Failure mode and effects analysis using a fuzzy-TOPSIS method: a case study of subsea control module

Athanasios J. Kolios*, Anietie Umofia and Mahmood Shafiee

Cranfield Energy and Power,
Cranfield University,
College Road, Cranfield, Bedfordshire,
MK43 0AL, UK
Email: a.kolios@cranfield.ac.uk
Email: aumofia@yahoo.com
Email: m.shafiee@cranfield.ac.uk
*Corresponding author

Abstract: Failure mode and effects analysis (FMEA) is one of the most common reliability engineering techniques used for identifying, evaluating and mitigating the engineering risks. In this paper, the potential failure modes of a subsea control module (SCM) are identified based on industry experts' opinions and experiences. This is followed by a comprehensive component based FMEA study using the risk-priority-number (RPN) where the most critical failure modes in the SCM are revealed. A fuzzy TOPSIS-based multiple criteria decision making methodology is then proposed to analyse and prioritise the most critical failure modes identified by the FMEA study. To this aim, a distinct ten-parameter criticality model is developed and, for the first time, is applied to evaluate the risks associated with SCM failures. The results indicate that the proposed fuzzy TOPSIS model can significantly improve the performance and applicability of the conventional FMEA technique in offshore oil and gas industry.

Keywords: failure mode and effects analysis; FMEA; multiple-criteria decision making; MCDM; the technique for order of preference by similarity to ideal solution; TOPSIS; subsea control module; SCM; risk assessment.

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Biographical notes: Athanasios Kolios is a Senior Lecturer in Risk Management and Reliability Engineering and the Director of the Energy Doctoral Training Programme at Cranfield University. His research expertise includes reliability analysis using non-intrusive stochastic expansions, risk-based design, analysis and operational management of offshore/marine structures, and integrity assessment of ageing structures. He has a track record in research council, industry sponsored and consultancy projects related to his area of expertise. He has authored more than 80 peer-reviewed journal and conference papers. He is a Chartered Engineer of the Institution of Mechanical Engineers and a Fellow of the Higher Education Academy.

Anietie Umofia is a Senior Subsea Engineer/Project Coordinator with Eni-Nigerian Agip Oil Company, Abuja, Nigeria. He holds a honourable Bachelor's degree in Electrical and Electronics Engineering (BEng) from University of Port Harcourt, a Master (MSc) in Offshore and Ocean Technology and a Doctoral (PhD) in Reliability of Subsea Systems from Cranfield University, United Kingdom. He has over 15 years oil and gas industry experience cutting across Shell, TOTAL and Eni, working on shallow, deep and ultra deep water offshore multi-billion dollars projects.

Mahmood Shafiee is a Lecturer in Engineering Risk Analysis at Cranfield University, UK. His expertise is in the fields of reliability engineering, maintenance and inspection planning, structural health assessment, aging and degradation modelling, probabilistic risk analysis, asset management, warranty and service reliability. He has over ten years of experience in the area of risk and reliability engineering within the oil and gas, renewable wind, railway, and manufacturing industry sectors. He has also published more than 60 papers in top tier journals and conference proceedings. He has been plenary speaker and program committee member of more than 20 international conferences.

1 Introduction

Failure mode and effects analysis (FMEA) is one of the most popular engineering techniques used to assess systems reliability among others such as fault tree analysis (FTA) and reliability block diagram (RBD) (Eid Al-Adwani, 2012; Lundteigen et al., 2009). The application of the FMEA technique dates back to the 1950-60s (Arhagba, 2010; Liu et al., 2013) and since then, it has been used in a wide range of industries including nuclear, aerospace, mechanical, automotive, medical, electronics and the onshore/offshore oil and gas industries. FMEA provides a structured approach to the examination of potential failure modes and impact of failures on product operation during field use or to the identification and correction of process problems prior to first execution (David et al., 2010; Wabnitz and Netherland, 2001). The technique is best applied during the planning and design stage of a system for optimal results. It is an assessment tool that allows the user to methodically list system components or process steps, identifying their functions, failure modes, effects and failure causes to rank their criticality or risk. The approach can easily be modified and applied to a wide range of engineering problems and applications allowing to adjust the criteria from what constitutes 'risk' to the respective purpose of the analysis.

The process starts out with a qualitative analysis of systems and their functions, followed by a quantitative evaluation of the potential risks as data becomes available as well as identification of corrective actions for all associated failure modes as the end result. The FMEA study is performed by developing a RPN which helps to compare and prioritise issues for necessary correction. In order to calculate the RPN values for each failure mode, three factors of risk namely the severity of impact (S), the likelihood of occurrence (O) and the likelihood of detection (D) should be rated (Ceccarelli, 2009). RPN is defined as the product of the values for these three risk factors and given by equation (1):

$$RPN = Severity(S) \times Occurrence(O) \times Detection(D) \tag{1}$$

where *S*, *O* and *D* are evaluated on a scale of 1–10 (1 = low – most favourable score, and 10 = high – least favourable score). For each failure mode, the values for *S*, *O* and *D* are determined and multiplied together to obtain RPN values, which are then prioritised and ranked. Focus is then given to failure modes possessing the highest RPN for the possibility of corrective actions.

Even though the FMEA technique has proven to be a vital and useful tool for preventing failures in system design, process and services, the RPN calculation has been extensively criticised in many studies (see, e.g. Braglia et al., 2003; Bowles, 2003). Below are listed some of the main drawbacks that have been identified (in relative order of importance):

- lack of consideration to the relative importance of *O*, *S* and *D*
- different combinations of *O*, *S* and *D* may produce equal RPN values but differing implications
- difficulty in precision on the prediction of the values for *O*, *S* and *D*
- varying methods for converting the scores of the risk factors
- the RPN is not capable of measuring the effectiveness of the corrective actions
- the values of the RPN are not continuous with many holes
- the interdependencies across the failure modes are not considered
- the RPN is highly sensitive to variations in the risk factors
- the RPN only considers three factors principally on safety terms.

A vast majority of the studies conducted on FMEA methodologies aim at bridging these gaps. According to Liu et al. (2013), the techniques proposed to overcome the FMEA drawbacks can be grouped into five key categories, namely multi-criteria decision making (MCDM); artificial intelligence (AI); mathematical programming (MP); hybrid approaches; others.

Fundamentally, each of the above techniques uses a different approach of implementation for coping with the deficiencies associated with the FMEA. Prominent approach across all these methodologies is the fuzzy concept. In this paper, an MCDM method by integrating the technique of order preference by similarity to ideal solution (TOPSIS) and fuzzy logic is proposed to prioritise the criticality of potential failures in the subsea control module (SCM). The method is principally used to overcome the obvious limitations with the traditional FMEA. The fuzzy approach is adopted as it eliminates the intrinsic difficulty of handling crisp values while evaluating the conventional RPN values (Guimaraes and Lapa, 2004). Furthermore, considering the vague nature of the three conventional FMCA risk factors – occurrence (*O*), severity (*S*) and detectability (*D*), they are expanded into ten explicit parameters. This is exemplified in a less generic case study from Sachdeva et al. (2009) where the conventional FMEA risk factors are broken down into six (failure occurrence, non-detection, maintainability, spare parts, economic safety and economic cost) for the criticality evaluation of maintenance plans. The scope of the methodology proposed in this paper is to allow more flexibility in the risk assessment of complex sytems, through reducing the bias of deterministic values and at the same time allow more represetnative criteria to be considered in the decision support process.

The rest of this paper is organised as follows. In Section 2, an overview of the SCM and its main elements is provided. In Section 3, the fuzzy-TOPSIS method to risk assessment is presented. In Section 4, the application of the method to a SCM is presented and the results are reported in Section 5. Section 6 concludes this study and suggests topics for future research.

2 Subsea control module

SCM is the brain of a subsea control system (SCS) which is one of the main components of a subsea production system (SPS). It is typically installed in a subsea Xmas tree, manifold or subsea distribution units (SDUs) and serves as a control centre responsible for the distribution of electrical and hydraulic power and the interpretation of all signals. Typically, a sealed dielectric fluid-filled container at 1-atm pressure protects the internal components from seawater intrusion. There are basically three types of SCM (Broadbent, 2010): the all-hydraulic SCM; the electro-hydraulic SCM; and the all-electric SCM.

Current SCMs are primarily designed for subsea valve operations and downhole safety valve control and monitoring of temperature and pressure at the wellhead. The functions of the SCM can be classified as: low pressure (LP) functions; high pressure (HP) functions; remote sensing; internal sensing; control fluid accumulation; and downhole gauges control.

The SCM receives LP, HP including multiplexed electrical power and signal from the surface via the umbilical. This operation happens in such a way that a hydraulic signal is transmitted to the appropriate hydraulic valve in the subsea Xmas tree, manifold, downhole instrumentation or any other subsea equipment. Electrical signals decoded by the subsea electronic module (SEM) operate solenoid directional control valves (DCVs), directing the fluid to the appropriate subsea system valves, safety valves or chemical injection functions. Signals from the subsea sensors are also encoded through the SEM in the SCM and sent back to the surface facility. The subsea control module mounting base (SCMMB) provides the connecting point between the SCM and the subsea Xmas tree functions and monitoring equipment. Tubing and electrical cables connect the SCMMB to the tree.

The SCM contains two fully redundant SEMs for controlling all subsea valve operations and communications with the topside. The two SEMs are completely independent of each other. If one SEM fails, the control link is switched to the next one for the provision of all control functions. Normally, the switching operation is performed manually by the topside control operator. Table 1 summarises the main parts that a SCM typically consists of.

One of the key components of the hydraulic system in the SCM is the DCV. DCVs are used in SCSs to provide hydraulic power to open and close hydraulically actuated process valves on subsea Xmas trees, manifolds and other similar subsea control equipment. Failure of a DCV can be very critical to subsea control operations.

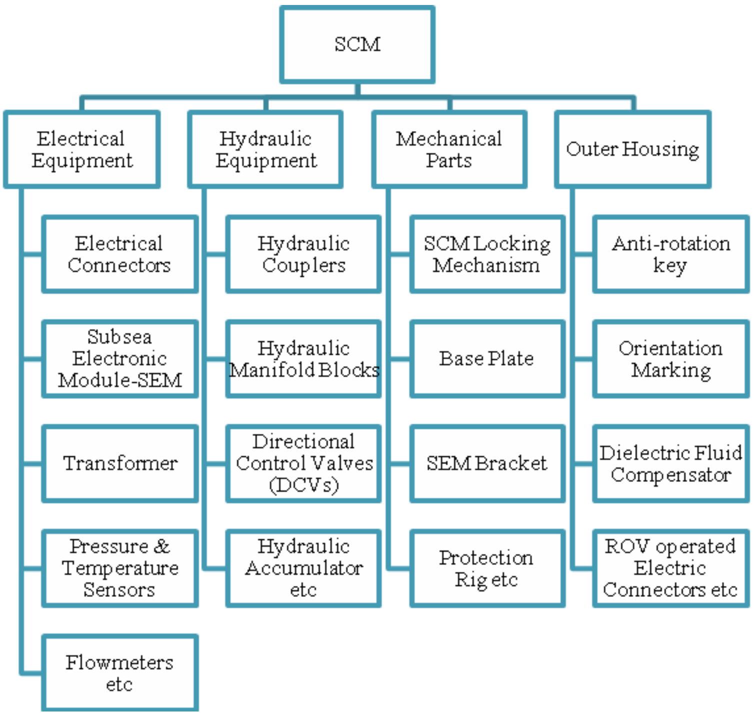
Table 1 Main parts of a SCM

A base plate	*Needle valves*	*Hydraulic couplers*
A latching mechanism	SEMs	Electrical connectors
Hydraulic filters	A compensation cover	SCM housing/cover
Selector valves	Electrical connectors	DHPT assemblies
Relief valves	Accumulators	Miscellaneous seals, fittings, fasteners and electrical components

A pressure compensation system in the SCM provides compensation for pressure and temperature variations as the SCM is lowered subsea during installation or retrieval. During installation, the SCM is lowered using a subsea control module running tool (SCMRT) onto the SCMMB where the hydraulic couplers and electrical connectors on the SCM base plate mate with their associated couplings and connectors on the SCMMB.

Typically, the SCM consists of four main parts: electrical equipment subsystem; hydraulic equipment subsystem; mechanical parts; and the SCM housing. Figure 1 represents a diagrammatic view of the sections and parts included in the SCM. To analyse the reliability of the SCM, the system should be broken down into its respective components or elements.

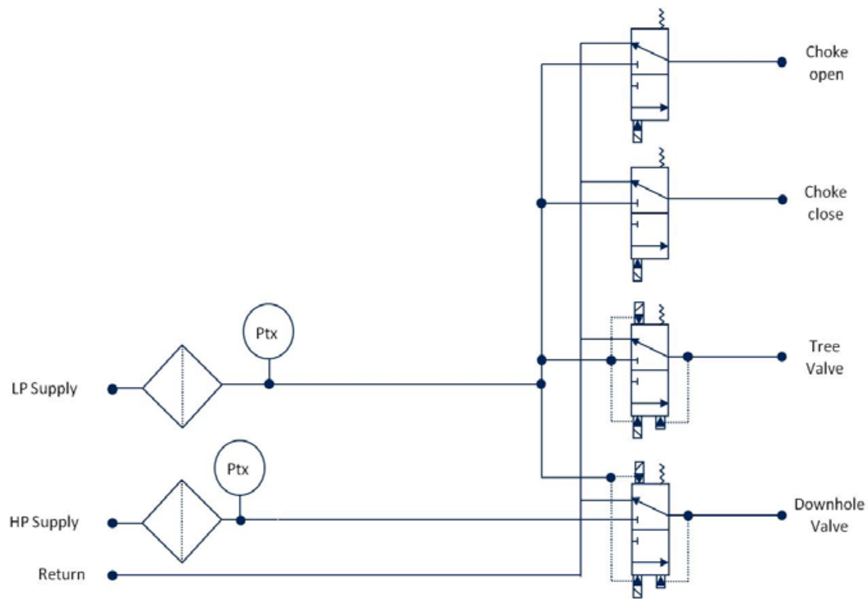
Figure 1 Schematic of the different sections of the SCM (see online version for colours)



The SCM contains three separately rated circuits: an LP circuit, an HP circuit and a return circuit at pressure values typically lower than the LP and HP circuitries (Rowntree, 2002; Beedie, 2010; Bavidge, 2013). Figure 2 shows the routing of the LP, HP and the return hydraulic lines in the SCM. The return circuit is common for spent fluid from both the LP and HP circuits.

Both the LP and HP circuits of the SCM are supplied via two separate supply lines termed 'A' and 'B', which enter the SCM via base mounted hydraulic couplers. Upon entering the SCM the fluid of each line is passed through filters and pressure transducers to remove contamination and enable individual line pressure measurement.

Figure 2 Hydraulic schematic of the SCM (see online version for colours)

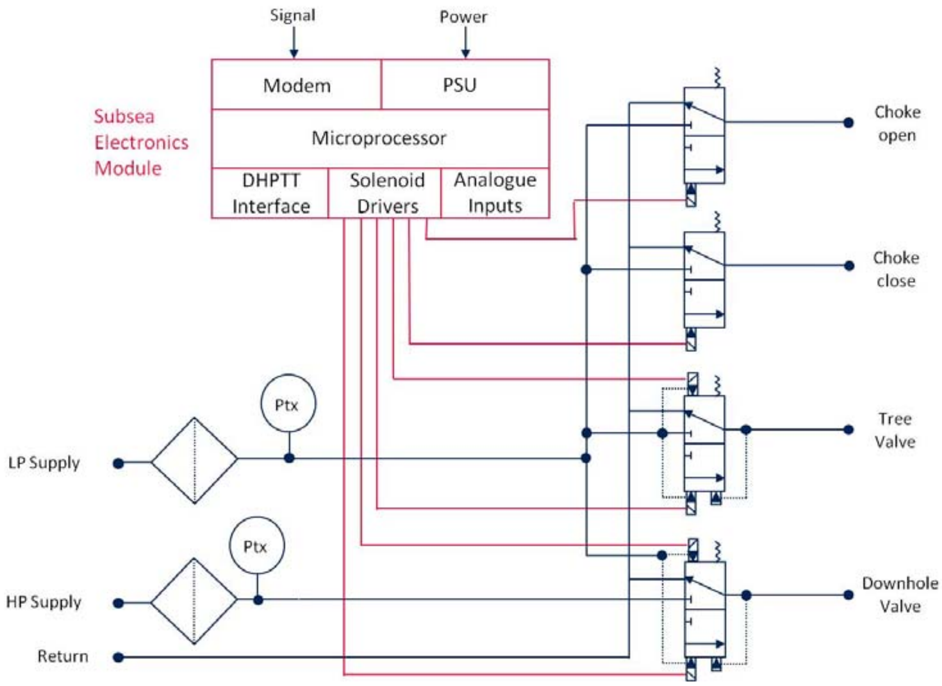


Within the SCM there are dual SEMs connected to the two redundant channels of the SCM. Within the SCM, each SEM is connected to all electrical components. The SEM is a computer-like electronic device responsible for the control of the hydraulic manifold system in the SCM using a selection of solenoid driven valves for the delivery of subsea hydraulic functions (Saul, 2006). It is also connected to internal and external sensor systems for production and subsea condition monitoring. Figure 3 illustrates an electrical schematic of the SCM showing the electrical distribution from the SEM to the SCM components. The red lines represent the routing of the electrical power lines from the SEM to each of the functional tree valves including the choke.

A typical configuration will require pilot valves with two solenoids each to operate, one to open and the other to close. The solenoids are driven by the solenoid drivers in the SEM. To open a tree valve, the appropriate solenoid is commanded from the master control station (MCS), the microprocessor in the SEM activates the solenoid driver which energises the open solenoid. This allows hydraulic fluid to flow into the function line to the tree valve actuator. The pressure in this line will rise very quickly to a value which allows the valve to latch open hydraulically. Thereafter, the valve will remain open as long as the hydraulic supply pressure remains above a prescribed value. To close a tree valve, the close solenoid is energised in a similar manner causing the spool in the valve to move, venting the hydraulic fluid from the tree valve actuator. The used fluid exits the SCM via the return line. It is worth mentioning here that most of the control valves in the

SCM when operated are latched open hydraulically. On electrical power failure to the SCM, these valves will stay as is.

Figure 3 Electrical functional schematic of the SCM (see online version for colours)



The SCM consists in principle of a pressure and temperature compensated, dielectric oil filled chamber, bound by a protective cover and baseplate. Within the dielectric chamber are housed all major hydraulic and electrical components. Incoming electrical supplies are provided via two electrical connectors located at the top of the unit. Hydraulic connections are made via couplers located in the baseplate of the SCM and hidden from view in normal operation by a protective skirt.

The SCM is designed to be locked to the mounting base through the use of a latch and lock mechanism. During the lock down sequence, the SCM is moved from an initial ‘landed’ position to a final fully ‘locked’ position, where all hydraulic and electrical connections are made and the SCM is torque tightened against a mechanical stop. The SCM housing is a very critical part because its failure results in the ingress of water to the internals of the system (Bai and Bai, 2010). This typically results in the corrosion of exposed metallic components and eventual failure of the entire system with time. The SCM is typically manufactured from either painted carbon steel, non-metallic materials or corrosion resistant alloys (primarily stainless steel).

3 Fuzzy-TOPSIS methodology for risk assessment

Several multi-criteria decision making (MCDM) techniques have so far been applied to analyse, evaluate and mitigate the risks associated with engineering systems, including simple additive weighting (SAW), analytic hierarchy process (AHP), analytic network process (ANP), TOPSIS, VIšekriterijumsko KOmpromisno Rangiranje (VIKOR), etc. TOPSIS is a linear weighting MCDM technique which was initially proposed by Hwang and Yoon (1981). The technique begins with creating a decision matrix:

$$X = \left[x_{ij} \right] \tag{2}$$

where x_{ij} is the rating of alternative i (i = 1, 2........,n) with respect to criterion j (j = 1, 2........,m). The next step is to normalise the judgement matrix $X = [x_{ij}]$ in which the equation below is used:

$$r_{ij} = \frac{x_{ij}}{\Sigma_{i=1}^{n} x_{ij}} \qquad i = 1, 2, \ldots\ldots, n \tag{3}$$

Afterwards, the weights for each comparison criterion should be computed. This is done by evaluating the entropy e_j of each criterion C_1, C_2 ,..., C_n . Let e_j represent the entropy of the j^{th} criterion (j = 1,2,……m). Then,

$$e_j = \frac{1}{\ln n} \Sigma_{i=1}^{n} r_{ij} \ln r_{ij} \qquad j = 1, 2, \ldots\ldots m \tag{4}$$

where $1/\ln n$ is a constant term which keeps the value of e_j between 0 and 1. The weights of each criterion are given by:

$$w_j = \frac{1 - e_j}{\Sigma_{j=1}^{m} \left(1 - e_j \right)} \tag{5}$$

The positive and negative ideal solutions are then determined using the equations (6)–(9). This provides a performance indicator for each of the criterion of comparison.

$$v^{+} = \left(\max_{i} \left(r_{i1} \right), \max_{i} \left(r_{i2} \right), \ldots\ldots \max_{i} \left(r_{in} \right) \right) \tag{6}$$

$$v^{+} = \left(v_1^{+}, v_{2,\ldots\ldots\ldots\ldots\ldots\ldots}^{+} v_n^{+} \right) \tag{7}$$

and

$$v^{-} = \left(\min_{i} \left(r_{i1} \right), \min_{i} \left(r_{i2} \right), \ldots\ldots \min_{i} \left(r_{in} \right) \right) \tag{8}$$

$$v^{-} = \left(v_1^{-}, v_{2,\ldots\ldots\ldots\ldots\ldots\ldots}^{-} v_n^{-} \right) \tag{9}$$

The distance of each criterion from the positive ideal solution (PIS) and the negative ideal solution (NIS) are then computed. The following equations are used for the calculation of Euclidean distance of each alternative to v^{+} and v^{-}:

$$d_i^{+} = \sqrt{\Sigma_{j=1}^{m} w_j \left(v_j^{+} - r_{ij} \right)^2} \tag{10}$$

$$d_i^{-} = \sqrt{\Sigma_{j=1}^{m} w_j \left(r_{ij} - v_j^{-} \right)^2} \tag{11}$$

where d_i^+ and d_i^- represent the distance of the i^{th} alternative from the PIS and NIS respectively. Finally, the preference order is ranked. In principle, TOPSIS method is performed in such a way that the alternative chosen would have the 'shortest distance' from the PIS and the longest distance from the NIS. Though TOPSIS is a very popular technique, it has some limitations, e.g. it uses the Euclidean distance algorithm which does not consider the correlation of attributes, or the weight coefficients are determined using an expert method or AHP, which all have some elements of subjectivity.

In order to reduce the subjectivity of the fuzzy TOPSIS methodology implemented in this paper, the following steps are applied:

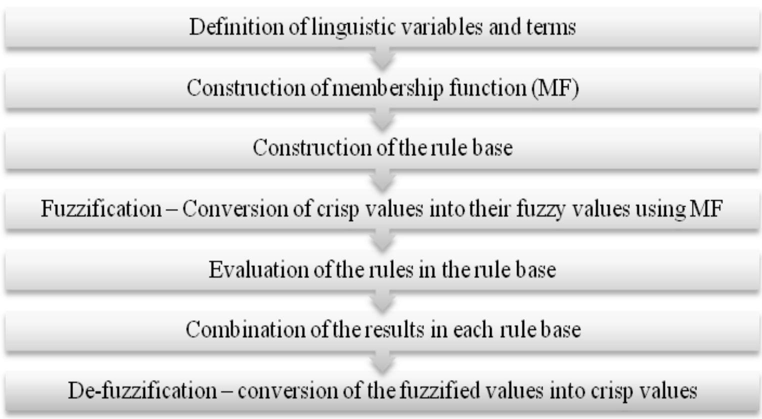
1 by asking ten experts, a better representation of the scoring of alternatives against attributes is obtained (rather than one deterministic value in conventional approaches)

2 through breaking down occurrence *O*, severity *S* and detectability *D* to more basic sub-criteria, the influence of an exaggerated value is reduced in comparison to multiplying the crisp values of *O*, *S* and *D*, addressing the limitation reported in the literature (Bowles, 2003; Kutlu and Ekmekçioğlu, 2012).

3.1 *The fuzzy logic to FMEA*

A number of approaches have been developed in the literature to overcome the limitations of classical techniques by combining MCDM methods and consideration of uncertainty in inputs (see, e.g. Zarghami et al., 2008; Kaya and Kahraman, 2010; Dinmohammadi and Shafiee, 2013; Ren et al., 2013; Perera et al., 2013; Madani et al., 2014; Shafiee, 2015; Şengül et al., 2015; Kolios et al., 2016a, 2016b). Fuzzy logic is a form of many-valued logic which deals with reasoning that is approximate rather than fixed and exact (Kumru and Yildiz, 2013). Compared to traditional binary sets where variables only take on true or false values, fuzzy logic variables may have a truth value that ranges in degree between 0 and 1. Fuzzy logic has been extended to handle the concept of partial truth, where the truth value may range between completely true and completely false (Matin et al., 2011; Medineckiene, 2015). Figure 4 summarises the main steps for a fuzzy logic algorithm.

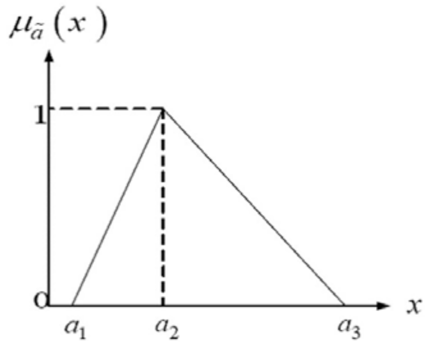
Figure 4 Main steps for a fuzzy logic algorithm



Linguistic variables are basically inputs or output variables of systems whose values are words or sentences instead of numerical values. Generally, it is usually decomposed into a set of linguistic terms (Wang and Lee, 2009; Chen, 2000). Membership functions in fuzzy logic system (FLS) are used in the fuzzification and de-fuzzification, i.e., mapping non-fuzzy values to fuzzy linguistic terms and vice versa. A membership function basically quantifies the value of a linguistic term. Different forms of membership functions exists – trapezoidal, piecewise linear, triangular, Gaussian or singleton (Chen, 2000; Wang and Lee, 2009).

The triangular membership function is the most popular among all (Kutlu and Ekmekçioğlu, 2012) and is represented with three points as follows: $A = (a_1, a_2, a_3)$. The membership function $\mu_A(x)$ for a triangular fuzzy number (TFN) is shown in Figure 5.

Figure 5 The membership function for a TFN



Key merits of using the TFNs are that they are typically less complex in computations; they provide more accurate ranking results; they are more effective in representing the judgement distribution of multiple experts (Braglia et al., 2003).

Let X be a nonempty set. A fuzzy set A in X is characterised by its membership function μ_A: $x \rightarrow [0, 1]$ where $\mu_A(x)$ expresses the degree of membership of element x in fuzzy set A for each $x \in X$.

$$\mu_A(x) = \begin{cases} \dfrac{x - a_1}{a_2 - a_1} \; if \; a_1 \le x \le a_2 \\ \dfrac{a_3 - x}{a_3 - a_2} \; if \; a_2 \le x \le a_3 \\ 0 \; if \; x < a_1 \; or \; x > a_3 \end{cases} \tag{12}$$

where a_1, a_2, a_3 are real numbers. Assuming that A and B are defined as:

$$A = (a_1, a_2, a_3) \quad and \quad B = (b_1, b_2, b_3), \tag{13}$$

then, the addition of these variables C will be represented as

$$C = (a_1 + b_1, a_2 + b_2, a_3 + b_3), \tag{14}$$

and the subtraction D and the multiplication are given by equations (15) and (16):

$$D = (a_1 - b_1, a_2 - b_2, a_3 - b_3), \tag{15}$$

$$E = (a_1.b_1, a_2.b_2, a_3.b_3). \tag{16}$$

Fuzzy FMEA allows both the quantitative data and qualitative linguistic information to be analysed in a consistent way making it possible for the risk factors – severity, occurrence and detectability to be combined in a more flexible structure.

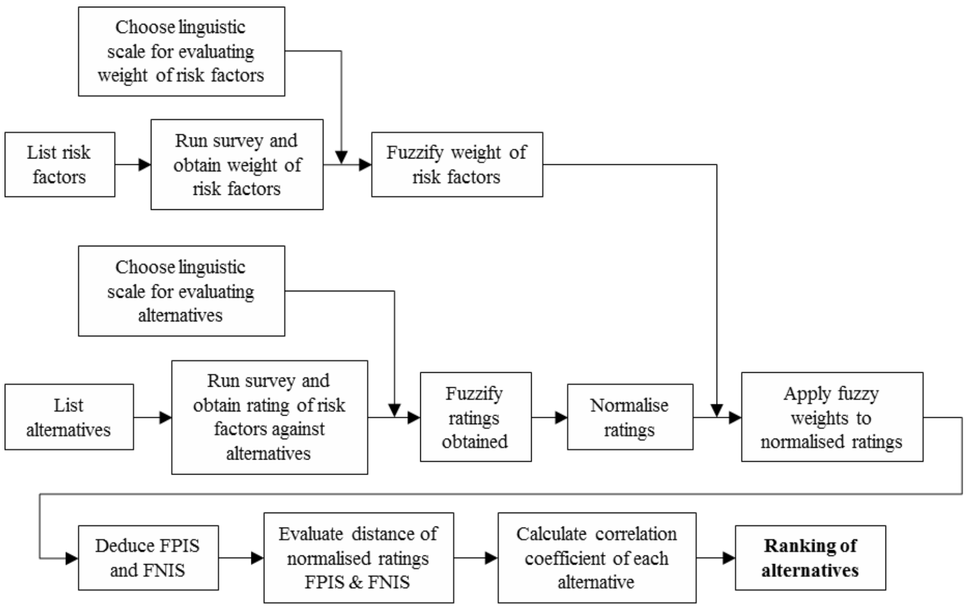
3.2 Fuzzy-TOPSIS method

The fuzzy multi-criteria decision making methodology is a popular method for bridging the gaps and limitations of the conventional FMEA approach (Kutlu and Ekmekçioğlu, 2012; Liu et al., 2013). In the fuzzy TOPSIS analysis, the alternative closest to the fuzzy positive ideal solution (FPIS) and farthest from the fuzzy negative ideal solution (FNIS) is selected as the optimal alternative (Madi, 2011; Kolios et al., 2010). FPIS is indicative of a higher performance compared to that of the FNIS, which is being attributed to a worse performance. According to Kim et al. (1997), the use of fuzzy TOPSIS has the following advantages:

- a sound logic that represents the rationale of human choice
- a scalar value that accounts for both the best and worst alternatives simultaneously
- a simple computation process that can be easily programmable
- the performance measures for all alternatives can be visualised.

Figure 6 provides a general overview on the fuzzy TOPSIS methodology.

Figure 6 Fuzzy TOPSIS methodology



In the fuzzy TOPSIS method, the importance (weight) of each evaluation criterion is expressed in linguistic terms as shown in Table 2 (Kolios et al., 2016a; Braglia, 2000; Erugrul and Karakaşoğlu, 2008).

Table 2 Linguistic scales for importance weight of each criterion (R_i)

Linguistic variable	*Corresponding TFN*		
Very low (VL)	0.0	0.0	0.1
Low (L)	0.0	0.1	0.3
Medium (M)	0.3	0.5	0.7
High (H)	0.7	0.9	1.0
Very high (VH)	0.9	1.0	1.0

Similarly, the linguistic scales for evaluating the SCM failure modes to the corresponding risk factors are depicted in Table 3 (Chen, 2000; Braglia, 2000).

Table 3 Linguistic scales for rating the SCM failure modes against the risk factors

Linguistic variable	*Fuzzy score*		
Very low (VL)	0	0	1
Low (L)	0	1	3
Medium low (ML)	1	3	5
Medium (M)	3	5	7
Medium high (MH)	5	7	9
High (H)	7	9	10
Very high (VH)	9	10	10

Consider K experts or decision makers using the linguistic variables shown in Tables 2 and 3 to evaluate the weight of each criterion and the rating of these criteria to the corresponding alternatives, the fuzzy rating and the importance weight of k^{th} decision maker about i^{th} alternatives with respect to j^{th} criterion are given respectively by:

$$x_{ij}^k = \left(a_{ij}^k, b_{ij}^k, c_{ij}^k\right) \quad \text{and} \quad w_{ij}^k = \left(w_{j1}^k, w_{j2}^k, w_{j3}^k\right) \tag{17}$$

where $i = 1, 2, \ldots, m$, and $j = 1, 2, \ldots, n$. Then the aggregated rating, x_{ij} of the alternative (i) in correspondence to the respective criterion (j) is given by: $x_{ij} = (a_{ij}, b_{ij}, c_{ij})$, where:

$$a_{ij} = \min_k \left\{a_{ij}^k\right\}, b_{ij} = \frac{1}{K}\Sigma_{ij}^k b_{ij}^k, \text{ and } c_{ij} = \max_k \left\{c_{ij}^k\right\}, \tag{18}$$

Similarly, the aggregated weight w_{ij} of each criterion is $w_{ij} = (w_{j1}, w_{j2}, w_{j3})$, where

$$w_{j1} = \min_k \left\{w_{jk1}\right\}, w_{j2} = \frac{1}{K}\Sigma w_{jk2}, \text{ and } w_{j3} = \max_k \left\{w_{jk3}\right\} \tag{19}$$

Accordingly, a fuzzy decision matrix of the alternatives can then be represented in the format below:

$$D = \begin{array}{c c} & \begin{array}{cccc} c_1 & c_2 & \ldots\ldots & c_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \\ A_m \end{array} & \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & x_{ij} & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix} \end{array} \tag{20}$$

where $W = (w_1, w_2, \ldots\ldots\ldots w_n)$ represents the weights of the criteria.

Here x_{ij} are built by failure modes $A_i = (i = 1, \ldots\ldots m)$, which are evaluated against criterion $C_j = (j = 1, \ldots\ldots n)$. To avoid complication, a linear scale transformation is used for the normalisation process of the criteria scale. The fuzzy normalised decision matrix is given by:

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{mn} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{11} & \cdots & r_{11} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & & r_{mn} \end{bmatrix} \tag{21}$$

where $i = 1, 2, \ldots m$, $j = 1, 2\ldots., n$. The normalised values for benefit and cost related criteria are as shown below:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), \textit{ and } c_j^* = \max_i c_{ij};\ (j \in B, \textit{ benefit criteria}) \tag{22}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{c_{ij}}\right), \textit{ and } a_j^- = \min_i a_{ij};\ (j \in C, \textit{ cost criteria}) \tag{23}$$

The normalisation process here preserves and maintains the TFNs within the range [0, 1]. Considering the weight of each criterion, the weighted normalised fuzzy matrix is computed as:

$$\tilde{V} = \left[v_{ij}\right]_{mn}, i = 1, 2\ldots m;\ j = 1, 2\ldots n \tag{24}$$

where

$$v_{ij} = \tilde{r}_{ij}(\cdot)\tilde{w}_j \tag{25}$$

The FPIS and FNIS of the i^{th} failure modes (A_i) are then defined by equations (26) and (27) as follows:

$$A^* = \left(\tilde{v}_1^*, \tilde{v}_2^*, \ldots\ldots, \tilde{v}_n^*\right) \tag{26}$$

where $v_j^* = \max_i \{v_{ij3}\}, \quad i = 1, 2, \dots m;\ j = 1, 2, \dots n$

$$A^- = \left(\tilde{v}_1^-, \tilde{v}_2^-, \dots\dots, \tilde{v}_n^-\right) \tag{27}$$

where $v_j^- = \min_i \{v_{ij1}\}, \quad i = 1, 2, \dots m;\ j = 1, 2, \dots n$

The distances (d_i^* and d_i^-) of the failure modes (A_i, i = 1, 2….m), from the FPIS (A^+) and FNIS (A^-) respectively are calculated using the following equations:

$$d_i^* = \Sigma_{j=1}^n d_v\left(\tilde{v}_{ij}, \tilde{v}_j^*\right), i = 1, , 2, \dots m. \tag{28}$$

$$d_i^- = \Sigma_{j=1}^n d_v\left(\tilde{v}_{ij}, \tilde{v}_j^-\right), i = 1, , 2, \dots m \tag{29}$$

where $d_v\left(\tilde{a}, \tilde{b}\right)$ denotes the Euclidean distance between two fuzzy numbers $\tilde{a}$ and $\tilde{b}$.

The closeness coefficient CC_i is then calculated to determine the ranking of each alternative (A_i, i = 1, 2,…..m). The closeness coefficient is given by:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*}, \tag{30}$$

where i = 1, 2, ……..m.

With respect to the evaluation of SCM failure modes using the fuzzy-TOPSIS methodology, the failure mode with the highest closeness coefficient CC_i (i.e., closest to the FPIS and farthest from the FNIS) represent the one with the highest risk. The components associated with higher risk failure modes will require a closer attention and focus for SCM design evaluation, close attention during manufacturing and would demand a good attention during installation and operations.

4 Case study application

It is reported in the industry that SCM is one of the components suffering from high failure rates in offshore SPS (Brandt and Eriksen, 2001). The SCM failures can have substantial economic and environmental consequences. The failure consequences are further amplified by increased water depth because a well support vessel (WSV) and a remote operated vehicle at a high cost will be required for the SCM retrieval, repair and replacement. The failure modes (F_i) under consideration include 30 potential drawn from a comprehensive evaluation of SCM failure modes considering each of the key components and subsystems in the SCM, as summarised in Table 4.

The failure modes listed in Table 4 are based on the SCM's intrinsic components and the requirement to deliver specified functions. Failures due to external factors such as installation errors, testing or equipment transportation are not included in this analysis.

Table 4 SCM failure modes (F_i) under consideration

F_1	Loss of power supply from the SEM unit	F_{16}	Loss of SCM pressure compensation
F_2	SCM housing check valve cracks open at lower pressure	F_{17}	HP DCV fails to open on command
F_3	Total loss of signal from the SEM module	F_{18}	LP DCV fails to open on command
F_4	Loss of LP hydraulic filtration	F_{19}	HP DCV shuts spuriously from the open position
F_5	Severe leakage from HP DCV	F_{20}	HP DCV fails to shut on demand from the open position
F_6	Loss of HP hydraulic filtration	F_{21}	LP DCV fails to shut on demand from the open position
F_7	Loss of HP accumulation	F_{22}	Loss of monitoring signal from the water ingress sensor
F_8	Severe leakage from LP DCV	F_{23}	LP selector valve spuriously closes
F_9	Severe leakage on the LP shuttle valve	F_{24}	LP DCV shuts spuriously from the open position
F_{10}	Severe leakage on the HP shuttle valve	F_{25}	Loss of electronic monitoring of the LP supply pressure
F_{11}	Loss of LP accumulation	F_{26}	Loss of electronic monitoring of the HP supply pressure
F_{12}	Shuttle valve fails to change over to the next HP supply line	F_{27}	Loss of electronic monitoring of the LP return flow
F_{13}	Severe leak in the LP common hydraulic header	F_{28}	Loss of electronic monitoring of the HP return flow
F_{14}	Shuttle valve fails to change over to the next LP supply line	F_{29}	Loss of the SCM internal pressure monitoring
F_{15}	LP selector valve fails to open	F_{30}	Loss of the SCM internal temperature monitoring

4.1 Conventional FMEA study

In the conventional FMEA analysis, the three risk factors of occurrence (*O*), severity (*S*) and detectability (*D*) are evaluated according to a scale of 1–10 (1 = no severity, nearly impossible occurrence, almost certain detection, and 10 = hazardous severity, extremely high probability of occurrence, and absolutely uncertain detectability) and then, the associated RPN is calculated for each of the failure modes. This involved a wide consultation of industry experts. The data used in this analysis were obtained through expert elicitation (EE). To ensure credibility, a systematic process was applied for obtaining and processing the data. Below are some steps that were taken during the survey in order to ensure a more objective and accurate results:

- Each of the experts was engaged in a structured interview. Twenty five experts were contacted, but ten of them responded.
- Experts were interviewed across different operating units and across continents from Europe, Africa through to Americas. This ensured the decisions were not skewed.

- The experts were chosen from major oil and gas operators, subsea equipment manufacturers and the engineering consultancy firms.
- The experts were given an opportunity to revise their assessments before sending in the final results.
- During the engagement, the experts were asked to state the rationale behind their evaluations.

4.2 Fuzzy-TOPSIS FMEA study

In this analysis, the three risk factors of occurrence (*O*), severity (*S*) and detectability (*D*) are broken down into more appreciable units for better comprehension. Table 5 shows the breakdown of the conventional risk factors into ten risk assessment criteria.

Table 5 Risk assessment criteria expanded from conventional FMEA risk factors

Risk factor	*Criteria*	*Description*
Occurrence	R_1	Occurrence associated with water depth
	R_2	Occurrence under normal operation
	R_3	Occurrence under extreme conditions
Severity	R_4	Direct cost of failure
	R_5	Indirect cost of failure
	R_6	Failure impact on environment
	R_7	Fatality associated with failure
	R_8	Risk to business – non-financial
Detection	R_9	Detectability
	R_{10}	Redundancy

The occurrence factor in the conventional FMEA represents the probability of the respective failure modes to occur. However, it does not in any way define the environment or functional boundary for which the probability is being predicted. This makes the value a bit vague and unrepresentative of the true setting for the evaluation of the failure probability. In order to make this more explicit and paint the picture of the true scenario, the occurrence factor is split into three different factors, namely:

- Occurrence associated with water depth (R_1): It represents the risk of failures in relation to increase in water depth. In the ocean environments, it has been proven that every 10 m increase in water depth results in a proportional hydrostatic pressure increase of 1 bar with attendant effect on subsea systems. The change in pressure, temperature, salinity and other depth-varying sea parameters constitute potential sources of failure to the SCM. The R_1 evaluates these in correspondence to each of the failure modes.
- Occurrence under normal operation (R_2): It evaluates the probability of the system failure under a defined set of functional design parameters. SCMs designed within a known operational boundary are still known to fail even with correctly defined functional parameters. This parameter is used in rating such failures.

- Occurrence under extreme conditions (R_3): Sometimes the SCM is found operate in unpredictable conditions that are outside their standard design specifications like higher pressure ratings, temperature range, salinity, etc. The R_3 factor evaluates the probability of failure occurrence when the system is operated beyond its defined design specification. For example, what is the probability that an SCM designed to operate with a maximum LP working pressure of 3,000 psi will fail if the actual flow pressure in the LP circuitry increases to 3,010 psi, which is outside its design limits.

In the same way as occurrence, the severity factor in FMEA study represents the impact of a failure mode on the user or customer if the corresponding failure occurs. The factor is a little vague because it only assesses the severity of a failure in terms of cost consequences and ignores the damages to environment or fatalities. For this reason, we split this parameter into the following risk factors:

- Direct cost of failure (R_4): SCM components' failure leads to loss in revenue as the part/subsystem may require repair or outright replacement. The risk factor R_4 represents the direct cost associated with repair or outright replacement of the faulty component (e.g. cost of SCM filter, cost of LP sensor, unit cost of DCV, etc.).
- Indirect cost of failure (R_5): It evaluates the level of secondary costs associated with restoring the component function back to service. A typical failure in the offshore environment requires hiring and sending a number of maintenance vessels to facilities which may be very expensive.
- Impact of failure on environment (R_6): This factor evaluates the impact of each failure on the offshore environment. It includes parameters like discharge to sea and failure impact on aquatic life.
- Fatality associated with failure (R_7): It assesses the severity of a failure mode in terms of number of lives lost. For SCMs operating in deep and ultra-deep waters, injuries are unlikely to happen since the operation is typically performed using the remote operated vehicles (ROVs). However, this may not be completely ruled out in shallow waters where divers are sometimes used. Loss of live may occur from failures associated with the high pressure systems or even from failures associated with the power units.
- Risk to business (non-financial) (R_8): not all of impacts associated with failures can actually be quantified in terms of cost, damage to environment or fatality. Some failures may have effect on the business in a global perspective which is presented by R_8. For example, a failure in the HP circuitry leading to a shutdown of the well will reduce the level of production.

Other risk factors used in our analysis are: detectability (R_9) and redundancy (R_{10}). These factors are principally safeguards, which are introduced into the system to enhance availability. The R_9 factor evaluates the ease for which a failure mode occurrence can be detected. Sensors are the primary means of failure detection in subsea systems. They provide process data and parameters for assessing the condition of an equipment or component. Examples of sensors in the subsea environment are combined pressure and temperature sensors, flow sensors, level sensors, pressure sensors, sand detectors/fluid cleanliness, temperature sensor, valve position sensor, etc. Nevertheless, not all failure modes can be detected using sensors. This factor evaluates the risks involved in the inability to detect the respective failure modes.

Due to the huge risk associated with failure of systems in the subsea environment, most systems are operated in redundancy. The risk factor R_{10} assesses the risks associated with the requirement and loss of redundancy in relation to the corresponding failure mode. For example, in a typical SCM, there are two SEMs operated in redundancy. If one fails, the system switches to the next one for continued operations. Loss of this redundant SEM means a loss of power to all the LP and DCVs and a total loss of communications from the downhole well system as well as a loss in signal to the topside operator. The impact here is severe as it leads to a total shutdown of the well and requires a support vessel for the retrieval of the SCM in order to fix the failure.

In this evaluation, the limitation for use of data from databases was examined, as the information is typically skewed to the function specification of the system under study including the specific environment being examined. To overcome this limitation, EE technique were applied. A survey was designed for evaluating the weight of the SCM risk factors including the rating of these risk factors to the corresponding failure modes. Ten reputable experts in the offshore subsea industry cutting across oil and gas operators, original equipment manufacturers (OEMs), and industry design consultants were surveyed for the exercise. The survey had two sections. The first section focused on the importance of the risk factors. This is called weight evaluation and represents the significance of the respective risk factors in the SCM system's reliability. In the second section, the risk factors were then used in establishing a rating with the respective failure modes.

5 Results and discussion

The failure modes (F_i) under consideration include 30 drawn from a comprehensive evaluation of SCM failure modes considering each of the key components and subsystems in the SCM and the corresponding possible causes of their failures. The results of the conventional FMEA study, including the lists of the failures modes, corresponding IDs, the RPN values and their rakings are given in Table 6.

The results of the RPN evaluations show the following as the top ten most critical failures in the SCM.

- loss of power supply from the SEM unit
- severe leakage on the LP shuttle valve
- severe leakage from HP DCV
- loss of HP accumulation
- total loss of signal from the SEM module
- SCM housing check valve cracks open at lower pressure
- severe leakage from LP DCV
- shuttle valve fails to change over to the next LP supply line
- loss of LP accumulation
- loss of HP hydraulic filtration.

To implement the FMEA study based on the fuzzy-TOPSIS technique, ten experts, D_1 to D_{10}, from the subsea industry were surveyed to obtain the weights (relative importance) of risk assessment parameters as shown in Table 7. The relative importance of these risk factors against the failure modes was also obtained. The evaluation is such that, for example, if increase in water depth increases the probability of occurrence of one failure mode, the rating value is expected to have a high value and vice versa. A high value for all the risk factors implies a big risk for the respective failure mode being evaluated.

Next, the experts use the linguistic variables as given in Table 3 to evaluate the rating of the risk factors to the corresponding failure modes. The fuzzy decision matrix and fuzzy weights of the failure modes using Tables 2 and 3 are shown in Table 8. Though the experts were selected from different countries, the values were relatively even with very minor deviations in the opinions provided.

Table 6 The results of the conventional FMEA study on SCM

Failure ID	*RPN*	*Failure mode ranking*	*Failure ID*	*RPN*	*Failure mode ranking*	*Failure ID*	*RPN*	*Failure mode ranking*
F1	288	1	F12	72	10	F18	42	19
F9	252	2	F10	70	12	F27	42	19
F5	144	3	F4	63	13	F17	36	23
F7	144	3	F13	56	14	F22	30	24
F3	140	5	F19	56	14	F20	28	25
F2	112	6	F26	54	16	F28	27	26
F8	96	7	F21	48	17	F23	24	27
F14	96	7	F15	48	17	F25	24	27
F11	84	9	F16	42	19	F29	18	29
F6	72	10	F24	42	19	F30	16	30

Table 7 Importance weights of the risk factors

	Importance weight evaluation									
	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}
R_1	VH	VH	VH	H	VH	VH	VH	VH	VH	VH
R_2	VH	H	H	VH	VH	VH	VH	VH	H	H
R_3	H	H	H	H	M	H	H	H	M	M
R_4	M	M	M	M	H	H	H	H	H	VH
R_5	VH	VH	VH	H	VH	VH	VH	VH	H	H
R_6	M	M	H	H	M	M	M	H	H	H
R_7	L	L	M	L	M	M	L	M	H	M
R_8	H	H	M	H	M	M	M	M	M	M
R_8	VH	H	H	VH	H	M	H	H	VH	VH
R_{10}	H	H	VH	H	VH	VH	VH	H	VH	H

Table 8 Fuzzy decision matrix for the failure modes (F_i) and the respective weights of the risk factors (R_i)

Failure mode ID	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}
	W_1	W_2	W_3	W_4	W_5	W_6	W_7	W_8	W_9	W_{10}
	(0.7, 0.99, 1.0)	(0.7, 0.96, 1.0)	(0.3, 0.78, 1.0)	(0.3, 0.75, 1.0)	(0.7, 0.97, 1.0)	(0.3, 0.7, 1.0)	(0.0, 3.9, 1.0)	(0.3, 0.6, 1.0)	(0.3, 0.9, 1.0)	(0.7, 0.95, 1.0)
F_1	(0, 0.8, 3)	(5, 7.8, 10)	(7, 9.9, 10)	(7, 9.4, 10)	(9, 10, 10)	(0, 0.3, 3)	(0, 0.1, 3)	(0, 2.1, 7)	(0, 0.9, 3)	(9, 10, 10)
F_2	(5, 9.3, 10)	(0, 0.9, 5)	(7, 9.6, 10)	(3, 5.0, 7)	(7, 9.9, 10)	(0, 3, 10)	(0, 0, 1)	(0, 0.7, 7)	(7, 9, 10)	(1, 4.8, 5)
F_3	(0, 1.8, 7)	(1, 5.2, 9)	(7, 9.4, 10)	(7, 9.3, 10)	(9, 10, 10)	(0, 0.7, 7)	(0, 0, 1)	(0, 1.7, 7)	(0, 0.2, 3)	(7, 9.8, 10)
F_4	(0, 0.4, 3)	(0, 0.9, 5)	(7, 9.5, 10)	(, 7.2, 10)	(5, 7.2, 10)	(0, 0.2, 3)	(0, 0, 1)	(0, 2.8, 5)	(7, 9.8, 10)	(7, 9.2, 10)
F_5	(0, 1.4, 5)	(0, 4.2, 7)	(7, 9.3, 10)	(3, 7.8, 9)	(7, 0.1, 3)	(7, 9.2, 10)	(0, 0.1, 3)	(5, 79)	(0, 2.0, 7)	(5, 8.2, 10)
F_6	(0, 0.1, 3)	(0, 2.8, 7)	(5, 8.7, 10)	(0, 1.0, 3)	(7, 9.6, 10)	(0, 1.2, 10)	(0, 0.1, 3)	(0, 1.0, 5)	(7, 9.4, 10)	(5, 8.0, 10)
F_7	(3, 5.6, 9)	(0, 0.7, 5)	(5, 8.9, 10)	(3, 6.4, 9)	(5, 7.2, 10)	(0, 0.4, 3)	(0, 0.1, 3)	(1, 3.8, 7)	(0, 2.8, 7)	(5, 7.4, 10)
F_8	(0, 1.5, 5)	(0, 1.3, 7)	(7, 9.5, 10)	(3, 5.4, 9)	(7, 9, 10)	(3, 5, 7)	(0, 0.1, 3)	(3, 3.6, 9)	(0, 0.4, 3)	(3, 7.8, 10)
F_9	(0, 1.6, 5)	(0, 1.4, 7)	(7, 9.9, 10)	(3, 5.8, 9)	(7, 9.9, 10)	(1, 5, 7)	(0, 0.1, 3)	(3, 5.4, 9)	(0, 2.0, 5)	(5, 8.2, 10)
F_{10}	(0, 2.0, 5)	(0, 1.0, 5)	(7, 9.6, 10)	(3, 6.2, 9)	(7, 9.9, 10)	(0, 1.6, 5)	(0, 0.1, 3)	(3, 5, 7)	(0, 1.2, 5)	(3, 8.2, 10)
F_{11}	(3, 6.4, 10)	(0, 0.7, 5)	(7, 9.6, 10)	(1, 6.4, 9)	(7, 9.6, 10)	(0, 0, 1)	(0, 0.1, 3)	(0, 2.8, 5)	(0, 2.2, 5)	(5, 7.8, 10)
F_{12}	(0, 1.0, 5)	(0, 0.5, 3)	(7, 9.6, 10)	(3, 6.2, 9)	(7, 9.1, 10)	(0, 0, 1)	(0, 0.1, 3)	(0, 1.2, 5)	(0, 0.7, 3)	(3, 7.4, 10)
F_{13}	(0, 0.8, 5)	(0, 0.4, 5)	(7, 9.7, 10)	(1, 6.4, 9)	(7,9.9, 10)	(0, 0, 1)	(0, 0.1, 3)	(5, 7.6, 10)	(0, 0.8, 3)	(5, 7.6, 10)
F_{14}	(0, 1.7, 5)	(0, 0.6, 3)	(7, 9.7, 10)	(1, 6.0, 9)	(7, 9, 10)	(0, 0.1, 3)	(0, 0.1, 3)	(0, 1.6, 7)	(0, 0.1, 3)	(5, 8.4, 10)
F_{15}	(0, 1.3, 5)	(0, 1.3, 5)	(5, 9.2, 10)	(3, 6.4, 9)	(5, 8.8, 10)	(0, 0, 1)	(0, 0.1, 3)	(0, 1, 3)	(0, 1.1, 5)	(3, 5.6, 9)
F_{16}	(7, 9.6, 10)	(7, 8.6, 10)	(7, 9.6, 10)	(3, 6.0, 9)	(7, 9.9, 10)	(0, 0, 1)	(0, 0, 1)	(3, 5, 7)	(0, 2.6, 5)	(3, 6.2, 9)
F_{17}	(0, 1.2, 5)	(0, 1.5, 5)	(5, 9.2, 10)	(1, 6.4, 9)	(5, 8.6, 10)	(0, 0.1, 3)	(0, 0, 1)	(0, 0.8, 3)	(0, 1.3, 5)	(5, 8.6, 10)
F_{18}	(1, 1.8, 7)	(0, 1.2, 5)	(5, 8.6, 10)	(0, 5.6, 9)	(5, 8.6, 10)	(0, 0.1, 3)	(0, 0, 1)	(0, 0.5, 3)	(0, 0.9, 5)	(3, 6.0, 10)
F_{19}	(0, 2.2, 5)	(0, 1.3, 5)	(5, 7.7, 10)	(0, 5.8, 9)	(5, 7.8, 10)	(0, 0.8, 3)	(0, 0.1, 3)	(0, 0.3, 3)	(0, 1.6, 7)	(3, 5.6, 9)
F_{20}	(0, 0.5, 3)	(0, 1.2, 5)	(7, 9.6, 10)	(0, 6.0, 9)	(5, 8.0, 10)	(0, 0.8, 3)	(0, 0.1, 3)	(0, 0.4, 3)	(0, 0, 1)	(3, 5.8, 9)
F_{21}	(0, 1.1, 5)	(0, 1.4, 5)	(5, 9.4, 10)	(1, 6.2, 9)	(5, 8.4, 10)	(0, 0.7, 3)	(0, 0.1, 3)	(0, 0.6, 3)	(0, 1.4, 5)	(3, 5.2, 9)
F_{22}	(0, 0.1, 3)	(0, 0.5, 3)	(7, 9.3, 10)	(0, 1.6, 5)	(5, 7.8, 10)	(1, 3, 5)	(0, 0.1, 3)	(0, 1, 7)	(0, 0.3, 3)	(3, 5.8, 10)
F_{23}	(0, 0, 1)	(0, 0.1, 3)	(5, 8.7, 10)	(0, 5.4, 9)	(5, 8.6, 10)	(0, 0, 1)	(0, 0.1, 3)	(0, 0.7, 3)	(0, 0.5, 7)	(3, 5.6, 10)
F_{24}	(0, 0.1, 3)	(0, 0, 1)	(5, 9.1, 10)	(1, 5.6, 9)	(5, 8.6, 10)	(0, 0.1, 3)	(0, 0.1, 3)	(1, 5.2, 9)	(0, 1.3, 7)	(1, 4.4, 10)
F_{25}	(0, 0.2, 3)	(0, 0.8, 5)	(5, 9.3, 10)	(0, 3.2, 7)	(7, 9, 10)	(0, 0.1, 3)	(0, 0.1, 3)	(0, 0.2, 3)	(0, 0.7, 5)	(1, 4.0, 7)
F_{26}	(0, 0.3, 3)	(0, 0.6, 5)	(7, 9.7, 10)	(0, 3.2, 7)	(5, 7.6, 10)	(0, 0.1, 3)	(0, 0.1, 3)	(0, 1.0, 5)	(0, 0.4, 5)	(1, 4.2, 10)
F_{27}	(0, 0.3, 3)	(0, 0.6, 5)	(5, 9.2, 10)	(0, 2.2, 7)	(0, 6.4, 9)	(0, 0.1, 3)	(0, 0.1, 3)	(0, 0.9, 5)	(0, 0.5, 5)	(1, 4.8, 10)
F_{28}	(0, 0.2, 3)	(0, 0.8, 5)	(7, 9.7, 10)	(0, 2.8, 7)	(3, 6.8, 9)	(0, 0.1, 3)	(0, 0.1, 3)	(0, 1.3, 5)	(0, 0.7, 5)	(1, 3.8, 7)
F_{29}	(0, 0.3, 3)	(0, 1.3, 5)	(7, 9.8, 10)	(0, 2.4, 7)	(3, 5.6, 9)	(0, 1, 3)	(0, 0.1, 3)	(0, 1.4, 5)	(0, 0.6, 5)	(1, 4.2, 7)
F_{30}	(0, 0.3, 3)	(0, 0.8, 5)	(5, 8.9, 10)	(0, 2.6, 7)	(3, 5.2, 9)	(0, 0, 1)	(0, 0.1, 3)	(0, 0.9, 3)	(0, 1.0, 5)	(1, 3.2, 7)

Using equations (2) and (3), the fuzzy decision matrix is normalised and the weights are applied. This produces a normalised weighed fuzzy matrix. Afterwards, FPIS and the FNIS are obtained as shown in Table 9.

Table 9 The fuzzy positive and negative ideal solution (FPIS, FNIS)

FPIS	[(1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1)]
FNIS	[(0, 0, 0), (0, 0, 0), (0.15, 0.15, 0.15), (0, 0, 0), (0, 0, 0), (0, 0, 0), (0, 0, 0), (0, 0, 0), (0, 0, 0), (0.07, 0.07, 0.07)]

The distance of the failure modes to the FPIS and FNIS are then evaluated using the vertex method [equations (28) and (29)]. A correlation coefficient for each failure mode is evaluated and then ranked.

In summary, the analysis presents the following failure modes given in Table 10 as the top ten most critical in the SCM.

Table 10 Top 10 failure modes from fuzzy TOPSIS analysis

Failure mode ranking	*Failure modes*	*Failure ID*
1	Severe leakage from HP DCV	F5
2	Severe leakage on the LP shuttle valve	F9
3	Loss of power supply from the SEM unit	F1
4	SCM housing check valve cracks open at lower pressure	F2
5	Loss of HP accumulation	F7
6	Total loss of signal from the SEM module	F3
7	Severe leakage from LP DCV	F8
8	Loss of HP hydraulic filtration	F6
9	Loss of LP accumulation	F11
10	Severe leakage on HP shuttle valve	F10

A correlation of 93.5% is observed between the top ten most critical failure modes obtained from the conventional FMEA study and those obtained from the fuzzy TOPSIS-based evaluation. The conventional FMEA analysis shows that F_1 (loss of power supply from the SEM unit) is the most critical failure in the SCM, while the fuzzy TOPSIS technique recognises the severe leakage from HP DCV (F_5) as the most critical failure mode. Even though F_1 is ranked in third place according to the fuzzy TOPSIS FMEA study, it still is known as a critical failure mode. F_9 (severe leakage in the LP shuttle valve) is ranked as the second most critical failure mode in both the analyses. The third most critical failure mode under the conventional FMEA methodology is loss of HP accumulation (F_7), whereas this is ranked as fifth critical failure mode according to the fuzzy TOPSIS analysis. A certain level of variations is observed between the rankings obtained on the basis of RPN values and those obtained using the fuzzy TOPSIS method. It is worth noting that the fuzzy TOPSIS analysis applies a weighted set of criteria for the evaluation while the failure mode, effects and criticality analysis (FMECA) evaluation assumes equal weights to its risk factors (occurrence, severity and detectability).

The results obtained from this study were also compared to data reported in Offshore and Onshore Reliability Data (OREDA) as a baseline database in the oil and gas industry. The OREDA JIP has established a comprehensive database with reliability and maintenance data for exploration and production equipment from a wide variety of geographic areas, installations, equipment types and operating conditions.

The following equipment's are covered in the OREDA reliability database – control systems (including topside controls, SCM, umbilicals), flowlines, manifolds, production risers, running tools, wellhead and Xmas trees, templates and subsea pumps. OREDA makes it possible to extract and analyse failures with some defined similarities, to calculate variables like failure rates, downtimes, to trend and perform benchmarking. The subsea database is used by the participating companies to record their real life data on their subsea experience. This provides a sound platform for the exchange of subsea info among participating companies and the users.

The analysis conducted on data obtained from OREDA was based on subsea installations located in water depths ranging from shallow water 22m to deepwater 1,300 m in a combination of satellite, manifold templates and clustered well developments. A total of 7,480 SCMs were used in the analysis in fields covering the North Sea, Gulf of Mexico (GoM), the West African waters, Guinean gulf, Adriatic Sea and West of Shetland. Again, a combination of driverless and diver-assist systems were analysed.

The analysis showed that the SEM has the highest number of failures as 42.7% of the component failed representing a whopping 70.30% of the entire number of failures recorded during the period of the failure survey. This is closely followed by the SCM solenoid valves in which a total of 66 failed representing a total of 17.98% failure during the same period. The analysis also revealed the SEM as the primary source for critical failures in the SCM. The SEM failures caused a total of 64.94% of the SCM critical failures. Critical failures in the SCM are the failures leading to loss in production from associated well. Normally, this will involve retrieval, repair and replacement or an outright replacement of the faulty SCM. The analysis also showed the failures of solenoid control valves as the second highest critical failures in the SCM. These are the LP and HP DCVs which are responsible for the control of the production tree valves, and the surface controlled subsurface safety valve (SCSSV), the intelligent control and chemical injection valves.

The fuzzy TOPSIS analysis shows that severe leakage from HP DCV (F_5) is the most critical failure mode in the SCM. The HP DCV controls the SCSSV, a primary well control barrier. It also controls the downhole intelligent control valves. These two functions are very critical to the performance of oil and gas production wells as any failure may lead to system breakdown and subsequently loss of production. The results also show that severe leakage on the LP shuttle valve (F_9) is the second most critical failure in the SCM. The valve is responsible for powering all LP valves in the subsea tree system, making it a key component of the SCM. On the third position is loss of power supply from the SEM unit (F_1).

In summary, the analysis shows that around 80% of the most critical failure modes in the SCM come from the DCVs while around 20% are in relation to the SEM. The analysis also demonstrates that leakage in DCVs is a major issue in SCMs as 40% of the most critical failures are related to this failure mode. The outcomes of the above analysis from OREDA validate the fuzzy TOPSIS analysis results shown above.

It should be noted that although the results may show little difference from a conventional FMEA for this particular application, the approach adopted could draw significantly greater differences in other problems, as the proposed method represents the decision making model in a more systematic way, reducing bias from the inputs. Further, the criteria selected are widely applicable to other offshore, marine and subsea applications due to their generic nature. The methodology developed can overcome some of the fundamental limitations of traditional FMECA, such as like the duplication of the RPNs, the unscientific nature of the crisp risk factors while careful selection of criteria can also consider condition-based risk assessment which can further expand the scope of semi-quantitative methods of risk assessment.

From a methodological point of view, the proposed approach allows for flexibility in the selection of the criteria of the analysis leading to a better defined ranking of risks and hence permitting more effective mitigation strategies, reliability-centred maintenance (RCM), risk-based inspection (RBI), etc. In the case where appropriate criteria are selected, a dynamic risk assessment can even take place, updating initial estimations with information about the current state of a system.

6 Conclusions

In this paper, a fuzzy TOPSIS-based FMEA model was presented to identify, analyse and evaluate the failure modes of a SCM. The analysis focused on thirty most critical failure modes in the SCM, where a criticality assessment was conducted and the failure modes were ranked using the conventional RPN technique. The FMEA study revealed that there are several major drawbacks in prioritising failure modes using the RPN technique, e.g., lack of consideration of the relative importance between risk factors, difficulty of allocating a crisp number to risk factors, etc. A fuzzy TOPSIS-based method was proposed to overcome these limitations and it eventually revealed the most critical failure modes as listed in Table 10.

A high level of correlation between the top ten most critical failure modes obtained from the conventional FMEA study and those obtained from the fuzzy TOPSIS-based evaluation was observed. However, the use of linguistic terms in the fuzzy TOPSIS approach enabled the experts to express their judgments more realistically and hence improving the applicability of the FMEA technique in offshore oil and gas industry. Comparison of the derived results with the reported failures through the OREDA database countersigned validity of the approach.

The methodology that has been followed in this paper, risk prioritisation through fuzzy-TOPSIS analysis, can be applied to other complex systems with the aim of improving the conventional FMEA technique to make it more practical for various industries.

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