is known as FMECA (Failure Mode, Effects and Criticality Analysis).

The model is a bottom-up approach to hazard analysis and is a powerful tool for a complete risk model (Singh, 2014). Unlike hazard and operability study (HAZOP), which is operational function-oriented, FMEA is oriented towards components, their functions and potential failures. It supports qualitative hazard identification decisions at the design and during operations as part of Risk Based Inspection following guidance such as API 581 (2016) or at other stages where there is insufficient information or when there is lack of data for quantitative hazard identification. The FMEA process is illustrated in Figure 1.

Examples of pipeline failure modes include corrosion, external damage and material defects. The severity could be marginal, critical or catastrophic and it is linked to the 'effects' numbers. The FMEA can be applied during all stages of the project lifecycle, including design, installation, operations and decommissioning.

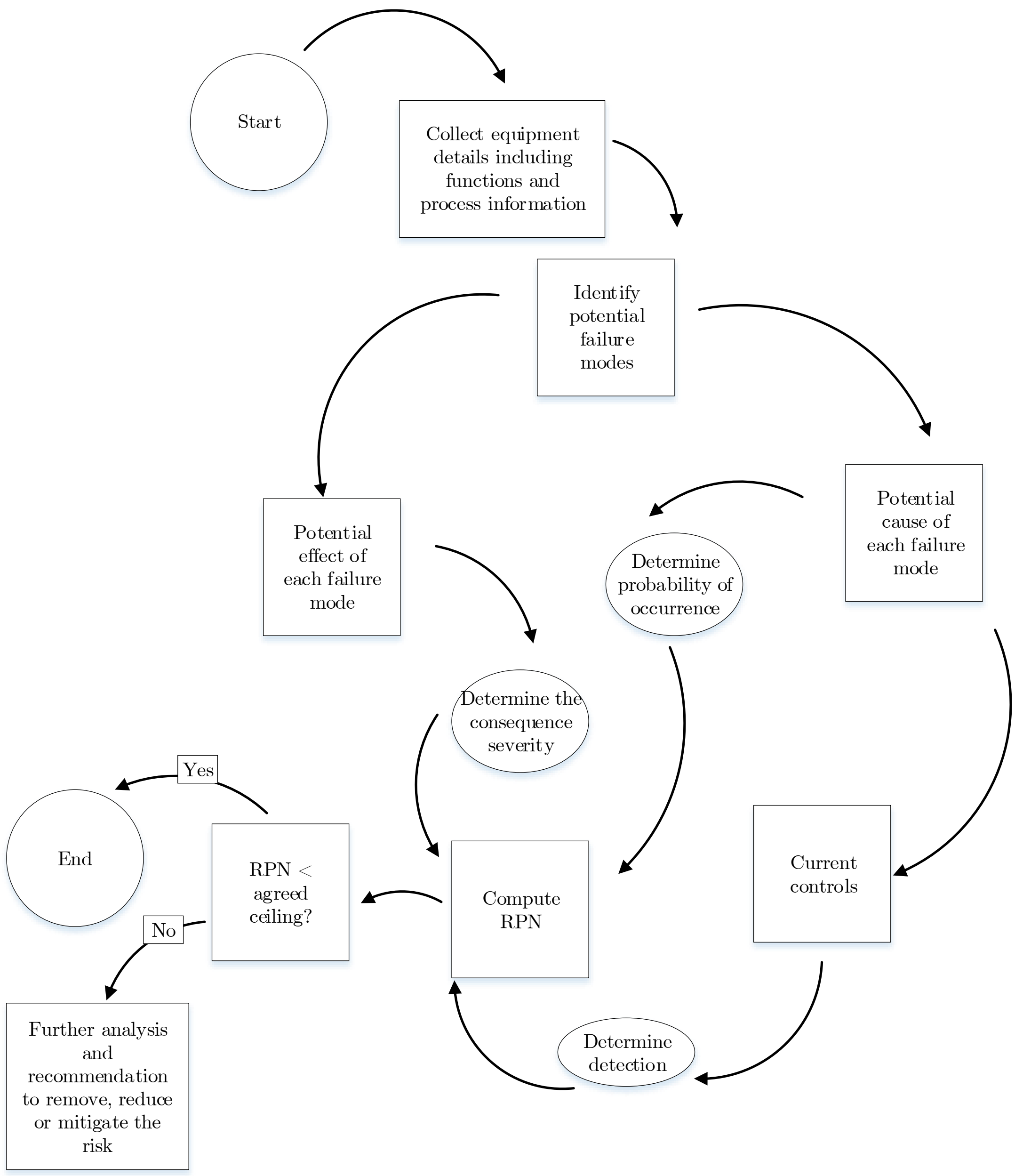

Figure 1: Example of Traditional FMEA Process

FMEA, when used during the design stage, has the potential to prevent failures thus avoiding a costly redesign, or enabling weaknesses to be identified and rectified before going on-site. The assessment includes calculating a qualitative risk prioritisation RPN (Risk Priority Number), derived as a product of the three ratings of the Occurrence likelihood, the Severity and the failure Detectability. The RPN gives a hierarchy of the criticality of the failures identified and can be calculated by allocating qualitative numbers to the three parameters, often based on expert elicitation, loss data and previous experience of the assembled team. Each of the three parameters has a numerical ranking, which is associated with the qualitative explanation for each of the numbers and is usually agreed with the assembled team before the commencement of the analysis.

Examples of a typical ranking for the three criteria are shown in Table 1, Table 2 and Table 3 (BSI, 2018; Norske Veritas, 2010).

Table 1: Failure Likelihood Rating

Likelihood Level	Description	Probability	Ranking
Very Low	Failure unlikely	$\leq 1\text{x}10^{-5}$	1
Low	Relatively few failures	$1\text{x}10^{-4}$	2
Average	Occasional failures	$1\text{x}10^{-3}$	3
High	Repeated failures	$1\text{x}10^{-2}$	4
Very High	Failure is almost inevitable	$\geq 1\text{x}10^{-1}$	5

Table 2: Failure Severity Rating

Severity Level	Description	Ranking
Negligible	A failure mode which could potentially degrade the system's functions but will cause no damage to the system and does not constitute a threat to life or injury.	1
Marginal	System operational with minor performance degradation.	2
Moderate	A failure mode, which could potentially degrade system performance function(s) without damage to the system or threat to life or injury.	3
Critical	A failure mode which could potentially result in the failure of the system's primary functions and therefore cause considerable damage to the system and its environment, but which does not constitute a serious threat to life or injury.	4
Catastrophic	A failure mode which could potentially result in the failure of the system's primary functions and therefore cause serious damage to the system and its environment and/or personal injury.	5

Table 3: Failure Detectability Rating

Detection Level	Description	Ranking
Highly Likely	Controls will almost certainly detect failure.	1
Likely	High chance for the design controls to detect failure.	2
Reasonably Likely	Reasonably likely chance for the design controls to detect failure.	3
Unlikely	Remote chance for the design controls to detect failure.	4
Highly Unlikely	Very remote chance for the design controls to detect failure.	5

2.1.1 Shortcomings of FMEA

Although the FMEA process is very powerful and widely adopted in the industry, it has many shortcomings which reduce its usefulness. Some of these shortcomings are summarised below (Liu *et al.*, 2011; Pillay & Wang, 2003; Gilchrist, 1993; Ben-Daya & Raouf, 1996).

- The assumption that three failure factors contribute equally towards the risk factor (RPN) of an event. This in practice is unlikely to be the case, at least in most circumstances. The Severity failure factor is often more important than other failure factors, which is why practitioners would often look at the Likelihood and Severity columns of the FMEA in isolation, in addition to looking at the overall RPN.
- Also, the analysis does not account for experience and expertise of the participating experts, they are all assumed to have the same level of experience and expertise.
- Different combinations of Likelihood (L), Severity (S) and Detectability (D) rankings may produce exactly the same RPN values. This may lead to a misleading conclusion, implying that these risks have the same priority, whilst they may, in reality, have widely different priorities. For example, if two events each have L, S and D of 5, 1, 10 and 5, 10, 1 respectively, they both will have an RPN of 50. This implies that the same level of attention is required to mitigate the two risks even though they are different. This may cause misapplication of limited resources and/ or cause a high-risk failure mode to be missed.
- The RPN, as a product of L, S and D is debatable. Some researchers question the rationale behind multiplying the numerical values of the failure factors to produce the RPN.
- The process relies on the subjective judgement of the team members in the absence of data for full quantitative analysis, or where the number of failure modes is such that a quantitative analysis is not possible. There is currently no formal way of addressing such subjectivity within the analysis.
- The current measure of using numerical rankings to score failure Likelihood, Severity and Detectability which, though precise, can be inaccurate and difficult to assign in the absence of quantitative data. Natural language utilisation could be preferable for practitioners and operatives, especially in developing countries, where the field operating staff are unlikely to be numerate and would struggle with linking an arbitrary number with the state of a piece of equipment's potential failure Likelihood, Severity or Detectability.

A modified FMEA process that addresses some of the limitations is therefore required to improve the effectiveness of the process and ensure the FMEA continues to be fit for future applications. Consequently, this study proposes integrating methods derived from Fuzzy Set Theory and Grey Relations Theory to address these shortcomings.

2.2 Fuzzy Set Theory

Fuzzy Set Theory was first introduced by Zadeh (1965). The theory was initially intended for applications on industrial controllers but this has advanced and the theory has found application in wider fields, including engineering, operational research, mathematics, expert systems, pattern recognition, robotics, medicine and computer science (Zimmermann, 2010).

Its application in the areas of risk analysis and risk assessment of safety systems in geographical areas where there is limited, or unreliable, data can be revolutionary, as it can explicitly accommodate the subjective and the uncertain nature of the input variables. The main benefit of FST is its introduction of the continuum of grades of membership and gradual transition between states. This enables and extends the Boolean logic from the traditional (crisp) variables to human intuitive fuzzy variables that allow for measurements and observation of uncertainties. Whilst crisp sets allow for full membership or non-membership at all, the fuzzy sets allow for partial membership, assigning a degree that ranges from 0 to 1.

Equally significant is the flexibility offered by FST in allowing the use of linguistic variables in estimating probabilities. The use of linguistic variables encompassing words and sentences in a natural or artificial language, as opposed to quantitative variables, ensures complex or ill-defined phenomena are better characterised and represented (Lavasani, 2010; Pillay & Wang, 2003).

The weakness of the Boolean logic or the classical set is that they are mutually exclusive; an object can either belong to one set or not. This precision assumes that the structures and parameters of the model are known and there is no ambiguity or vagueness. This bivalent membership is represented mathematically by:

$$X_A = \begin{cases} 1, x \in A \\ 0, x \notin A \end{cases} \tag{1}$$

The above equation indicates that element x in universe X can only be a full member of set A or not. With the fuzzy set, the membership can be denoted as:

$$\bar{A} = \{(x, \mu_{\bar{A}}(x) \mid x \in X) \text{ and } 0 \le \mu_{\bar{A}}(x) \le 1\} \tag{2}$$

$\mu_{\bar{A}}(x)$ is the membership function of the element χ in universe X for the fuzzy set $\bar{A}$. A $\mu_{\bar{A}}(x)$ of 1 indicates full membership, and 0 indicates no membership. Any number in between represents a degree to which $\mu_{\bar{A}}(x)$ belongs to a certain membership class.

Fuzzy numbers can be represented by different graph shapes depending on the application context. The most common types of fuzzy numbers are triangular and trapezoidal. This study adopts the triangular numbers as they are simple to compute and useful in supporting illustration and information processing. These can be represented as follows:

$$\mu_{\bar{A}}(x) = \begin{cases} 0, x \le b \\ \dfrac{x-b}{m-b}, x \in (b, m) \\ 1, x = m \\ \dfrac{c-x}{c-m}, x \in (m, c) \\ 0, x \ge c \end{cases} \tag{3}$$

where m is the mean value, b and c are the lower and upper bounds respectively, for the values of $\mu_{\bar{A}}(x)$ above zero.

The FST approach has been implemented by authors such as (Senouci *et al.*, 2014; Kabir *et al.*, 2016; Yuhua & Datao, 2005; Dong *et al.*, 2014) to assess the risk of pipeline failure. The researchers applied the methodology as a modification to other main models, forming a modified methodology such as Fuzzy-BN (Kabir *et al.*, 2016) or Fuzzy-AHP (Dong *et al.*, 2014). However, most of the studies did not cover all the pipeline failure causes, suffer from the limitation of the main models adopted or are unable to incorporate uncertainties due to lack of knowledge or ignorance.

2.3 Grey Relations Theory (GRT)

In this work, we propose incorporating the approximate reasoning approach known as GRT. This theory was developed by Deng (1989; 1982) and addresses decisions characterised by incomplete information, incorporating known and unknown variables. It also explores system behaviour using relational analysis and model construction, and deals with uncertain systems with partially-known information through generating, excavating and extracting useful information from what is available (Liu *et al.*, 2016). GRT can also be used to analyse relationships between discrete qualitative and quantitative series whose components are existent, countable, extensible and independent (Zhou & Thai, 2016).

As uncertainty and poor information pervade every aspect of society, GRT receives a wide application in different fields including agriculture, medicine, geography traffic and the judicial system (Julong, 1989).

GRT application within a modified FMEA has been adopted in a number of studies (Chang *et al.*, 1999; Pillay & Wang, 2003; Zhou & Thai, 2016). The major benefits of using GRT within FMEA include the ability to assign different weighting coefficients to the failure factors and that it does not require a utility function of any form.

Developing the model involves multiple stages including establishing a comparative series, a standard series and calculating the difference between the two series. Using the Chen and Klein (1997) derivation, the comparative series formula is defined as follows:

$$K(x) = \frac{\sum_{i=0}^{n}(b_i - c)}{\sum_{i=0}^{n}(b_i - c) - \sum_{i=0}^{n}(a_i - d)} \tag{4}$$

where K(x) is the comparative series, a_i and b_i are the middle numerical values of the selected linguistic variable, d is the maximum membership function, c is the minimum membership function, a_0 is the minimum numerical value of the linguistic variable and b_0 is the maximum numerical value of the linguistic variable. n is the number of decision factors.

The determination of the Grey Relations Coefficient, represented as $\gamma\left(x_0(m), x_n(m)\right)$, can be obtained using Equation 5 below for each risk factor of the identified failure modes.

$$\gamma\left(x_0(m), x_n(m)\right) = \frac{\min_n \min_m |x_0(m) - x_n(m)| + \zeta \max_n \max_m |x_0(m) - x_n(m)|}{|x_0(m) - x_n(m)| + \zeta \max_n \max_m |x_0(m) - x_n(m)|} \tag{5}$$

m represents the assessed factors. $x_0(m)$ is the value from the standard series and can either be the minimum or maximum value; $x_n(m)$ is the value from the comparative series and also can be the minimum or maximum. ζ is an identifier and can be assumed as 0.5 (Julong, 1989).

Finally, the Degree of Relations and ranking of the factors is calculated as follows:

$$\Gamma(x_i, x_j) = \sum_{k=1}^{n} \beta_k \gamma\{x_0(m), x_n(m)\} \tag{6}$$

β_k is the weighting coefficient for the failure factors and $\gamma\{x_0(m), x_n(m)\}$ is the Grey Relation Coefficient, as obtained from Equation 5. n is the number of decision factors. Note that the total of all weighting coefficients $\sum_{k=1}^{n} \beta_k$ shall be equal to unity.

Application of the GRT as part of the proposed methodology further enhances the methodology by allowing each failure factor to be assigned different weighting to align with its perceived contribution towards risk prioritisation, which in turn determines which hazards the client would allocate available resources to.

2.4 Modified FMEA

The traditional FMEA, as outlined earlier, whilst simple and widely adopted in the industry, has many weaknesses that make its outcome inconsistent and may inadvertently result in directing limited resources to wrongly prioritised risks.

To address these shortfalls, a modified FMEA is proposed, using a Fuzzy Rule Base, derived from Fuzzy Set Theory, and Grey Relations approach. These approaches would correct some of the flaws in the traditional FMEA by ensuring that each expert and factor can be assigned a weighting. It will also further expand the RPN so that different risk implications are outlined for events with similar RPN values when assessed using the traditional FMEA (Pillay & Wang, 2003). Whilst these approaches have been applied in other domains, this paper extends their application to the oil and gas cross-country pipelines and further refine the IF-THEN consequent risk linguistic terms to include belief degrees. The proposal in this paper expands our understanding and versatility of the models. The use of the two-step approach would allow operators to use the results of the initial step, FRB-FMEA, during the screening stage when the knowledge of the relative ranking of the risks suffices. During the detailed stage when the contribution of each failure factor is important, the second step, integrating the Grey Theory, could be used. Using the integrated approach enables the operatives to prioritise the failure factors for optimum risk reduction.

3 Methodology

The general outline of the methodology and the steps involved in conducting the modified FMEA analysis is presented in this section. The modified methodology is developed to provide a framework upon which the pipeline risk assessment work will be anchored.

Figure 2 shows the flowchart of the proposed modified approach.

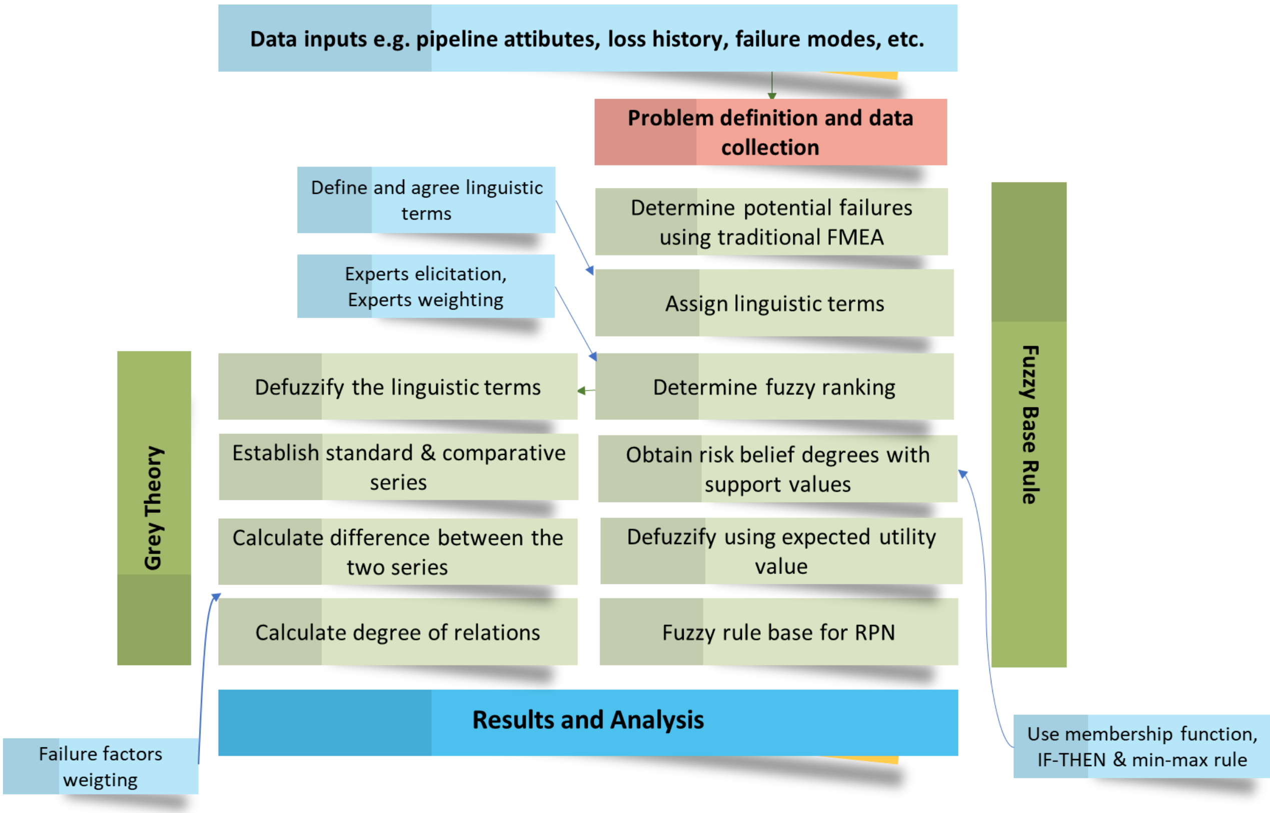

Figure 2: Proposed Methodology

3.1 Failure Mode and Effects Analysis (FMEA)

The traditional FMEA has been used as the basis of the initial stage of the pipeline risk assessment. The method is then modified using the FRB and GRT (see Section 3.4). The FMEA approach provides the baseline for the study and affords comparison with the modified approach, to assess the potential improvements which the new approach may provide.

The FMEA workshop outcome is often recorded in a worksheet or using bespoke software and include at least the following:

1. Identifying the number of failure modes that are being assessed. The number to be assessed depends on the complexity of the system being considered and the level of refinement required for the assessment.

2. Identifying the system or the subsystem that is being assessed. This could be a unit or a whole complex. For the pipeline system that is being evaluated in this assessment, the entire system is divided into subsystems encompassing the geographical coverage of the pipeline and includes associated equipment like the pigging and the pumps.
3. Listing the number of items that are being assessed, which represents the equipment whose failure mode is to be identified and analysed.
4. Outlining the event, which is the individual failure mode that is the subject of detailed analysis.
5. Outline the cause(s) of the failure, including both primary and secondary causes. These include, for example, corrosion, structural failure and sabotage.
6. Identifying the presence of the systems in place, if any, to detect or reveal the failure and includes provisions such as alarms, surveillance and third-party reporting.
7. Identifying and summarising the effect of the failure event both local (*i.e.* where the event has taken place) and system wide. Examples of such effects include leak, lack of flow and inability to operate the pipeline.
8. Identifying the safeguards put in place to reduce the likelihood and the potential consequence of any failure event and include, for example, leak detection, impact protection and burial depth of the pipes.

After the worksheet has been filled out with the causes and their detectability, and the effects have been agreed, a numerical ranking is assigned. Usually, every member of the FMEA team will assign their ranking and the average is calculated. The RPN is then calculated as the product of the rankings for the three parameters.

3.2 Fuzzy Rule Base Method

The proposed FRB method, developed using the Fuzzy Set Theory, improves the traditional FMEA by using utility functions when determining the Likelihood, Severity and Detectability ratings during the assessment. It also offers a new way of determining the risk rankings of failure events. The new method – FRB – compensates for the lack of data by integrating expert's opinion and weighting into the analysis. The use of linguistic variables ensures that the method aligns with natural or artificial language synthesis for decision making under uncertainty.

3.2.1 Expert Selection

The first task of the assessment includes selecting and appointing multiple experts with relevant experience, in our case on pipeline operations and management or on any other equipment being assessed. The expert selection process ensures that a broad spectrum of the equipment's lifecycle is covered by their experience, including but not limited to, design, construction, operation, maintenance and process safety. Due to the differences in the relevance of their experience and competence, a weighting can be introduced for a holistic consideration of each expert's contribution. This can be achieved by using the following equation:

$$A(x) = \sum_{i=1}^{t} C_i a_i(x) \tag{7}$$

where $\sum_{i=1}^{t} C_i = 1$, C_i is the degree of competence of experts *i*, *t* is the number of experts, $a_i(x)$ is the given proposition and $A(x)$ is the weighted failure factor.

The weighting outlining the degree of competence of the experts is determined based on their relevant experience in pipeline design, operations and management. In our case study, the weighting has been agreed on upfront by the stakeholders.

The next step is to agree on the assessment baselines with the selected experts, including the qualitative ranking of the Likelihood, Severity and Detectability ratings and their linguistic variables. The ranking could be 5-point or 10-point, depending on the agreed criteria. However, the 5-point ranking criteria will align with IF-THEN rules (Wang, 1997) and will be used for this study.

3.2.2 Fuzzy Membership Function Construction

The next step is to set up the fuzzy membership functions for the Likelihood, Severity, Detectability and Risk factors. The fuzzy membership functions are developed with the experts' involvement and agreement. The selection criteria of the experts and the eventual membership function developed should be realistic and non-biased, resulting from the collective agreement of all the experts. Fuzzy membership function is used to transform the weighted ranking of the failure factors assigned by the experts into linguistic terms and belief degrees.

A set, A, with objects in some relevant universe, X, is defined as elements of x that satisfy the membership property defined for A. In traditional 'crisp' sets theory each element of x either is or is not an element of A. Elements in a fuzzy set (denoted by,~ *e.g.*, Ã) can have a continuum of degrees of membership ranging from complete membership to complete non membership as outlined in Section 2.2.

A numerical scale to represent the degree of membership is used as a convenient way to represent gradation in the degree of membership. Precise degrees of membership generally do not exist. Instead, they tend sometimes to reflect subjective 'ordering' of the element in the universe. In the FRB analysis, the linguistic variable is determined to be the Likelihood (L), the Severity (S) and the Detectability (D). Each of the three linguistic variables has five linguistic terms describing them. These linguistic terms are Very Low, Low, Average, High and Very High, for example. The interpretations of these linguistic terms are given in Tables 1, 2 and 3.

The linguistic terms can also be represented in a membership function diagram shown in Figure 3, as an example. The membership function for the linguistic terms, can be determined using Equation 3. The triangular membership function has been considered for this study and each linguistic term is evaluated within its limits on an arbitrary scale from 0 to 1.

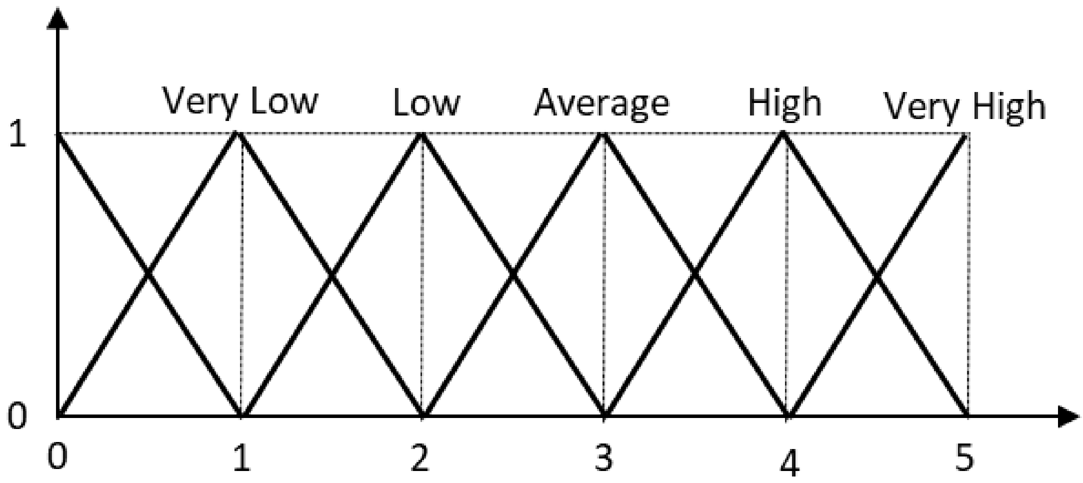

Figure 3: Graphical Representation of Membership Function for the Linguistic Terms

3.2.3 Brainstorming using Traditional FMEA Approach

The traditional FMEA approach is used to brainstorm on the failure factors by the selected experts using the linguistic terms. For each failure factor identified, each expert will assign a linguistic term for the potential Likelihood, consequence Severity and its Detectability. Each of the linguistic terms assigned by the experts is then converted into ranking values and, together with the weight of each expert, Equation 7 is used to determine the weighted ranking for each of the failure factors identified.

3.2.4 Application of IF-THEN Rule

Once the crisp weighted values have been obtained for each of the potential failure factors, the membership function diagrams, outlined in Figure 3, are employed to obtain belief degree values. For example, if the crisp weighted value for the Likelihood of a potential failure is 2.3, the corresponding membership functions and belief degrees will be *0.67 low*, *0.33 average*.

The 125 IF-THEN rules base (Wang, 1997) is then used to obtain the consequent Risk linguistic variables for each of the failure factors identified. The IF-THEN rule provides structured statements by using continuous membership functions. The rule requires inputs, which are the three failure factors combined in a structured manner to give an output variable that determines the linguistic term and belief degree for the Risk priority. The Risk linguistic terms could be, for example, "0.5 *very low* and 0.5 *low"* or "0.1 *moderate* and 0.9 *high"*.

The membership function diagram gives two outcomes of membership functions and belief degrees for each failure factor. If it is repeated for the three failure factors, this gives six membership functions and belief degrees, resulting in eight IF-THEN rule combinations for each of the potential risk factors.

3.2.5 Truth Value of the Membership Function

Using the min-max inference method (Zadeh, 1992; Wang *et al.*, 2004; Dantsoho, 2015), a membership function truth value of the Risk factor is calculated using the IF-THEN consequences. The minimum or truth values of the rule are assumed as the lowest non-zero belief degrees of the antecedents' rule for the failure factors. The truth value belief degrees are then used as the consequent (Risk) values.

For example, if a potential Risk factor has *0.67 low* Likelihood, *0.33 likely* Detectability and *0.67 moderate* Severity, the fuzzy truth values for the consequent Risk factor will be the lowest combination of non-zero belief degrees as ((min (0.67, 0.33, 0.67, 0.79), *low*) and (min (0.67, 0.33, 0.67, 0.21), *moderate)*; that is *0.33 low* and *0.21 moderate.* Table 4 also shows how the minimum values are obtained. The Risk factor's consequent linguistics terms are obtained using the IF-THEN Rule.

Table 4: Obtaining Minimum Values

Minimum Values				
If Likelihood is	**Severity is**	**Detectability is**	**And the Risk is**	**Then min value of Risk is**
0.67, low	0.67, moderate	0.33, likely	0.79 low	0.33, low & 0.21 moderate
0.67, low	0.67, moderate	0.33, likely	0.21 moderate	

In most instances, the same linguistic terms for the Risk factors appear more than once, sometimes with the same or a different truth value. In such instances, the maximum of the truth values of the consequent Risk factor with the same linguistic term would be selected. The consequent linguistic term "low" has truth values of 0.16, 0.33 and 0.47. The resulting Risk membership function/value is therefore *0.47 low.* The belief degree with support value for this potential Risk factor is *0.24 high*, *0.53 moderate* and *0.47 low.* Example *of* obtaining the maximum truth values is also illustrated in Table 5.

Table 5: Using Max Values to Obtain Belief Degree with Support Values

	Risk Membership Function/Value for Low	**Risk Membership Function/Value for Moderate**	**Risk Membership Function/Value for High**
	0.33, low	0.21, moderate	0.24, high
	0.47, low	0.53, moderate	
	0.33, low	0.33, moderate	
	0.16, low	0.33, moderate	
Max	**0.47, low**	**0.53, moderate**	**0.24, high**

3.2.6 Defuzzification using Expected Utility Method

Following Yang (2001), the expected utility method is adopted here for the defuzzification process. Defuzzification aims to combine the linguistic terms and the support values to create a crisp value representing the risk results, which enables ranking of the identified risks. The ranking determines the prioritisation of the decision-making in selecting the failure modes to expend resources on or to assess the risk further in detail.

Assume H_n is the evaluation grade, and $u(H_n)$ is its utility value. $u(H_n)$ can be arrived at by using experts' preference or, if there is no such preference, by assuming the value to be equidistantly distributed in the normalised utility space. $u(H_n)(n = 1, \ldots \ldots N)$ can be calculated as follows (Dantsoho, 2015):

$$u(H_n) = \frac{V_n - V_{\min}}{V_{\max} - V_{\min}} \tag{8}$$

where V_n is the ranking value for evaluation grade or linguistic term (H_n) under consideration, V_{max} is the ranking value for the most ideal evaluation grade (H_N) and V_{min} is the ranking value for the least preferred evaluation grade (H_1).

The expected utility value, $u(S(E))$, for the potential risk can be calculated as:

$$u(S(E)) = \sum_{n=1}^{N} \beta_n(E)\, u(H_n) \tag{9}$$

$\beta_n(E)$ is the belief degree for the evaluation grade H_n.

Combining the two equations we obtain the following expression to determine the utility value.

$$u(S(E) = \sum_{n=1}^{N} \beta_n(E)\, \left(\frac{V_n - V_{\min}}{V_{\max} - V_{\min}}\right) \tag{10}$$

3.3 Approximate Reasoning

GRT application within a modified FMEA has been used in numerous studies (Chang *et al.*, 1999; Pillay & Wang, 2003; Zhou & Thai, 2016); this is made possible as FMEA has all the characteristics that enable GRT to be applied. Its major benefits include the ability to assign different weighting coefficients to the failure factors and the fact that it does not require a utility function of any form (Chang *et al.*, 2001).

3.3.1 Establish Comparative Series

Comparative series are the linguistic terms for the Likelihood, Severity and Detection factors, and the decision factors for the case to be assessed. The comparative series are obtained using the Chen and Klein (1997) formula as reproduced in Equation 4.

The comparative series for use in this project can be expressed as

$x_n = (x(L), x(D), x(S)) \in x$

where

$x_n(l) = L, D, S$ represents the failure factors of Likelihood, Detectability and Severity of the failure mode x_n.

If there are failure modes of $(x_1, x_2, ...x_n)$ for instance and the linguistic terms for the failure modes are $(x_1(L), x_1(D), x_1(S))$, $(x_2(L), x_2(D), x_2(S)), \ldots. (x_n(L), x_n(D), x_n(D))$, then the series can be represented in a matrix as shown below:

$$x = \begin{bmatrix} x_1 \\ x_2 \\ . \\ . \\ x_n \end{bmatrix} = \begin{bmatrix} x_1(L) & x_1(D) & x_1(S) \\ x_2(L) & x_2(D) & x_2(S) \\ . & . & . \\ . & . & . \\ x_n(L) & x_n(D) & x_n(S) \end{bmatrix} \tag{11}$$

3.3.2 Determine the Standard Series

This is the objective series that represents the desired level of risk and is expressed as $x_0(L), x_0(D), x_0(S)$. Since the ideal level of risk is no risk at all, the standard series could be taken as the lowest level of all the failure factors for the linguistic terms, for example, *very low* for the Likelihood failure factor. The standard series could be represented as:

$$x_0 = [x_0(L), x_0(D), x_0(S)] \tag{12}$$

3.3.3 Determine Difference between Comparative and Standard Series

The difference between the two series, D_0, is calculated by a matrix as shown below:

$$D_0 = \begin{bmatrix} \Delta_{01}(L) & \Delta_{01}(D) & \Delta_{01}(S) \\ \Delta_{02}(L) & \Delta_{02}(D) & \Delta_{02}(S) \\ . & . & . \\ . & . & . \\ \Delta_{0N}(L) & \Delta_{0N}(D) & \Delta_{0N}(S) \end{bmatrix} \tag{13}$$

where $\Delta_{0n}(m) = \| x_0(m) - x_n(m) \|$, $x_0(m)$ is the standard series and $x_n(m)$ is the comparative series.

3.3.4 Grey Relation Coefficient

The Grey Relation Coefficient, represented as $\gamma\left(x_0(m), x_n(m)\right)$, can be obtained using Equation 5 for each Risk factor of the failure modes identified.

3.3.5 Grey Relation and Ranking

The final stage of the assessment is calculating the Degree of Relations and the ranking of the failure modes. To obtain the degree of relation, the weighting coefficient of each failure factor will have to be decided depending on its contribution to the severity of the consequent event.

The Grey Relation is obtained using Equation 6.

3.4 The Proposed Modified Approach

The traditional FMEA, as outlined earlier, whilst simple and widely adopted in the industry, has a number of weaknesses that make its outcomes inconsistent and may inadvertently result in directing limited resources to wrongly prioritised risks. The drawbacks were outlined in Section 2.1.1.

To address the shortfalls, a modified FMEA is proposed, using FRB and GRT approaches. These approaches would correct some of the flaws in the traditional FMEA by ensuring that each expert and factor can be assigned a weighting. This would further expand the RPN so that different risk implications are outlined for events with similar RPN values when assessed using the traditional FMEA (Pillay & Wang, 2003).

The methodology for the modified FMEA, as outlined in Figure 2, is proposed as follows:

i. Define pipeline system boundaries for analysis, including identifying the system.

ii. Obtain the details of the equipment on the selected pipeline section and its component functions and gather all the data available for the system.

iii. Generate equipment failure modes using brainstorming sessions or by using a historical failure data, if available.

iv. Using experts' elicitation, establish Likelihood, Severity and Detectability values of each identified failure mode using linguistic terms. Where quantitative data is available, this will be incorporated into the assessment.

v. Defuzzify the failure factors to obtain crisp values for use with the membership function graph. The weighting for each of the experts based on their relevant expertise will be taken into account.

For Fuzzy Base Rule:

vi. Use fuzzy membership function, IF-THEN rule and min-max rule to establish the failure Risk belief degree and support value.

vii. Defuzzify the belief degree and support value using the expected utility value and rank the risk numbers obtained.

For Grey Relation Theory:

viii. Establish comparative and standard series and calculate the difference between the two.

ix. Introduce weighting to each of the failure factors.

x. Calculate the degree of relation and rank the risk numbers obtained.

4 Case Study: Application to Nigeria’s 2B ‘Cross-Country’ Pipeline

The proposed modified FMEA incorporating FRB, and GRT approaches are implemented in a case study of one of Nigeria’s pipeline systems, which is System 2B shown in Figure 4. The pipeline runs between Lagos and Ilorin in south-western Nigeria. The relevant pipeline connects Lagos (including the Atlas Cove import jetty) in south-western Nigeria to Mosimi and terminating at Ilorin in north-central Nigeria. The total length of the system is circa 500km with the following sections: SPM (Single Point Mooring) to Atlas Cove, Atlas Cove to Mosimi, Mosimi to Ikeja/Lagos, Mosimi to Ibadan and Ibadan to Ilorin. The system includes the following: Oil pipeline, Pipeline manifold, Pigging (pig launchers and receivers), Metering system, Pumps, Utility systems and Future tie-in connections. The pipeline has a high level of reported loss of containment with the associated consequence of fire and explosion.

The modified FMEA case study will investigate all the equipment highlighted above. However, not all potential failure modes will be identified. This study will outline the common failures based on case histories, experts’ input and those failures with the most severe outcomes. This study reviews the failure modes and their causes. Detailed studies include the effect of those failures locally on the equipment itself and globally on the system as a whole. It also highlights the systems in place to reveal such failures and any safeguards in the system to reduce or mitigate the consequences of the failures.

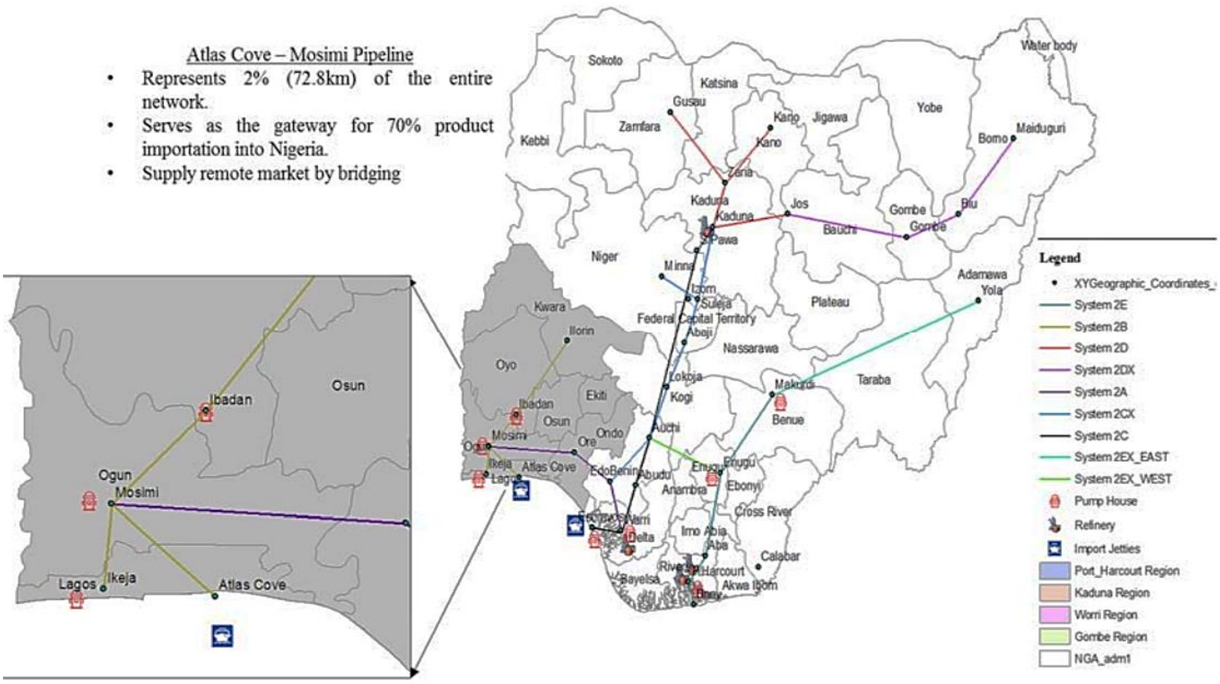

Figure 4: Nigeria's Map Showing the Pipeline System

Failure events have been generated from the possible failures of similar equipment obtained from global case history, the local failure data and input from field operatives and experts, based on their experience. These are provided in Table 6.

Table 6: Pipeline System 2B Failure Modes used as a Basis for the Analysis

No	Item ID	ID	Equipment Function	Failure Mode	Cause
1	1	1	Oil Pipeline	Product Leak/Rupture	External leakage from pinhole, flange or following impact or welding failure.
2	1	2	Oil Pipeline	Product Leak/Rupture	Deliberate - pipeline damage for product theft or vandalism.
3	1	3	Oil Pipeline	Product Leak/Rupture	Pipeline failure due to corrosion and structural weakness.
4	1	4	Oil Pipeline	Blockage	Line restricted by a partial or complete blockage.
5	2	1	Pipeline Manifold / Block Valve	Product Leak/Rupture	External leakage from pinhole, flange or following impact or welding failure.
6	2	2	Pipeline Manifold / Block Valve	Product Leak/Rupture	Deliberate - damage for product theft or vandalism.
7	2	3	Pipeline Manifold / Block Valve	Product Leak/Rupture	Pipeline failure due to corrosion and structural weakness.
8	2	4	Pipeline Manifold / Block Valve	Blockage	Line restricted by a partial or complete blockage.
9	2	5	Pipeline Manifold / Block Valve	Line Valve Failure	Actuated valve failed to shut.
10	2	6	Pipeline Manifold / Block Valve	Line Valve Failure	Actuated valve failed to open.
11	2	7	Pipeline Manifold / Block Valve	Line Valve Failure	Actuated valve failed, partly open.
12	3	1	Pumps	Product Leak	External leakage from pinhole, flange, seals, following impact or sabotage.
13	3	2	Pumps	Pump Fault	Pump reduced performance due to bearing, impeller problem or partial blockage.
14	3	3	Pumps	Pump Failure	Pump stops due to power loss or shaft breakage.
15	3	4	Pumps	Pump Failure	Pump stops due to loss of common power supply.
16	3	5	Pumps	Pump Failure	Standby pump fails to start on demand when duty pump fails.
17	4	1	Utility	Loss of Supply	Loss of utility or power.
18	4	2	Utility	Reduced Supply	Restriction in supply due to faulty instrument, valve, controller or pump.
19	4	3	Utility	Electrical Over-supply	High supply due to power surge.
20	5	1	Metering Package	Instrumentation Fault	Flow mismatch or inaccurate reading.
21	5	2	Metering Package	Product Leak	Leakage from pinhole, flange, following impact or sabotage.
22	5	3	Metering Package	Blockage	Line restricted by partial or complete blockage, for example, a stuck sphere.
23	6	1	Pig Launcher/ Receiver	Product Leak/Rupture	Leakage from pinhole, flange, following impact or sabotage.
24	6	2	Pig Launcher/ Receiver	Blockage	Line restricted blockage, for example, stuck sphere across main isolation valve.

No	Item ID	ID	Equipment Function	Failure Mode	Cause
25	6	3	Pig Launcher/ Receiver	Valve Failure / Problems with Valve Sequencing	Unable to isolate pig unit due to jammed, passing or failed valve.
26	6	4	Pig Launcher/ Receiver	Door Failure	Unable to seal pig unit due to jammed or failed door mechanism.
27	7	1	Future Tie-in Connection	Product Leak/Rupture	External leakage from pinhole, flange, following impact or sabotage.

Relevantly experienced operatives and experts have been selected for the assessment, their input forms the basis of the results of the traditional and the modified approaches.

4.1 Traditional FMEA

The aim of the modified FMEA process is to improve the traditional process. To appreciate the proposed improvement and to afford comparison, it is proposed that this study undertakes a traditional FMEA using numerical rankings as the basis for comparison. The process entails the selected experts to identify the numerical ranking of each failure mode representing the failure Likelihood, consequent Severity and its Detectability.

In assigning the numerical ranking by expert judgement, the operator of the pipeline has provided as much information about the state of the pipeline as possible. The summary of the numerical ranking is shown in Table 7.

Table 7: Traditional FMEA Results

S/N	Item ID	Event ID	Equipment Description/ Function	Failure Mode	Likelihood	Detection	Severity	RPN
1	1	1	Oil Pipeline	Product Leak/Rupture	2.3	2.7	3.3	20
2	1	2	Oil Pipeline	Product Leak/Rupture	4.0	1.3	4.3	22
3	1	3	Oil Pipeline	Product Leak/Rupture	3.0	3.0	3.3	30
4	1	4	Oil Pipeline	Blockage	2.7	2.0	3.3	18
5	2	1	Pipeline Manifold/Block Valve	Product Leak/Rupture	1.7	2.0	3.3	11
6	2	2	Pipeline Manifold/Block Valve	Product Leak/Rupture	2.7	2.3	4.3	27
7	2	3	Pipeline Manifold/Block Valve	Product Leak/Rupture	2.7	2.7	4.0	29
8	2	4	Pipeline Manifold/Block Valve	Blockage	2.3	2.0	3.7	17
9	2	5	Pipeline Manifold/Block Valve	Line Valve Failure	1.7	1.7	3.3	10
10	2	6	Pipeline Manifold/Block Valve	Line Valve Failure	1.3	2.7	3.0	11
11	2	7	Pipeline Manifold/Block Valve	Line Valve Failure	2.3	3.3	2.7	20
12	3	1	Pumps	Product Leak	4.0	1.3	3.0	16
13	3	2	Pumps	Pump Fault	3.3	2.7	2.7	24
14	3	3	Pumps	Pump Failure	3.3	1.0	3.7	12
15	3	4	Pumps	Pump Failure	3.7	1.0	4.0	15
16	3	5	Pumps	Pump Failure	2.7	2.0	4.0	22
17	4	1	Utility	Loss of Supply	3.7	1.0	4.0	15
18	4	2	Utility	Reduced Supply	2.7	3.3	2.3	20
19	4	3	Utility	Electrical Over-supply	3.0	1.3	3.7	14
20	5	1	Metering Package	Instrumentation Fault	3.0	3.3	2.0	20
21	5	2	Metering Package	Product Leak	3.0	2.7	3.0	24

S/N	Item ID	Event ID	Equipment Description/ Function	Failure Mode	Likelihood	Detection	Severity	RPN
22	5	3	Metering Package	Blockage	2.7	2.3	3.3	20
23	6	1	Pig Launcher/Receiver	Product Leak/Rupture	3.7	2.7	3.3	33
24	6	2	Pig Launcher/Receiver	Blockage	2.0	2.0	3.3	13
25	6	3	Pig Launcher/Receiver	Valve Failure/Problems with Valve Sequencing	2.0	2.0	2.3	9
26	6	4	Pig Launcher/Receiver	Door Failure	2.3	2.0	2.7	12
27	7	1	Future Tie-in Connection	Product Leak/Rupture	2.0	3.3	2.7	18

4.2 Fuzzy Rule Base FMEA

The modified FMEA using the Fuzzy Base Rule has been applied to the 2B Pipeline system's hazards identification. The process uses the same experts' input as the traditional FMEA but utilises the FRB linguistic terms in allocating ranking for the failure modes, which is the failure Likelihood, Severity of failure and its Detectability. The fuzzy terms include, for example, *very low, low, average, high and very high* for Likelihood failure mode. The details of the linguistic terms for the failure modes are outlined in Tables 1-3.

The linguistic terms assigned by each expert for each of the failure modes are converted into the relevant numerical ranking and each is then multiplied with the weighting as was established in Equation 7. Table 8 gives two examples of the experts' assigned linguistic terms for failure Likelihood, Severity and Detectability failure modes and their corresponding numerical value equivalent, including the weighted ranking for the failure modes. The weighted ranking is required as part of the process of obtaining belief degrees with support values.

Table 8: Example Linguistic Terms and Ranking Oil Pipeline.

Failure Mode	**Likelihood Linguistic Terms**			**Likelihood Equivalent**	**Ranking**		**Weighted Ranking**
Experts	**#1**	**#2**	**#3**	**#1**	**#2**	**#3**	
Likelihood							
Product Leak	High	High	High	4	4	4	4.0
Blockage	Average	Low	Average	3	2	3	2.7
Detection							
Product Leak	Highly Likely	Highly Likely	Likely	1	1	2	1.3
Blockage	Highly Likely	Likely	Reasonably Likely	1	2	3	2.0
Severity							
Product Leak	Catastrophic	Critical	Critical	5	4	4	4.3
Blockage	Catastrophic	Moderate	Marginal	5	3	2	3.3

One of the strengths of the FRB system is its continuity of membership, allowing the use of the crisp values to obtain membership functions and belief degrees. The belief function for the Likelihood of a failure due to a product leak with 4.0 ranking is *1 high.* The belief function for the Likelihood of failure due to a blockage with a 2.7 ranking is *0.33 low* and *0.67 average*. This is shown in Figure 5 and Figure 6.

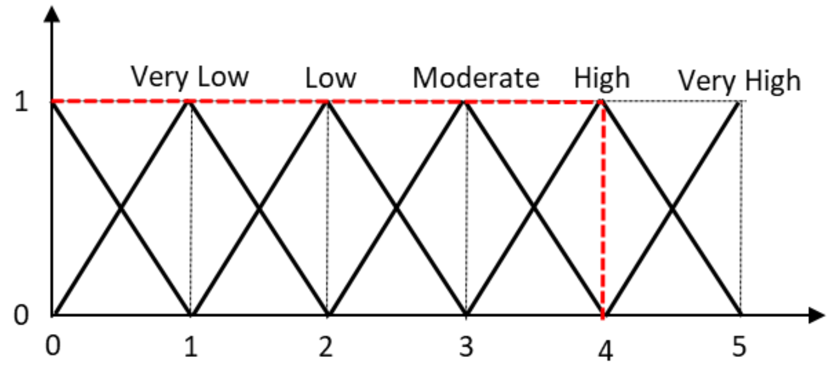

Figure 5: Membership Function of Product Leak Failure Likelihood with 4.0 Ranking

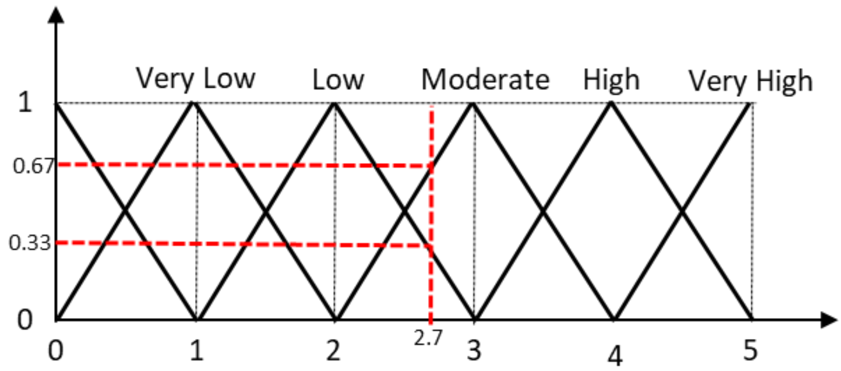

Figure 6: Membership Function of Blockage Failure Likelihood with 2.7 Ranking

Table 9 shows the membership functions and their belief degrees values for an oil pipeline product leak and blockage failure mode for the Likelihood, Detection and Severity values.

Table 9: Membership Functions for Oil Pipeline Failure Mode

Failure Mode	**Likelihood**		**Detection**		**Severity**	
	Ranking	Membership Function	Ranking	Membership Function	Ranking	Membership Function
Product Leak	4.0	*1, high*	1.3	*0.67, highly likely & 0.33, likely*	4.3	*0.67, critical & 0.33 catastrophic*
Blockage	2.7	*0.33, low & 0.67, average*	2.0	*1, likely*	3.3	*0.67, moderate & 0.33, critical*

The next step is applying the 125 IF-THEN rules with a belief structure (Wang, 1997) to the linguistic terms to determine the consequent Risk function of the failure modes.

Once the Risk linguistic variables are determined, the min-max rule is used to obtain the minimum truth value of the belief degrees.

Table 10 shows the minimum values of the consequent Risks for the product leak and blockage failure modes. The maximum rule is then applied to determine the maximum truth value associated with each of the Risk linguistic variables. Table 11 shows how the maximum rule has been applied to determine the truth value.

The Risk linguistic terms and their respective maximum belief values are then used to arrive at the expected utility value, which is the final element required to prioritise the failure modes. The expected utility values are obtained using Equation 10.

Table 12 details the fuzzy inputs and the defuzzified ranking of the failure modes.

Table 10: Application of IF-THEN and Min Rules to Determine Risk Linguistic Variables and Min Membership Function

Metering Package		Minimum Values							
Product leak	If **Likelihood** is	1, high	1, high	1, high	1, high				
	Severity is	0.67, critical	0.67, critical	0.33, catastrophic	0.33, catastrophic	0.67, critical	0.67, critical	0.33, catastrophic	0.33, catastrophic
	Detectability is	0.67, highly likely	0.33, likely	0.67, highly likely	0.33, likely	0.67, highly likely	0.33, likely	0.67, highly likely	0.33, likely
	Consequent **Risk** with belief structure	0.58 low, 0.42 moderate	0.86 moderate, 0.14 high	0.63 moderate, 0.37 low	0.65 moderate, 0.35 high	0.58 low, 0.42 moderate	0.86 moderate, 0.14 high	0.63 moderate, 0.37 low	0.65 moderate, 0.35 high
	Then **Min value of Risk** is	0.58, low & 0.42, moderate	0.33, moderate & 0.14, high	0.33, moderate & 0.33, low	0.33, moderate & 0.33, high	0.58, low & 0.42, moderate	0.33, moderate & 0.14, high	0.33, moderate & 0.33, low	0.33, moderate & 0.33, high
Blockage	If **Likelihood** is	0.33, low	0.33, low	0.33, low	0.33, low	0.67, average	0.67, average	0.67, average	0.67, average
	Severity is	0.67, moderate	0.67, moderate	0.33, critical	0.33, critical	0.67, moderate	0.67, moderate	0.33, critical	0.33, critical
	Detectability is	1, likely		1, likely		1, likely		1, likely	
	Consequent **Risk** with belief structure	0.79 low, 0.21 moderate	0.79 low, 0.21 moderate	0.58 low, 0.42 moderate	0.58 low, 0.42 moderate	0.53 moderate, 0.47 low	0.53 moderate, 0.47 low	0.84 moderate, 0.16 low	0.84 moderate, 0.16 low
	Then **Min value of Risk** is	0.33, low & 0.21, moderate	0.33, low & 0.21, moderate	0.33, low & 0.33, moderate	0.33, low & 0.33, moderate	0.53, moderate & 0.47, low	0.53, moderate & 0.47, low	0.33, moderate & 0.16, low	0.33, moderate & 0.16, low

Table 11: Application of Max Rule to Determine Maximum Value for Risk

Pipeline – Product Leak			Pipeline Blockage	
Risk membership function/value for				
low	Moderate	High	low	moderate
0.58, low	0.33, moderate	0.14, high	0.33, low	0.53, moderate
0.58, low	0.33, moderate	0.33, high	0.33, low	0.53, moderate
0.33, low	0.33, moderate	0.14, high	0.33, low	0.33, moderate
0.33, low	0.33, moderate	0.33, high	0.33, low	0.33, moderate
	0.33, moderate		0.47, low	0.21, moderate

		0.33, moderate		0.47, low	0.21, moderate
		0.42, moderate		0.16, low	0.33, moderate
		0.42, moderate		0.16, low	0.33, moderate
Max	**0.58, low**	**0.65, moderate**	**0.33, high**	**0.47, moderate**	**0.53, moderate**

Table 12: Fuzzy FMEA Ranking

No	Item ID	Event ID	Likelihood	Severity	Detectability	Fuzzy Risk Ranking	De-fuzzified Ranking
1	1	1	0.67, low & 0.33, average	0.67, moderate & 0.33, critical	0.33, likely & 0.67, reasonably likely	0.47, low & 0.53, moderate & 0.24, high	0.563
2	1	2	1, high	0.67, critical & 0.33, catastrophic	0.67, highly likely & 0.33, likely	0.58, low & 0.42, moderate & 0.33, high	0.603
3	1	3	1, average	0.67, moderate & 0.33, critical	1, reasonably likely	0.67, moderate & 0.67, high	0.838
4	1	4	0.33, low & 0.67, average	0.67, moderate & 0.33, critical	1, likely	0.47, low & 0.53, moderate	0.383
5	2	1	0.33, very low & 0.67, low	0.67, moderate & 0.33, critical,	1, likely	0.67, low & 0.29, very low & 0.33, moderate	0.333
6	2	2	0.33, low & 0.67, average	0.67, critical & 0.33, catastrophic,	0.67, likely & 0.33, reasonably likely	0.33, low & 0.67, moderate & 0.33, high	0.665
7	2	3	0.33, low & 0.67, average	1, critical	0.33, likely & 0.67, reasonably likely	0.33, low & 0.67, moderate & 0.49, high	0.785
8	2	4	0.67, low & 0.33, average	0.33, moderate & 0.67, critical	1, likely	0.58, low & 0.42, moderate	0.355
9	2	5	0.33, very low & 0.67, low	0.67, moderate & 0.33, critical	0.33, highly likely & 0.67, likely	0.33, very low & 0.67, low & 0.33, moderate	0.333
10	2	6	0.67, very low & 0.33, low	1, moderate	0.33, likely & 0.67, reasonably likely	0.67, low & 0.33, moderate & 0.29, very low	0.333
11	2	7	0.67, low & 0.33, average	0.33, marginal & 0.67, moderate	0.67, reasonably likely & 0.33, unlikely	0.47, low & 0.53, moderate & 0.24, high	0.563
12	3	1	1, high	1, moderate	0.67, highly likely & 0.33, likely	0.67, low & 0.37, moderate & 0.08, high	0.413
13	3	2	0.67, average & 0.33, high	0.33, marginal & 0.67, moderate	0.33, likely & 0.67, reasonably likely	0.33, low & 0.67, moderate & 0.24, high	0.598
14	3	3	0.67, average & 0.33, high	0.33, moderate & 0.67, critical	1, highly likely	0.67, low & 0.33, moderate	0.333
15	3	4	0.33, average & 0.67, high	1, critical	1, highly likely	0.58, low & 0.42, moderate	0.355
16	3	5	0.33, low & 0.67, average	1, critical	1, likely	0.33, low & 0.67, moderate & 0.24, high	0.598
17	4	1	0.33, average & 0.67, high	1, critical	1, highly likely	0.58, low & 0.42, moderate	0.355

No	Item ID	Event ID	Likelihood	Severity	Detectability	Fuzzy Risk Ranking	De-fuzzified Ranking
18	4	2	0.33, low & 0.67, average	0.67, marginal & 0.33, moderate	0.67, reasonably likely & 0.33, unlikely	0.47, low & 0.53, moderate & 0.24, high	0.563
19	4	3	1, average	0.33, moderate & 0.67, critical	0.67, highly likely & 0.33, likely	0.67, low & 0.33, moderate	0.333
20	5	1	1, average	1, marginal	0.67, reasonably likely & 0.33, unlikely	0.53, moderate & 0.67, low	0.433
21	5	2	1, average	1, moderate	0.33, likely & 0.67, reasonably likely	0.67, moderate & 0.24, high & 0.33, low	0.598
22	5	3	0.33, low & 0.67, average	0.67, moderate & 0.33, critical	0.67, likely & 0.33, reasonably likely	0.47, low & 0.53, moderate & 0.24, high	0.563
23	6	1	0.33, average & 0.67, high	0.67, moderate & 0.33, critical	0.33, likely & 0.67, reasonably likely	0.67, moderate & 0.33, high & 0.33, low	0.665
24	6	2	1, low	0.67, moderate & 0.33, critical	1, likely	0.67, low & 0.33, moderate	0.333
25	6	3	1, low	0.67, marginal & 0.33, moderate	1, likely	0.67, low & 0.21, moderate	0.273
26	6	4	0.67, low & 0.33, average	0.33, marginal & 0.67, moderate	1, likely	0.67, low & 0.33, moderate	0.333
27	7	1	1, low	0.33, marginal & 0.67, moderate	0.67, reasonably likely & 0.33, unlikely	0.47, low & 0.53, moderate	0.383

4.3 Grey Relation Theory FMEA

The application of the GRT to the modified FMEA is similar to that of the FRB in that it requires similar inputs and shares similar natural language utilisation. The input values for the Likelihood, Severity and Detectability factors are the linguistic variables, which have the same meaning as described in Section 2.1. The linguistic terms for Likelihood are *very low, low, average, high* and *very high*. The linguistic terms for Severity are *negligible, marginal, moderate, critical* and *catastrophic,* whilst the linguistic terms for Detectability are *highly likely, likely, reasonably likely, unlikely* and *highly unlikely*.

Using the Chen and Klein formula (Chen & Klein, 1997), the comparative series of the failure factors are obtained. The Chen and Klein formula is outlined in Equation 4. The comparative series calculation is undertaken for the linguistic terms provided by the experts for the three failure factors. For example, the Likelihood linguistic term selected by expert #3 for the pipeline product leak failure factor used in the previous example is *high*, thus the comparative series is:

$$K(x) = \frac{(4-0)+(5-0)}{((4-0)+(5-0))-((4-5)+(3-5))}$$

$$= 0.75$$

The input for the calculation and the results are shown in Table 13. *Av K(*x*)* is the average of the comparative series of the three experts, taking into consideration the weight assigned to each expert based on their relevant experience and expertise.

Table 13: Comparative Series - Product Leak/Blockage Failure Modes

		Likelihood			Detection			Severity		
Experts		1	2	3	1	2	3	1	2	3
Product leak		HI	HI	HI	HL	HL	LI	CA	CR	CR
	d	5	5	5	5	5	5	5	5	5
	c	0	0	0	0	0	0	0	0	0
	a_0	3	3	3	0	0	1	4	3	3
	b_0	5	5	5	2	2	3	5	5	5
	a_i	4	4	4	1	1	2	5	4	4
	b_i	4	4	4	1	1	2	5	4	4
	K(x)	0.75	0.75	0.75	0.25	0.25	0.42	0.91	0.75	0.75
	Av		**0.75**			**0.31**			**0.80**	
Blockage		AV	LO	AV	HL	LI	RL	CA	MO	MA
	d	5	5	5	5	5	5	5	5	5
	c	0	0	0	0	0	0	0	0	0
	a_0	2	1	2	0	1	2	4	2	1
	b_0	4	3	4	2	3	4	5	4	3
	a_i	3	2	3	1	2	3	5	3	2
	b_i	3	2	3	1	2	3	5	3	2
	K(x)	0.58	0.42	0.58	0.25	0.42	0.58	0.91	0.58	0.42
	Av		**0.53**			**0.42**			**0.64**	

Note: HI is high, HL is highly likely, CA is catastrophic, CR is critical, AV is average, LO is low, LI is likely RL is reasonably likely, MO is moderate and MA is marginal

The comparative series of the two failure modes is summarised below, using Equation 11.

For product leak: $S_c(leak) = \left[\ |0.75| \quad |0.31| \quad |0.80|\ \right]$

For blockage: $S_c(blockage) = \left[\ |0.53| \quad |0.42| \quad |0.64|\ \right]$

Once a comparative series is obtained, a standard series is also calculated; this enables the difference between the two to be assessed. The standard series are the ideal failure factors values to be aimed at, which for Likelihood, Severity and Detectability should be *very low, negligible* and *highly likely*, respectively.

Using Equation 4, the standard series for the three failure factors is calculated as 0.25.

$$K(x) = \frac{(1-0)+(2-0)}{((1-0)+(2-0))-((1-5)+(0-5))}$$

$$= 0.25$$

The difference between the standard series and the comparative series for the two failure modes is shown below. The difference is obtained by subtracting the standard series from the average comparative series for the three failure factors using Equation 13.

For the product leak, the difference (D_0) is:

$$D_0(leak) = \left[\ \|0.75-0.25\| \quad \|0.31-0.25\| \quad \|0.80-0.25\|\ \right]$$

$$D_0(leak) = \left[\ \quad |0.50| \qquad\qquad |0.06| \qquad\qquad |0.55| \quad\ \right]$$

For the blockage, the difference D_0 is:

$$D_0(blockage) = \left[\ \|0.53-0.25\| \quad \|0.42-0.25\| \quad \|0.64-0.25\|\ \right]$$

$$D_0(blockage) = \left[\ \quad |0.28| \qquad\qquad |0.17| \qquad\qquad |0.39| \quad\ \right]$$

The next step is obtaining the Grey Relations coefficient, $\gamma\left(x_0(1), x_n(1)\right)$, for the three failure factors – Likelihood, Severity and Detectability. This is obtained by applying Equation 5.

Finally, the degree of relation is calculated using Equation 6, taking into account the agreed weighting coefficient for each of the failure factors.

Table 14 shows the input and the results of all the failure modes.

Table 14: Degree of Relation Inputs for all Failure Modes

#	Equipment Description	Failure Modes	Failure Factors	Grey Relation Co-efficient	Weighting Co-efficient	Degree of Relation
1	Oil Pipeline	Product Leak/Rupture	Likelihood	0.75	0.33	0.69
			Severity	0.63	0.33	
			Detection	0.70	0.33	

#	Equipment Description	Failure Modes	Failure Factors	Grey Relation Co-efficient	Weighting Co-efficient	Degree of Relation
2	Oil Pipeline	Product Leak/Rupture	Likelihood	0.57	0.33	0.68
			Severity	0.54	0.33	
			Detection	0.92	0.33	
3	Oil Pipeline	Product Leak/Rupture	Likelihood	0.66	0.33	0.65
			Severity	0.63	0.33	
			Detection	0.66	0.33	
4	Oil Pipeline	Blockage	Likelihood	0.70	0.33	0.71
			Severity	0.63	0.33	
			Detection	0.80	0.33	
5	Oil Pipeline	Line Valve Failure	Likelihood	0.85	0.33	0.76
			Severity	0.63	0.33	
			Detection	0.80	0.33	
6	Pipeline Manifold/ Block Valve	Product Leak/Rupture	Likelihood	0.70	0.33	0.66
			Severity	0.54	0.33	
			Detection	0.75	0.33	
7	Pipeline Manifold/ Block Valve	Product Leak/Rupture	Likelihood	0.70	0.33	0.66
			Severity	0.57	0.33	
			Detection	0.70	0.33	
8	Pipeline Manifold/ Block Valve	Blockage	Likelihood	0.75	0.33	0.71
			Severity	0.60	0.33	
			Detection	0.80	0.33	
9	Pipeline Manifold/ Block Valve	Line Valve Failure	Likelihood	0.85	0.33	0.78
			Severity	0.63	0.33	
			Detection	0.85	0.33	
10	Pipeline Manifold/ Block Valve	Line Valve Failure	Likelihood	0.92	0.33	0.76
			Severity	0.66	0.33	
			Detection	0.70	0.33	
11	Pipeline Manifold/ Block Valve	Line Valve Failure	Likelihood	0.75	0.33	0.69
			Severity	0.70	0.33	
			Detection	0.63	0.33	
12	Pumps	Product Leak	Likelihood	0.57	0.33	0.72
			Severity	0.66	0.33	
			Detection	0.92	0.33	
13	Pumps	Pump Fault	Likelihood	0.63	0.33	0.68
			Severity	0.70	0.33	
			Detection	0.70	0.33	
14	Pumps	Pump Failure	Likelihood	0.63	0.33	0.74
			Severity	0.59	0.33	
			Detection	1.00	0.33	
15	Pumps	Pump Failure	Likelihood	0.60	0.33	0.72
			Severity	0.57	0.33	
			Detection	1.00	0.33	
16	Pumps	Pump Failure	Likelihood	0.70	0.33	0.69
			Severity	0.57	0.33	
			Detection	0.80	0.33	
17	Utility	Loss of Supply	Likelihood	0.60	0.33	0.72
			Severity	0.57	0.33	
			Detection	1.00	0.33	
18	Utility	Reduced Supply	Likelihood	0.70	0.33	0.69
			Severity	0.75	0.33	
			Detection	0.63	0.33	
19	Utility	Electrical Over-supply	Likelihood	0.66	0.33	0.73
			Severity	0.59	0.33	
			Detection	0.92	0.33	
20	Metering Package	Instrumentation Fault	Likelihood	0.66	0.33	0.69
			Severity	0.80	0.33	

#	Equipment Description	Failure Modes	Failure Factors	Grey Relation Co-efficient	Weighting Co-efficient	Degree of Relation
			Detection	0.63	0.33	
21	Metering Package	Product Leak	Likelihood	0.66	0.33	0.67
			Severity	0.66	0.33	
			Detection	0.70	0.33	
22	Metering Package	Blockage	Likelihood	0.70	0.33	0.69
			Severity	0.63	0.33	
			Detection	0.75	0.33	
23	Pig Launcher/ Receiver	Product Leak/Rupture	Likelihood	0.59	0.33	0.64
			Severity	0.63	0.33	
			Detection	0.70	0.33	
24	Pig Launcher/ Receiver	Blockage	Likelihood	0.80	0.33	0.74
			Severity	0.63	0.33	
			Detection	0.80	0.33	
25	Pig Launcher/ Receiver	Valve Failure /Problems with Valve Sequencing	Likelihood	0.80	0.33	0.78
			Severity	0.75	0.33	
			Detection	0.80	0.33	
26	Pig Launcher/ Receiver	Door Failure	Likelihood	0.75	0.33	0.75
			Severity	0.70	0.33	
			Detection	0.80	0.33	
27	Future Tie-in Connection	Product Leak/Rupture	Likelihood	0.80	0.33	0.71
			Severity	0.70	0.33	
			Detection	0.63	0.33	

Note that for Grey Relation, the higher the value for a failure mode, the lower the relative risk of the failure, when compared to other failure modes.

5 Discussion

The results for the case study have been presented in Section 4.1 for the traditional FMEA, Section 4.2 for the Fuzzy Base Rule FMEA and Section 4.3 for the Grey Relation Theory FMEA. Table 15 presents the results and a comparison of the rankings. The results show a slight variation of the risk rankings depending on the FMEA approach used.

To allow for a comparison with the traditional approach, our initial analysis assumes that all experts have the same weighting, in terms of experience, and all the failure factors have the same weighting. The results indicate that each of the approaches produces similar but different risk priority rankings, but with the majority of the results broadly following the same pattern. The potential failures that have the same input produce fairly similar results. For example, failure events 15 (pump failure) and 17 (loss of supply) have the same linguistic variables and ranking. With the equal weighting that has been applied to the experts and the failure factors, the resulting risk ranking for the traditional FMEA is 18 for both events, the ranking using the FRB approach is 17 for both events whilst using GRT the ranking is 19 and 18, respectively.

Table 15: Comparison of the Different FMEA Results and Ranking

S/N	Equipment Description	Failure Mode	Results			Ranking		
			RPN	FRB	GRT	RPN	FRB	GRT
1	Oil Pipeline	Product Leak/Rupture	20	0.563	0.690	9	9	9
2	Oil Pipeline	Product Leak/Rupture	22	0.603	0.676	7	5	6

3	Oil Pipeline	Product Leak/Rupture	30	0.838	0.650	2	1	2
4	Oil Pipeline	Blockage	18	0.383	0.708	14	15	15
5	Pipeline Manifold/Block Valve	Product Leak/Rupture	11	0.333	0.759	24	20	24
6	Pipeline Manifold/Block Valve	Product Leak/Rupture	27	0.665	0.662	4	3	4
7	Pipeline Manifold/Block Valve	Product Leak/Rupture	29	0.785	0.656	3	2	3
8	Pipeline Manifold/Block Valve	Blockage	17	0.355	0.712	16	17	16
9	Pipeline Manifold/Block Valve	Line Valve Failure	10	0.333	0.778	26	20	26
10	Pipeline Manifold/Block Valve	Line Valve Failure	11	0.333	0.762	24	20	25
11	Pipeline Manifold/Block Valve	Line Valve Failure	20	0.563	0.690	9	9	9
12	Pumps	Product Leak	16	0.413	0.716	17	14	17
13	Pumps	Pump Fault	24	0.598	0.676	5	6	6
14	Pumps	Pump Failure	12	0.333	0.740	22	20	22
15	Pumps	Pump Failure	15	0.355	0.721	18	17	19
16	Pumps	Pump Failure	22	0.598	0.687	7	6	8
17	Utility	Loss of Supply	15	0.355	0.720	18	17	18
18	Utility	Reduced Supply	20	0.563	0.690	9	9	9
19	Utility	Electrical Over-supply	14	0.333	0.725	20	20	20
20	Metering Package	Instrumentation Fault	20	0.433	0.695	9	13	13
21	Metering Package	Product Leak	24	0.598	0.674	5	6	5
22	Metering Package	Blockage	20	0.563	0.690	9	9	9
23	Pig Launcher/Receiver	Product Leak/Rupture	33	0.665	0.641	1	3	1
24	Pig Launcher/Receiver	Blockage	13	0.333	0.739	21	20	21
25	Pig Launcher/Receiver	Valve Failure/Problems with Valve Sequencing	9	0.273	0.779	27	27	27
26	Pig Launcher/Receiver	Door Failure	12	0.333	0.747	22	20	23
27	Future Tie-in Connection	Product Leak/Rupture	18	0.383	0.707	14	15	14

When the model is rerun with experience of the experts taken into consideration, by assigning a weighting of 0.4, 0.1 and 0.5 to experts 1, 2, and 3, respectively, the FRB ranking changes from 17 to 25 for both failure events. This shows the significant impact that a weighted input could have on the overall results and, thus, the failure factors that the operator should concentrate on to reduce the pipeline's likelihood of failure.

Also, the impact of the use of a failure factor's weighting in GRT can also be seen on failure items 15 (pump failure) and 17 (loss of supply). The two failure events have the same weighting of 0.33 for the Likelihood, Severity and Detectability factors, giving a risk ranking of 19 and 18, respectively. However, when the weighting factors are changed to 0.4, 0.4 and 0.2, the risk ranking changes to 6 and 5, respectively.

It can be seen that the modified approaches utilised in this work allow for a more intuitive and transparent way to accommodate a combination of objective and subjective inputs and to produce results that take into account several factors, which are not accommodated by the traditional approach. According to Ramezani and Memariani (2011), these modelling approaches also benefit from the integration of the data-driven and physics-based models, complementing human investigative reasoning. The approach also allows experts to contribute directly to model building, is transparent to the user in such a way that a decision can be elucidated and engenders trust in the system by the users.

Pipeline failures have been moving up the agenda of the stakeholders in the industry due to the increase in the number of incidences both in developed and emerging countries (Ralby, 2017; Okoli & Orinya, 2013; Cech *et al.*, 2017; Hopkins, 2008). The consequences of these failures, including loss of life, environmental pollution and economic losses, are also increasing (Yeeles & Akporiaye, 2016; Carlson *et al.*, 2015). The improved and effective hazard identification process is one of the important tools in reducing such incidences by detecting potential failure and directing limited resources to areas that provide the most benefit in reducing such failure. This modified FMEA approach, if used, provides a tool that could help improve the operational efficiency and reduce pipeline failures.

6 Conclusions

This work develops modified models of identifying hazards of pipeline systems where the lack of historic data requires the integration of the experiences of field operatives in a formalised manner. The approach improves on the traditional approaches by addressing some of the identified drawbacks. This has been achieved by incorporating a fuzzy rule-based system and the grey theory into the FMEA.

The traditional FMEA has been a versatile tool in safety assessments to maintain system integrity and anticipate and prevent failures. The process is effective when there is historical data for precise numerical inputs. However, where there is inadequate or unreliable data, which is the case especially in developing countries, the FMEA can produce a wrong output, resulting in the misdirection of limited resources and the creation of a false sense of security (Liu *et al.*, 2011). The use of FRB and GRT ensures that, in addition to the limited data available, the experience of experts and operatives and the weighted contribution of each failure factor can be better incorporated into the FMEA. Additionally, the use of linguistic terms ensures that the inputs are more aligned with the natural language synthesis, to which field operatives and practitioners are more familiar with.

The modified FMEA approach has several advantages, and these are summarised below:

- It provides an opportunity to incorporate experts' experience and knowledge as part of the input when data is limited or uncertain.
- It augments the lack of data, allowing for more refined and representative results. It affords the operatives and experts the chance to express the failure modes in a language they normally use on a day-to-day basis.
- The process makes up for the weakness of the traditional FMEA where a small variation of one failure input can produce a disproportionate impact on the results.

- It introduces a weighting to both the input of experts (based on their experience) and to each failure factor, thus ensuring that the results reflect the actual contribution of each expert. It also ensures the failure factors with the most impact on the results are appropriately captured.

The operation of pipeline systems in developing countries is often associated with a high level of uncertainty because of inadequate data and complex socio-economic factors, among others. Its operation in such a challenging environment in which both technical and human and organizational malfunctions may contribute to a range of possible accidents requires a novel framework to address the identified challenges. The application of this modified FMEA integrating both FRB and GRT would help to address those challenges.

Although the modified FMEA proposed still relies on the subjective inputs of the selected experts and the assumptions made by the analyst, it can be a useful additional tool for pipeline risk analysis not only in Nigeria but also on any other geographical areas with similar challenges.

The proposed approach, first using FRB, which does not include weighting of the failure factors, would be ideal for use during the early phase of the hazard identification assessment where only the relative ranking of the hazards is important. The further integration of the Grey Relations Theory, which incorporates the weighting for failure factors can be used during the detailed stage where the contribution of each failure factor towards the RPN is important for efficient allocation of resources for optimum decision making relating to cross-country pipelines.

The application of the modified approach in the oil and gas cross-country pipeline domain widens the models' versatility and helps to address practical problems, such as refining the IF-THEN consequent risk to include belief degrees, addressing data uncertainty and allocating weighting to both the failure factors and the participating experts.

Acknowledgments

This research is partially supported by the Federal Government of Nigeria through the Petroleum Technology Development Fund.

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