Linguistic Assessment Approach for Hierarchical Safety Analysis and Synthesis

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Summary. Engineering systems in industry are most often concerned with safety issues. Many of these systems are intended to work properly even in contexts where information is missing, incomplete or unreliable. This chapter introduces a safety model based on the concept of approximate reasoning for safety analysis. Parameters of the safety level, including failure rate, failure consequence severity and failure consequence probability, are all described by fuzzy linguistic variables. A fuzzy rule-base is used to capture the uncertainty and the non-linear relationships among these parameters. A safety estimate for possible causes of a technical failure can be obtained by the approximate reasoning approach. A safety synthesis is then applied to integrate all possible causes for a specific technical failure, or applied at the safety estimate made by a panel of experts. The synthesis is based on an ordinal fuzzy linguistic approach by means of a direct computation on linguistic values instead of the approximation approach by their associated membership functions. The use of the ordinal fuzzy linguistic approach makes the safety analysis more effective. Subsequently, the ranking and interpretation of the final safety synthesis of a concerned system are also described. Application of this proposed approach is demonstrated by a real-world case study in the offshore engineering.

1 Introduction

The growing technical complexity of large engineering systems such as offshore platforms and offshore support vessels, together with the intense public concern over their safety, has stimulated the research and development of novel safety analysis methods and safety assessment procedures.

Many typical safety assessment approaches (such as probabilistic risk assessment approach) may be difficult to use in situations with a lack of information and past experiences, or ill-defined situation for risk analysis [10, 16],

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e.g., at the initial design stages. In certain circumstances, probability theory can be a powerful tool. However, the type of uncertainty encountered in engineering projects (e.g., offshore) does not always adhere to the axiomatic basis of probability theory, simply because uncertainty in these projects is usually caused by the inherent fuzziness of the estimates of the parameters rather than randomness.

In addition, the safety of a system is affected by various factors, such as design, manufacturing, installation, commissioning, operations and maintenance [14]. The safety of a structure is often determined by all the associated failure events of each individual component that makes up the structure. Problems may then arise such as how to synthesize uncertain evaluations of the safety analysis for all the failure events of a component in a rational way, as well as how to attain an evaluation of this component safety. The problem may be ultimately generalized to estimate the safety of a hierarchy system.

This work aims to establish a framework that provides a basis and hence a tool for safety analysis and synthesis in engineering systems. In particular this framework deals with information that may be unquantifiable due to its nature and that may be imprecise, ill-defined, and incomplete. It will further provide a subjective safety modelling for safety analysis using an approximate reasoning approach to capture uncertainty and non-linear casual relationships in safety assessments.

Fuzzy logic approach [20] provides a systematic way to represent linguistic variables. It can be used as a powerful tool complementary to traditional methods to deal with imprecise information, especially linguistic information. Actually, linguistic variables are commonly used to represent risk factors in risk analysis [1,2,9,10,13–15]. It does not require an expert to provide a precise point of a potential risk. Approximate reasoning [19–21] based on fuzzy IF-THEN rules can model the safety of the system without employing precise quantitative analyses [5].

Moreover, the use of linguistic variables implies "Computing with Words" processes. In the literature there are two main linguistic computational approaches:

(1) The linguistic computational approach based on the Extension Principle [20, 21], that operates over the associated membership functions of the linguistic variables.
(2) The linguistic computational symbolic approach (or the ordinal fuzzy linguistic approach) which acts by a direct computation on labels [4,6,17,18]. An extended ordinal fuzzy linguistic approach, called the 2-tuple linguistic representation model has been presented in [7,8] to improve the accuracy of the computing with words processes.

Our proposed framework will use for the safety synthesis the 2-tuple linguistic representation approach in order to facilitate the computing with words processes and the comprehension of the safety estimate.

This paper is organized as follows. Section 2 introduces a framework for modelling system safety by an approximate reasoning approach and for safety synthesis by the 2-tuple linguistic representation approach. A case study based on the collision risk of a floating production storage offloading (FPSO)-shuttle tanker during a tandem offloading operation is presented in Sect. 3 to demonstrate this proposed approach. A conclusion of the approach presented in the paper is provided in Sect. 4.

2 A Safety Model – A Framework for Safety Analysis and Synthesis

A generic framework for modelling system safety by an approximate reasoning approach and for safety synthesis by the ordinal fuzzy linguistic approach is depicted in Figs. 1 and 2, respectively.

The proposed framework consists of six major phases:

(i) Identify all the anticipated causes/factors to the technical failure of an engineering system;
(ii) Identify and name the linguistic variables for the antecedent parameters that define the safety level, i.e., *failure rate, consequence severity* and *failure consequence* probability as well as the linguistic variables for the

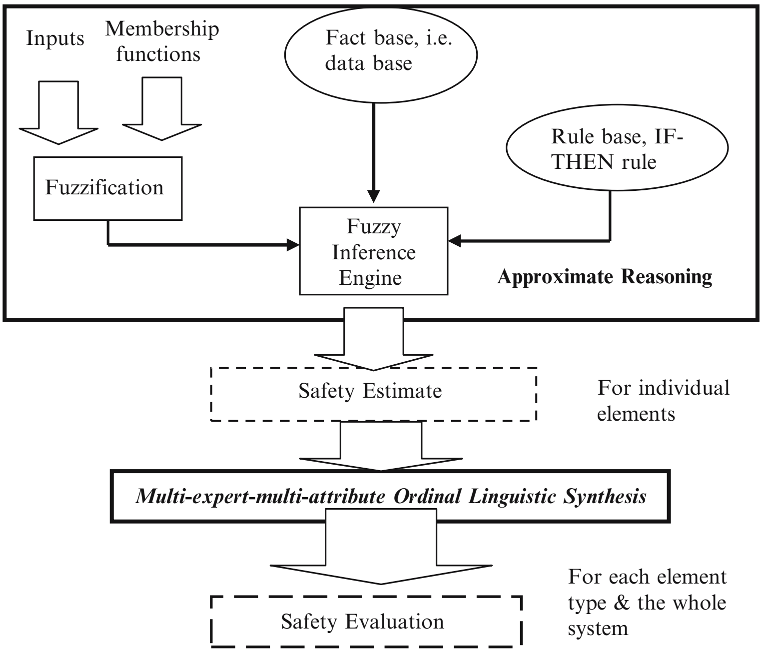

Fig. 1. A generic qualitative safety assessment framework

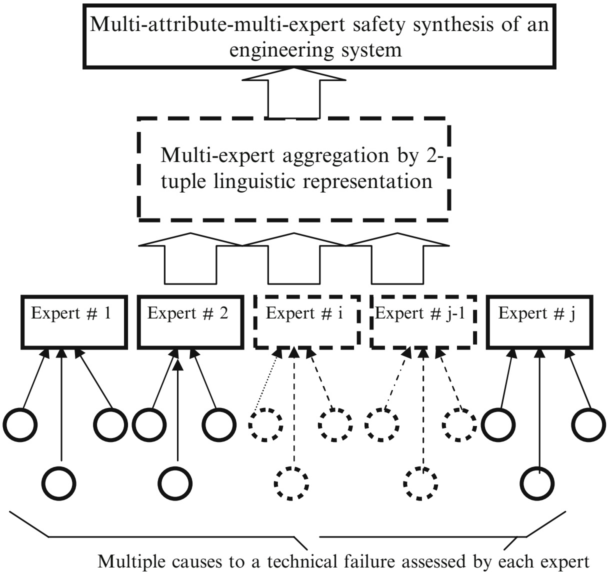

Fig. 2. Multi-attribute-multi-expert safety synthesis

consequent, i.e., *safety estimate* and create fuzzy membership functions for all related linguistic variables for the antecedent parameters;

(iii) Construct the fuzzy rule bases;

(iv) Create resultant safety estimate for a particular cause to a technical failure using a fuzzy inference method;

(v) Safety synthesis using the ordinal fuzzy linguistic approach;

(vi) Ranking and interpretation of the final safety synthesis of a system.

Each phase of the framework is described in detail as follows.

Phase #1: Identification of causes/factors

In this phase, all anticipated causes/factors to the technical failure of an engineering system are identified. This needs the judgment from a panel of experts $E = \{e_1, \ldots, e_p\}$ during a brainstorming session at the early stages of the system.

Phase #2: Identify and name the linguistic variables for the antecedent and the consequent attributes and create fuzzy membership functions for all related linguistic variables for the antecedent parameters

The three fundamental parameters used to assess the safety level of an engineering system on a subjective basis are the *failure rate* (**FR**), the *consequence severity* (**CS**) and the *failure consequence probability* (**FCP**). Subjective assessments (using linguistic variables instead of ultimate numbers in probabilistic terms) are more appropriate for their analysis because these three parameters are always associated with great uncertainty [9, 10, 13–15].

The granularity of the linguistic term sets used for describing each fundamental parameter is decided according to the situation of the case of interest. The recent literature survey indicates that linguistic term sets with a granularity from four to seven labels are commonly used to represent risk factors in risk analysis [1, 2, 9, 10, 13–15].

A membership function is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The simplest membership functions are the triangular membership function and trapezoidal membership function. Both of these memberships are commonly used to describe risks in safety assessment [15].

It is possible to have some flexibility in the definition of membership functions to suit different situations. The application of categorical judgments has been quite positive in several practical situations [12]. It is also common and convenient for safety analysts to use categories to articulate safety information. The fuzzy membership functions are generated utilizing linguistic categories identified in knowledge acquisition and consisting of a set of overlapping curves. The typical linguistic variables used to describe **FR, CS** and **FCP** are defined and characterized as follows [13].

FR describes failure frequencies in a certain period, which directly represents the number of failures anticipated during the design life span of a particular system or an item, as illustrated in Fig. 3. Table 1 describes the range of the frequencies of failure occurrence and defines the fuzzy set of **FR**. To estimate the **FR**, one may choose to use such linguistic values as "*very low*," "*low*," "*reasonably low*," "*average*," "*reasonably frequent*," "*frequent*," and "*highly frequent*."

CS describes the magnitude of possible consequences, which is ranked according to the severity of failure effects. To estimate the **CS**, one may choose to use such linguistic values as "*negligible*," "*marginal*," "*moderate*," "c*ritical*" and "*catastrophic*." The fuzzy **CS** set definition is shown in Fig. 4. Table 2 shows the criteria used to rank the **CS** of failure effects.

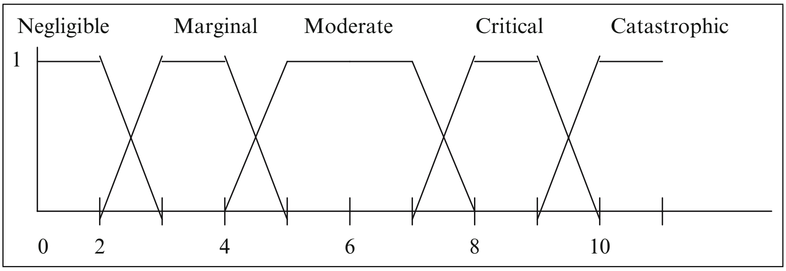

Fig. 3. Fuzzy failure rate set definition

Table 1. Failure rate (**FR**)

Rank	**FR**	Meaning (general interpretation)	Failure rate (1/year)
1,2,3	Very low	Failure is unlikely but possible during lifetime	$<10^{-6}$
4	Low (Lo)	Likely to happen once during lifetime	0.25×10^{-5}
5	Reasonably low (RLo)	Between low and average	0.25×10^{-4}
6	Average (A)	Occasional failure	10^{-3}
7	Reasonably Frequent (RF)	Likely to occur from time to time	0.25×10^{-2}
8, 9	Frequent (F)	Repeated failure	0.125×10^{-1}
9,10	Highly frequent (HF)	Failure is almost inevitable or likely to exist repeatedly	$>0.25 \times 10^{-1}$

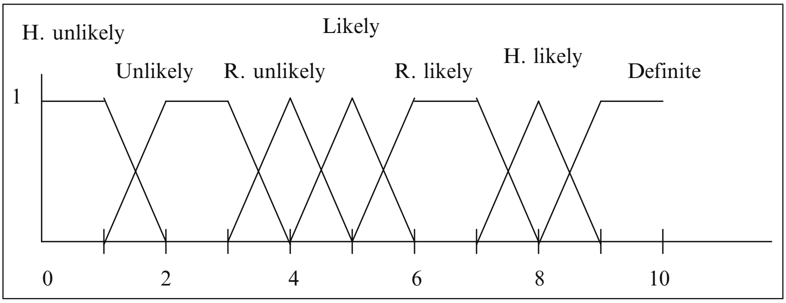

Fig. 4. Fuzzy consequence severity set definition

FCP defines the probability of the possible consequences given the occurrence of the event. To estimate the **FCP**, one may choose to use such linguistic values as "*highly unlikely*," "*unlikely*," "*reasonably unlikely*," "*likely*," "*reasonably likely*," and "*definite*." Table 3 and Fig. 5 describe the **FCP**.

The descriptions of these linguistic variables have been detailed in [13] and the fuzzy membership functions for these linguistic variables are generated utilizing linguistic categories identified in knowledge acquisition [13].

Safety estimate is the output attribute used in this study to produce a safety assessment for a particular cause to a technical failure. This variable is described and determined by the above three parameters and also assessed linguistically, in a linguistic term set noted as, S_{T}, in this paper:

$$S_{\mathrm{T}} = \{\text{“}Poor\text{”}, \text{“}Low\text{”}, \text{“}Average\text{”}, \text{“}High\text{”}, \text{“}Good\text{”}\}$$

Table 2. Consequence Severity (**CS**)

Rank	**CS**	Meaning (generic offshore structure/system interpretation)
1	Negligible (N)	At most a single minor injury or unscheduled maintenance required (service and operations can continue)
2, 3	Marginal (Ma)	Possible single or multiple minor injuries or/and minor system damage. Operations interrupted slightly, and resumed to its normal operational mode within a short period of time (say less than 2 h)
4, 5, 6	Moderate (Mo)	Possible multiple minor injuries or a single severe injury, moderate system damage. Operations and production interrupted marginally, and resumed to its normal operational mode within, say no more than 4 h
7, 8	Critical (Cr)	Possible single death, probable multiple severe injuries or major system damage. Operations stopped, platform closed, shuttle tanker's failure to function. High degree of operational interruption due to the nature of the failure such as an inoperable platform (e.g. drilling engine fails to start) or an inoperable convenience subsystem (e.g. DP, PRS)
9, 10	Catastrophic (Ca)	Possible multiple deaths, probable single death or total system loss. Very high severity ranking when a potential failure mode (e.g. fire and explosion) affects safe platform operation and/or involves noncompliance with government regulations

Any linguistic term, s_i, of the above linguistic term sets has the following characteristics:

(1) The set is ordered: $s_i \leq s_j$ if $i \leq j$.
(2) There is the negation operator: $\mathrm{Neg}(s_i) = s_j$ such that $j = T - 1 - i$.
(3) There is the maximization operator: $\mathrm{Max}(s_i,\ s_j) = s_i$ if $s_j \leq s_i$.
(4) There is the minimization operator: $\mathrm{Min}(s_i,\ s_j) = s_i$ if $s_i \leq s_j$.

Phase #3: Construct a fuzzy rule-base

Fuzzy logic systems are knowledge-based or rule-based ones in the form of fuzzy IF–THEN rules [21]. The starting point of constructing a fuzzy logic system is to obtain a collection of fuzzy IF–THEN rules from human experts or based on domain knowledge.

In our case, we assume that the three antecedent parameters, **FR, CS** and **FCP** can be described by J_i linguistic terms $\{A_{ij},\ j = 1, \ldots, J_i\},\ i = 1,\ 2,\ 3$, respectively. One consequent variable ***safety estimate*** is described by a linguistic term set $S_T = \{D_0,\ D_2, \ldots, D_{T-1}\}$ with T linguistic terms. Let $A_i^k \in \{A_{ij},\ j = 1, \ldots, J_i\}$ be a linguistic term corresponding to the *ith*

Table 3. Failure consequence probability (**FCP**)

Rank	**FCP**	Meaning
1	Highly unlikely (HU)	The occurrence likelihood of possible consequence is highly unlikely given the occurrence of the failure event (extremely unlikely to exist on the system or during operations)
2,3	Unlikely (U)	The occurrence likelihood of possible consequences is unlikely but possible given that the failure event happens (improbable to exist even on rare occasions on the system or during operations)
4	Reasonably unlikely (RU)	The occurrence likelihood of possible consequences is reasonably unlikely given the occurrence of the failure event (likely to exist on rare occasions on the system)
5	Likely (Li)	It is likely that consequences happen given that the failure event occurs (a programme is not likely to detect a potential design or operations procedural weakness)
6,7	Reasonably likely (RLi)	It is reasonably likely that consequences occur given the occurrence of the failure event (i.e. exist from time to time on the system or during operations, possibly caused by a potential design or operations procedural weakness)
8	Highly likely (HL)	It is highly likely that consequences occur given the occurrence of the failure event
9,10	Definite (D)	Possible consequences happen given the occurrence of a failure event (i.e. likely to exist repeatedly during operations due to a anticipated potential design and operations procedural drawback)

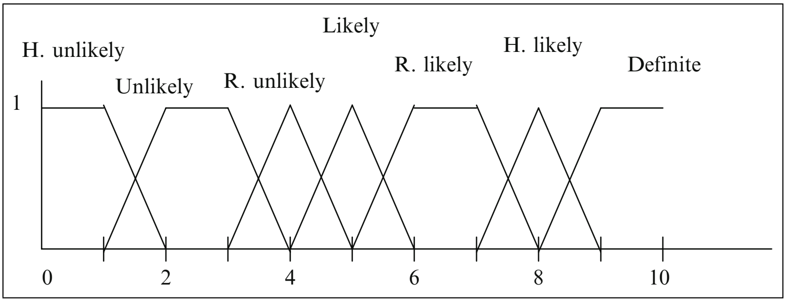

Fig. 5. Fuzzy failure consequence probability set definition

attribute of the kth rule, with $i = 1, 2, 3;\ k \in \{1, \ldots, N\}$. Thus the kth rule in a rule base can be written as:

$$R_k : \text{IF } \mathbf{FR} \text{ is } A_1^k \text{ AND } \mathbf{CS} \text{ is } A_2^k \text{ AND } \mathbf{FCP} \text{ is } A_3^k \text{ THEN } \textit{\textbf{safety estimate}} \text{ is } D_k \tag{1}$$

Here $\{A_1^k,\ A_2^k,\ A_3^k\}$ is called the *packet of antecedents* and for convenience, denoted as A^k (i.e., the packet of antecedents in the kth rule, $k \in \{1, \ldots, N\}$).

For the case study in Sect. 3, we suppose that a linguistic term set with seven labels is used for **FR** (i.e., $J_1 = 7$); one with five labels for **CS** (i.e., $J_2 = 7$), and a seven labels term set for **FCP** (i.e., $J_3 = 7$). They have been described in Phase #2, respectively. In addition, we also suppose that $T = 5$, and $D_t \in S_T = \{s_0 = \text{`}Poor\text{'},\ s_1 = \text{`}Low\text{'},\ s_2 = \text{`}Average\text{'},\ s_3 = \text{`}High\text{'},\ s_4 = \text{`}Good\text{'}\}$ $(t = 0, \ldots, 4)$.

A sample of 245 rules of a rule-base will be used in the case study in Sect. 3 for safety estimate [13]:

- Rule # 1: IF **FR** is *very low* AND **CS** *is negligible* AND **FCP** is *highly unlikely* THEN ***safety estimate*** is *good*
- Rule # 2: IF **FR** is *very low* AND **CS** is *negligible* AND **FCP** is *unlikely* THEN ***safety estimate*** is *good*
- ...
- Rule # 244: IF **FR** is *highly frequent* AND **CS** is *catastrophic* AND **FCP** is *highly likely* THEN ***safety estimate*** is *poor*
- Rule # 245: IF **FR** is *highly frequent* AND **CS** is *catastrophic* AND **FCP** is *definite* THEN ***safety estimate*** is *poor*

Phase #4: Fuzzy inference scheme

The inference procedure is basically composed of three steps, summarized as follows:

Step 4.1: *Discretization of an input into the distributed representation of the linguistic values in antecedents*

This step determines the degrees of membership of an input to each linguistic value in the antecedent, i.e., the matching degree between the input and the antecedents.

An input may be uncertain and can be obtained from history data or expert's experiences. This framework offers the following numerical forms to suit conditions under study:

- A single deterministic value with 100 % certainty;
- A closed interval defined by an equally likely range;
- A triangular distribution defined by a most likely value, with lower and upper least likely values;
- A trapezoidal distribution defined by a most likely range, with lower and upper least likely values.

The input is transformed into a distributed representation of linguistic values in antecedents. In general, we may consider a linguistic term in the antecedent as an evaluation grade, the input for an antecedent attribute, A_i, can be assessed to a distribution representation of the linguistic term sets using matching degrees:

$$f(A_i^*) = \{(A_{ij};\ \alpha_{ij}),\ j = 1, \ldots, J_i\},\ i = 1, 2, 3, \tag{2}$$

f is the distribution representation of a linguistic term, A_i^* $(i = 1, 2, 3)$ that is the input for **FR, CS, FCP** respectively, and α_{ij}, represents the matching degree to which A_i^* belongs to the jth defined linguistic term A_{ij} of the ith antecedent parameter, that is computed by means of a matching function.

A simple matching function, τ, to compute α_{ij} is given as follows [21]:

$$\begin{aligned} &\alpha_{ij} = \tau(A_i^*,\ A_{ij}) = \max_x[\min(\mu_{A_i^*}(x), \mu_{A_{ij}}(x))], \\ &\alpha_{ij} \in [0, 1]\ (i = 1,\ 2,\ 3 \text{ and } j = 1,\ 2, \ldots, J_i) \end{aligned} \tag{3}$$

where x covers the domain of the input A_i^*. In fact, this is *the highest point of intersection* of the input A_i^* and the fuzzy linguistic term A_{ij}.

Finally, an input to the rule-base can be expressed as follows:

$$\mathbf{FR} \text{ is } f(A_1^*) \text{ AND } \mathbf{CS} \text{ is } f(A_2^*) \text{ AND } \mathbf{FCP} \text{ is } f(A_3^*) \tag{4}$$

where f is given by (2) and (3).

Comparing (4) with each rule given in (1), an input can be decomposed into the following form:

$$\mathbf{FR} \text{ is } (A_1^k; \alpha_1^k) \text{ AND } \mathbf{CS} \text{ is } (A_2^k; \alpha_2^k) \text{ AND } \mathbf{FCP} \text{ is } (A_3^k; \alpha_3^k) \tag{5}$$

Here $A_i^k \in \{A_{ij},\ j = 1, \ldots, J_i\}$, $i = 1, 2, 3$; $\alpha_i^k \in \{\alpha_{ij};\ i = 1, 2, 3$ and $j = 1,\ 2, \ldots, J_i\}$. The final objective in this phase is to infer the conclusion using the rule-base (1) for the given input (4).

If the numerical values for the antecedent parameters (e.g., **CS**) are not available at all, then, the assessment of the antecedent parameters can also be carried out based only on experts' subjective judgements, i.e., they can be directly assessed to a distribution representation of each corresponding linguistic value with the degree of credibility. The corresponding f is a kind of subjective assignment. For example, **CS** could be assessed by a subjective distribution vector as follows:

$$\mathbf{CS}:\ \{(\mathit{marginal},\ 0.7),\ (\mathit{moderate},\ 0.2),\ (\mathit{critical},\ 0.1)\}.$$

This input assessment means that we are only 70% sure that **CS** is *marginal*, 20% sure that **CS** is *moderate*, and 10% sure that **CS** is *critical.*

Step 4.2: *Selection of "AND" connectives to reflect the dependencies of the antecedent parameters of a rule.*

Since the IF-part of a given rule has more than one antecedent parameter, the fuzzy operator AND is applied to obtain one global matching degree for that rule.

It should be noted that the *minimum* operator considers only one of several antecedent parameters and does not allow for any compensation among them. Due to this fact, in the safety estimate, we consider "AND" as that the consequent of a rule is not believed to be true unless all the antecedent parameters of the rule are activated. Therefore, in such cases we propose the use of the *product* operator as the AND connective to reflect the dependencies of the three parameters **FR, CS**, and **FCP**, i.e., the global matching degree α_k that the input $A^*{}_i (i = 1, 2, 3)$ belongs to the packet of antecedents A^k in the kth rule can be calculated as follows:

$$\alpha_k = \prod_{i=1}^{3} \alpha_i^k. \tag{6}$$

If the relative importance of the antecedent parameters is considered, the following weighted multiplicative aggregation function is used to calculate α_k:

$$\alpha_k = \prod_{i=1}^{3} \left(\alpha_i^k\right)^{\bar{\delta}_i} \tag{6a}$$

where

$$\bar{\delta}_i = \frac{\delta_i}{\max\limits_{i=1,\ldots,3} \{\delta_i\}} \text{ so } 0 \leq \bar{\delta}_i \leq 1. \tag{6b}$$

δ_i is the weight of the ith parameter ($i = 1,\ 2,\ 3$). Note that $0 \leq \alpha_k \leq 1$, $\alpha_k = 1$ if $\alpha_i^k = 1$ for all $i = 1, 2, 3$, and $\alpha_k = 0$ if $\alpha_i^k = 0$ for any $i = 1, 2, 3$. Also, the contribution of an antecedent parameter towards α_k is positively related to the weight of the attribute. In other words, the more important attribute the greater role in determining α_k.

Step 4.3: *Rule combination using an aggregation operator to create a resultant safety estimate*

To reach a final conclusion, all rules must be combined since the conclusion is based on the testing of all the rules in a fuzzy inference system. The input of the aggregation process is the list of global matching degrees for the antecedents in each rule. The classical fuzzy inference method infers the output with the greatest matching degree. Hence, the Arithmetic Mean aggregation function is suggested to use in this study. The assessment done by the *ith* expert e_i on the *lth* potential cause a_l to a technical failure by the aggregation of the consequent across the rules, i.e., the *safety estimate* $S(e_i(a_l))$, is expressed as follows:

$$S\left(e_i\left(a_l\right)\right) = \left\{\left(Poor; \vartheta_{0i}^l\right); \left(Fair; \vartheta_{1i}^l\right), \left(Average; \vartheta_{2i,}^l\right); \left(Low; \vartheta_{3i,}^l\right); \left(Good; \vartheta_{4i}^l\right)\right\}, \tag{7}$$

where $\vartheta_{ti}^l = \frac{\sum\limits_{r \in K_t} \alpha_r}{|K_t|}$ $(t = 0, \ldots, T = 4)$, $\alpha_r = \prod\limits_{i=1}^{3} \alpha_i^r$, e_i represents the *ith* expert $(i = 1, \ldots, p)$ and a_l represents the *lth* $(l = 1, \ldots, q)$ potential cause to a technical failure. Let R be the number of all the rules fired in the evaluation, K_t represents the set of all the fired rules in which D_t $(t = 0, \ldots, 4)$ is the output term, here $D_t \in S_T \cdot |K_t|$ is the cardinality of the set K_t, hence $R = \sum\limits_{t=0}^{4} |K_t|$. Note that $S(e_i(a_l))$ actually can be viewed as a fuzzy set on S_T, $\vartheta_{ti}^l \in [0, 1]$ represents the membership degree of which the *safety estimate* belongs to D_t.

Phase #5: Safety synthesis

To achieve a logical and effective evaluation process, it is necessary to break down the complex systems into the simpler sub-systems in a hierarchical manner. The hierarchical framework of attributes or experts is used to guide the overall evaluation of multi-attributes or multi-experts or a combination of multi-attributes-multi-experts decision problems as shown in Figs. 1 and 2.

The first four phases of the framework mainly focus on the safety assessment of a single cause to a technical failure done by an expert. This phase is concerned with the safety synthesis of a system at various levels, such as:

- A synthesis of the safety estimates of various causes to a technical failure done by an expert; or
- A synthesis of the safety estimates of a specific cause to a technical failure done by a panel of experts; or
- A combination of the above two forms, i.e., a multi-attribute-multi-expert safety synthesis (see Fig. 2).

Considering that the safety level is expressed as a linguistic variable in qualitative nature, it is difficult to establish their membership functions. The ordinal fuzzy linguistic approach is considered here to use the direct computation on linguistic values instead of using their membership functions. In this framework, particularly a 2-tuple linguistic representation model [7,8] is used to perform the safety synthesis of an engineering system with a structure that is capable of being decomposed into a hierarchy of levels. The number of levels required in safety synthesis is determined by the degree of complexity of a system under scrutiny or the number of experts taking part in the assessment.

The safety synthesis procedure can be summarised as the following five steps:

Step 5.1: *Transforming the safety estimate into the linguistic 2-tuple.*

Advantages of the 2-tuple linguistic representation to manage linguistic information over classical models were shown in [8], some concepts and properties are referred to [7,8].

In this phase we transform the fuzzy set $S(e_i(a_l))$ obtained in (7) on the S_T into a linguistic 2-tuple over the S_T. A function χ_i^l is introduced that transforms a fuzzy set in a linguistic term set S_T into a numerical value in the interval of granularity of S_T, $[0, T-1]$, T is the cardinality of S_T; $F(S_T)$ denotes the set of all fuzzy sets on the S_T:

$$\begin{aligned}&\chi_i^l : F(S_T) \to [0, T-1], \chi_i^l(\{(s_t; \vartheta_{ti}^l), t = 0, \ldots, T-1\})\\ &= \frac{\sum_{t=0}^{T} t\vartheta_{ti}^l}{\sum_{t=0}^{T} \vartheta_{ti}^l} = \beta_i^l \in [0, T-1]\,. \qquad (8)\end{aligned}$$

Then its 2-tuple linguistic representation is calculated by the operator Δ:

$$\begin{aligned}&\Delta : [0; T-1] \to S_T \times [-0.5, 0.5),\\ &\Delta(\beta_i^l) = (s_{round(\beta_i^l)}, \lambda = \beta_i^l - \mathrm{round}(\beta_i^l)),\ \text{where } \lambda \in [-0.5, 0.5). \qquad (9)\end{aligned}$$

Here $S_T = \{s_0 = \text{'}Poor,\text{'}\ s_1 = \text{'}Low,\text{'}\ s_2 = \text{'}Average,\text{'}\ s_3 = \text{'}High,\text{'}\ s_4 = \text{'}Good\text{'}\}$, $T = 5$. $\beta_i^l \in \{0, \dots, T-1\}$ is obtained using (8). Therefore, applying the Δ function to β_i^l $(i = 1, \dots, p;\ l = 1, \dots, q)$ we shall obtain a safety estimate (by the *ith* expert on the *lth* potential cause to a technical failure) whose values are linguistic 2-tuple, e.g., if $\beta_i^l = 1.2$, then its 2-tuple representation is (*Low*, 0.2). There is always a Δ^{-1} function, such that, from a linguisitc 2-tuple it returns its equivalent numerical value $\beta \in [0,\ g]$.

$$\Delta^{-1} \quad : \ S \times [-0.5,\ 0.5) \rightarrow [0;\ g],\ \Delta^{-1}(s_i;\ \lambda) = \lambda + i = \beta. \tag{10}$$

Step 5.2: *Relative weights assignment*

It is highly unlikely for the selected experts to have the same importance, and usually, weights of importance need to be utilised. Each expert is assigned with a weight to indicate the relative importance of his or her judgment in contributing towards the overall safety evaluation process. The analyst must decide which experts are more authoritative. Weights are then assigned accordingly.

In [7, 8], some of the 2-tuple linguistic aggregation operators were presented, such as the Arithmetic Mean operator and the Weighted Mean operator by means of the linguistic 2-tuples. Therefore, to aggregate the linguistic 2-tuples, we shall choose one of these operators and apply it for combining the linguistic 2-tuples, obtaining as a result an aggregation linguistic 2-tuple assessed in S_T for safety synthesis as follows.

Step 5.3: *The synthesis of 2-tuple expression of safety estimates of a specific cause to a technical failure done by a panel of experts by using the 2-tuple weighted mean aggregation operator.*

$$\begin{aligned} \beta^l &= \text{W\_AM}^* \left((w_1;\ \beta_1^l), \dots, (w_p;\ \beta_p^l) \right), \\ &= \Delta \left(\frac{\sum_{i=1}^{p} \Delta^{-1}(\Delta(\beta_i^l)) \cdot w_i}{\sum_{i=1}^{p} w_i} \right) = \Delta \left(\frac{\sum_{i=1}^{p} \beta_i^l \cdot w_i}{\sum_{i=1}^{p} w_i} \right). \end{aligned} \tag{11}$$

$W = \{w_1, \dots, w_p\}$ is the associated experts' weight vector, Δ and Δ^{-1} are given in (9) and (10) respectively.

Step 5.4: *Ranking and interpretation of the safety synthesis*

The safety estimate results obtained from the approximate reasoning have been transformed into the 2-tuple linguistic representations. Moreover, based on the multi-expert synthesis results on each potential cause from Step 5.3, this step compares the overall 2-tuple representation of the risk level by a panel of experts. Then the identified potential causes are ranked on the basis of their 2-tuple expressions. The ranking results for risks due to various potential causes may help designers understand the anticipated technical problem, so that an improved risk reduction measure can be incorporated or a more innovative design can be carried out in order for higher safety level.

The following are some concepts on the comparison of the linguistic 2-tuples [7, 8] used in the ranking process.

Let $(s_k,\ \lambda_1)$ and $(s_l;\ \lambda_2)$ be two linguistic 2-tuples, with each one representing a counting of information, then

- if $k < l$ then $(s_k,\ \lambda_1)$ is smaller than $(s_l,\ \lambda_2)$
- if $k = l$ then
  (1) if $\lambda_1 = \lambda_2$ then $(s_k,\ \lambda_1)$, $(s_l,\ \lambda_2)$ represent the same information
  (2) if $\lambda_1 < \lambda_2$ then $(s_k,\ \lambda_1)$ is smaller than $(s_l,\ \lambda_2)$
  (3) if $\lambda_1 > \lambda_2$ then $(s_k,\ \lambda_1)$ is bigger than $(s_l,\ \lambda_2)$

Step 5.5: *The synthesis of safety estimate of various causes to a technical failure by using the 2-tuple Arithmetic Mean aggregation operator.*

$$\mathrm{AM}^*(\beta^1, \ldots, \beta^q) = \Delta(\frac{1}{q}\sum_{l=1}^{q}\beta^l). \tag{12}$$

Finally, a multi-attribute-multi-expert safety synthesis can be obtained.

3 Case Study: Collision Risk of FPSO & Shuttle Tanker During a Tandem Offloading Operation

Floating production storage offloading (FPSO) systems combine traditional process technology with marine technology, and thus are dependent on the technical design and the operational safety control [11]. It is essential that the anticipated hazards due to technical factors can be identified, risk control options be proposed, and risk reduction or control measures be taken to reduce the risk to as low as reasonably practical (ALARP). Scenarios involving potential major hazards, which might threaten an FPSO or loss of operational control, are assessed at an early stage in the design of new facilities to optimise technical and operational solutions [13]. Collision between a FPSO and a shuttle tanker in tandem offloading operation has caused a growing concern in the North Sea as well as the rest of the world [11].

In this section, safety assessment is carried out on risks introduced by the collision of FPSO and shuttle tanker during tandem offloading operation. Only the technical failures caused risk is assessed here, though the operational failure has been also recognised as one of the major causes of collision. For the purpose of safety modelling, it is assumed that each antecedent parameter (i.e., **FR, CS**, and **FCP**) will be fed to the proposed safety model in term of any of the four input forms described in Phase #3 of Sect. 2.

According to the literature survey, the technical failures that might cause collisions between an FPSO and a shuttle tanker during tandem offloading operations are malfunction of propulsion systems [3]. The four major causes to these technical failures are:

(1) Controllable pitch propeller (CPP) failure
(2) Thruster failure

(3) Position reference system (PRS) failure
(4) Dynamics positioning system failure (DP)

A panel of five experts from different disciplines participated in risk analyses of the above four identified causes to the technical failures. They used different input forms to describe the collision risk scenario in terms of **FR, CS** and **FCP**.

The safety estimate of each technical failure is assessed by five experts separately. The assessment made by the five experts in terms of **FR, CS**, and **FCP** is depicted in Table 4 for collision between FPSO and shuttle tanker during tandem offloading operation due to controllable pitch propeller (CPP) caused technical failure. Other three kinds of assessments are depicted in Tables 5–7, respectively.

A sample of the 245 rules in the rule base [13] is used in this case study. For illustration, we take CPP for example, Expert # 1 used triangular form to address the inherent uncertainty associated with the data and information

Table 4. Experts' inputs for the technical failure caused by malfunction of the controllable pitch propeller (CPP)

Expert	Shape of input form	FR	CS	FCP
E # 1	Triangular	(6.5, 8, 9.5)	(7.5, 8.5, 9.5)	(5.5, 7, 8.5)
E # 2	Triangular	(5.5, 7.5, 9)	(7, 8.5, 10)	(5, 7.5, 9.5)
E # 3	Closed interval	[6,8]	[7,9]	[6.5, 9]
E # 4	Trapezoidal	{5.5, 6.5, 9, 10}	{5.5, 7, 8, 10}	{5, 7, 8, 8.5}
E # 5	Single deterministic	7.75	8.25	7.6

Table 5. Experts' inputs for the technical failure caused by malfunction of the thruster

Expert	Shape of input form	FR	CS	FCP
E # 1	Triangular	(6, 7, 7.5)	(6.5, 7, 8)	(4.5, 5.5, 6)
E # 2	Triangular	(6, 6.5, 8)	(7, 8, 9)	(6, 7.5, 8)
E # 3	Closed interval	[5.5, 7.5]	[6,8]	[6,8]
E # 4	Trapezoidal	{5, 6, 7, 8}	{5, 7, 8, 9}	{5, 6, 7, 9}
E # 5	Single deterministic	7.15	7.95	7.25

Table 6. Experts' inputs for the technical failure caused by malfunction of the position reference system (PRS)

Expert	Shape of input form	FR	CS	FCP
E # 1	Triangular	(6.5, 7, 7.5)	(8, 8.5, 9)	(5.5, 7, 8)
E # 2	Triangular	(6, 7.5, 8)	(7.5, 8, 9.5)	(5, 6, 7)
E # 3	Closed interval	[6.5, 8]	[7, 7.5]	[6.5, 7.5]
E # 4	Trapezoidal	{6, 7, 8, 9}	{5, 7, 8, 8.5}	{6, 7, 8, 9}
E # 5	Single deterministic	7.5	7.2	7.1

Table 7. Experts' inputs for technical failure caused by malfunction of the dynamics positioning system (DP)

Expert	Shape of input form	FR	CS	FCP
E # 1	Triangular	(7, 7.5, 8)	(7.5, 8.5, 9)	(6, 7, 7.5)
E # 2	Triangular	(6.5, 7, 8)	(6.5, 7, 8.5)	(5.5, 6, 7)
E # 3	Closed interval	[7,9]	[7.5, 9.5]	[7,8]
E # 4	Trapezoidal	{6.5, 7, 7.5, 8}	{6, 6.5, 7, 8}	{6.5, 7, 7.5, 9}
E # 5	Single deterministic	7.95	8.25	7.9

available, while carrying out the assessments on the three input parameters. The **FR** is described triangularly as (6.5, 8.0, 9.5) on the fuzzy scale. The most likely value is 8.0, 6.5 and 9.5 are the lower and upper least likely values, respectively.

The safety estimates made by the five experts for the technical failure caused by malfunction of the controllable pitch propeller (CPP) are performed separately according to the proposed fuzzy-logic-based approximate reasoning approach. The safety estimate assessed by Expert # 1 for the potential cause # 1 (CPP) to a technical failure has the result as follows by using (7):

$$S\left(e_1\left(a_1\right)\right) = \left\{(good; 0), (low; 0), (average; 0), (high; 0.0764), (poor; 0.1999)\right\}.$$

The output can be interpreted in such a way that the safety estimate of the system is "*high*" with a membership degree of *0.0764* and "*Poor*" with a membership degree of *0.1999*. Furthermore, it can be transformed into a linguistic 2-tuple value in S_T using (8) and (9):

$$\chi_1^1(\{(s_t, \vartheta_{t1}^1), t = 0, \ldots, 4\}) = \frac{\sum_{t=0}^{4} t\vartheta_{t1}^1}{\sum_{t=0}^{4} \vartheta_{t1}^l} = 0.2765 = (Poor,\ 0.2765).$$

The similar computations are performed for the safety assessments by all five experts using the proposed fuzzy-logic-based approximate reasoning approach for all four technical failures. The results attained for thrusters, PRS and DP caused technical failures by the five experts are shown in Table 8.

As shown in Fig. 1, the aggregation operators on the 2-tuple linguistic representations are used to synthesise the information thus produced to assess the safety of the whole system. This step is concerned with the safety synthesis of a system at various configurations such as: the first type is multi-attribute synthesis, and the second type is multi-expert evaluation of a particular failure mode. The last one is a multi-attribute-multi-expert synthesis and evaluation.

Table 9 shows the results of multi-expert safety synthesis on the collision risk between FPSO & shutter tanker due to the CPP, thrusters, PRS and DP caused technical failure, obtained using the weighted mean operator on the 2-tuple linguistic representations. The synthesis is carried out with the relative weights assigned to each expert by the 2-tuple weighted mean aggregation operator.

Table 8. Safety estimate by each expert on collision risk between FPSO & shutter tanker due to CPP, the thrusters, PRS and DP caused technical failure

Expert #		E # 1	E # 2	E # 3	E # 4	E # 5
CPP	Safety estimate	{(Poor; 0.1999), (Low; 0.0764)}	{(Poor; 0.3170), (Low; 0.1385)}	{(Poor; 0.9118), (Low; 1)}	{(Poor; 0.4314), (Low; 0.3165), (Average; 0.1309)}	{(Poor; 0.1299)}
	2-Tuple expression	(Poor, 0.2765)	(Poor, 0.3041)	(Low, −0.4769)	(Low, −0.3419)	(Poor, 0)
Thruster	Safety estimate	{(Poor; 0.2571), (Low; 0.1634), (Average; 0.0438)}	{(Poor; 0.3101), (Low; 0.5262)}	{(Poor; 0.6664), (Low; 0.7223), (Average; 0.5005)}	{(Poor; 0.2955), (Low; 0.3435), (Average; 0.2428)}	{(Poor; 0.25)}
	2-Tuple expression	(Low, −0.4594)	(Low, −0.3708)	(Low, −0.0878)	(Low, −0.0526)	(Poor, 0)
PRS	Safety estimate	{(Poor; 0.1222), (Low; 0.0294)}	{(Poor; 0.3635), (Low; 0.2823)}	{(Poor; 0.5), (Low; 0.5003)}	{(Poor; 0.4019), (Low; 0.3907)}	{(Poor; 0.25)}
	2-Tuple expression	(Poor, 0.1939)	(Poor, 0.4423)	(Low, −0.4999)	(Poor, 0.4929)	(Poor, 0)
DP	Safety estimate	{(Poor; 0.125)}	{(Poor; 0676), (Low; 0.0479)}	{(Poor; 0.125)}	{(Poor; 0.4405), (Low; 0.3536)}	{(Poor; 0.125)}
	2-Tuple expression	(Poor, 0)	(Poor, 0.4157)	(Poor, 0)	(Poor, 0.4453)	(Poor, 0)

Regardless of the weight difference between each expert allocated, the potential risk caused by the thruster failure is always the lowest and DP the highest from Table 9. As the relative weights of the panel experts change as $\{W_{\mathrm{E}\#1}, W_{\mathrm{E}\#2}, W_{\mathrm{E}\#3}, W_{\mathrm{E}\#4}, W_{\mathrm{E}\#5}\} = \{5, 4, 3, 2, 1\}$, DP caused technical failure is ranked first, whereas the potential risk induced by PSR and DP are ranked second and third, respectively. As the relative weights change to {4, 5, 1, 2, 3}, then DP is ranked first, CPP second, PSR third and thrusters last. The results of other weight configurations are depicted in Table 10. The

Table 9. Multi-expert synthesis on each attribute (expert with different weights)

Expert's	Weight				Ranking			
E #1	E #2	E #3	E #4	E #5	CPP	Thruster	PSR	DP
1	1	1	1	1	(Poor, 0.3524)	(Low, −0.3941)	(Poor, 0.3259)	(Poor, 0.1720)
5	4	3	2	1	(Poor, 0.3656)	(Low, −0.3433)	(Poor, 0.3483)	(Poor, 0.1700)
1	2	3	4	5	(Poor, 0.3391)	(Low, −0.4450)	(Poor, 0.3034)	(Poor, 0.1740)
4	5	1	2	3	(Poor, 0.2977)	(Low, −0.4590)	(Poor, 0.2982)	(Poor, 0.1976)
3	4	5	1	2	(Poor, 0.3546)	(Low, −0.3569)	(Poor, 0.3563)	(Poor, 0.1403)

Table 10. Safety ranking (experts with different weights) based on the 2-tuple linguistic representation

Expert's	Weight				Ranking			
E #1	E #2	E #3	E #4	E #5	CPP	Thruster	PSR	DP
1	1	1	1	1	3	4	2	1
5	4	3	2	1	3	4	2	1
1	2	3	4	5	3	4	2	1
4	5	1	2	3	2	4	3	1
3	4	5	1	2	2	4	3	1

Table 11. Multi-attribute-multi-expert safety synthesis by the experts carrying different weights

Expert's	Weight				Safety synthesis
E #1	E #2	E #3	E #4	E #5	
1	1	1	1	1	(Poor, 0.3640)
5	4	3	2	1	(Poor, 0.3852)
1	2	3	4	5	(Poor, 0.3429)
4	5	1	2	3	(Poor, 0.3336)
3	4	5	1	2	(Poor, 0.3736)

ranking results for risks, which are based on various potential causes as assessed by a panel of experts, can lay out a guideline for the designers to enhance the safety level of FPSO.

The results of multi-attribute-multi-expert safety synthesis for other weight variance configurations are depicted in Table 11, which is based on Table 8 using the 2-tuple mean operators on multi-attributes.

4 Conclusions

The framework for modelling system safety proposed in this paper introduced a subjective safety modelling for engineering risk analysis, which is done by combination of the approximate reasoning approach and the ordinal fuzzy linguistic assessment approach.

The safety assessment using the approximate reasoning approach can formulate the domain human experts' experience and the safety engineering knowledge. At the same time, information with different properties from various sources can be transformed into the knowledge base and used in the fuzzy inference process. The safety synthesis approach based on the 2-tuple ordinal linguistic representation is computationally simple and quick.

The results obtained from the case study on collision risk between FPSO and shuttle tanker has shown that such a framework provides the safety analysts and designers with a convenient tool for risk analysis, especially in the initial concept design stages where the related safety information is scanty or with great uncertainty involved. The method described forms a supplement to the methodologies already used in engineering safety assessment.

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