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A Robust Decision-Making Method for Weighting and Ranking Risk Factors, a Case Study in Oil Engineering

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Abstract. This paper firstly distinguishes between risk and Risk Factor (RF), as fundamental concepts in risk management. The need for the current study lies in the fact that although there are various risk analysis methods, but there is no well-defined frameworks for RF analysis. Manifestly, most of the researches on RF have concentrated on identifying them, expressing relationships among them, and descriptive discussion on their root causes, rather than numerically analysing them. Additionally, most of the risk-related methods (e.g. the classical Failure Mode and Effects Analysis (FMEA)) are very sensitive to nuanced changes on inputs. Thus, the paper is to design a robust RF analysis method. The paper proposes a new method called Risk Influential Factor Analysis (RIFA) for evaluation of RFs. Additionally, for getting reliable results, weighting RFs is done by a novel idea named Weight Estimation by Steady Trend (WEST). The WEST is established on the basis of a well-known branch of Multiple Attribute Decision-Making (MADM), called surrogate weighting. Therewith, in analysis section, the paper shows that (I) employing the suggested hybrid RIFA-WEST methodology leads to robust results, (II) compared to the classical FMEA, the RIFA has not many drawbacks to it, and (III) the WEST is comparable with many of the existing surrogate weighting methods. The proposed methodology is applied in a case study from one of the upstream oil engineering disciplines, i.e. Chemical Enhanced Oil Recovery (CEOR).

Key words: risk management, RF analysis, MADM, surrogate weighting, robustness, CEOR.

1. Introduction

The risk analysis has often been one of the basic matters for any real-life activities such as business and engineering (Turskis *et al.*, 2019; Liu, 2025). From a variety of concepts in risk analysis, there are two major ones: risk and Risk Factor (RF). Risk is defined as measures of likelihood and severity of an incident (Haimes, 2008). In some situations, other measures are taken into account, e.g. detectability of incident, manageability of incident,

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etc. RF is a characteristic, condition, or behaviour that increases the likelihood of getting a risk. As an example, lifestyle habits, genetics and family history, diet, poor sleep, stress, age, smoking cigarettes, etc., are RFs to the risk of heart attack. As another example, the contributing RFs to corrosion (internal and external) of a gas pipe are soil chemistry, humidity, salt water, gas velocity, gas pressure, type of gas being transported, etc.

Let's continue with Hillson and Simon (2007) who wrote "many people confuse RFs with risks themselves. An RF, however, describes existing conditions that might give rise to risks. For example, there is no uncertainty about the statement, we have never done a project like this before; so, it cannot be a risk, but this statement could result in a number of risks". Explained another way, RF may be an issue, decision, or concern that may ultimately drive the materialization of risk. Hence, we can discuss about chance of risk happening, whereas using this measure for RF may be meaningless. Consequently, analysts have to distinguish between risk analysis and RF analysis.

For risk analysis, if there are sufficient objective data and verified facts, analysts absolutely tend to quantitative approach (Quantitative Risk Analysis or QRA), e.g. statistical and probabilistic methods such as regression analysis, Bayesian Networks (BN), and Fault Tree Analysis (FTA). Sometimes there is no other way but to employ semi-quantitative or qualitative methods. For instance, in project management environment, in most cases analysts can only access subjective data, i.e. opinions provided by Subject Matter Experts (SMEs); in this case, they can not to benefit from quantitative approach. Semi-quantitative risk analysis has been extensively employed in safety and environmental science. For semi-quantitative analysis of risks, there exist several methods with different application contexts, for instance:

- Analysis of failures in a technical system: Failure Mode and Effects Analysis (FMEA) (Ardeshir *et al.*, 2016; Jin *et al.*, 2024), Fine-Kinney (Fine, 1971), Safety and Critical Effect Analysis (SCEA) (Karasan *et al.*, 2018), and so on.
- Analysis of natural hazards: Seriousness-Manageability-Accessibility-Urgency-Growth (SMAUG) (Kepner and Tregoe, 1981), Frequency-Seriousness-Manageability-Awareness-Urgency-Growth-Outrage (FSMAUGO) (IID, 2007), and so on.
- Analysis of technical hazards: Hazard and Operability analysis (HAZOP) (Feng *et al.*, 2021), Hazard Identification and Risk Assessment (HIRA) (Khan and Abbasi, 2004), and so on.
- Analysis of risks in a project management environment: Probability-Impact matrix (Seyedhoseini and Hatefi, 2009), Influence-Predictability matrix (Elkjaer and Felding, 1999), Probability-Impact-Vulnerability-Outrage-Threat (PIVOT) (Dobson and Leemann, 2010), and so on.

Obviously, we find out that the respective literature has amply focused on risk ranking, but this is a fact that the literature has not paid adequate attention to analysis of RFs using a semi-quantitative or qualitative tool. Even, most of the qualitative methods in the literature focused on identifying RFs, rather than numerically evaluating them. In the absence of a suitable and specific RF analysis method, in many situations analysts have used general statistical tools such as survey questionnaires, e.g. Hafizuddin-Idris *et al.* (2022), and (Oliver *et al.*, 2004). When identifying the causes of a risk, it is important to distinguish between causal factors and root causes. A causal factor is often identified as the direct cause of a risk, whereas a root cause is seen as deeper issue that contributes to risk. Root Cause Analysis (RCA) is a general title for any process for identifying reasons a risk occurred. There are a number of RCA methods such as cause and effect diagram and 5-whys. A cause-and-effect diagram is a visual method for RCA that organizes cause-and-effect relationships into categories. The 5-whys method acts by taking five iterations of the questioning process to investigate the deeper and deeper root causes of a risk. Anyway, in most RCAs, methodologies and results are descriptive, e.g. Nascimento and e-Melo (2013), and Tilocca *et al.* (2024). Ferjencik (2014) provided a complete description on the RCA categories, and proposed an improved RCA structure. According to Kindinger and Darby (2000), Los Alamos National Laboratory (LANL) has developed a qualitative project risk analysis method called Risk Factor Analysis (RFA). In this method, after identification of general RFs, analysts determine each RF contributes which risks, then numerical values are assigned to the risk categories (Low = 1, Medium = 2, High = 3), and finally "RF total" regarding each RF is calculated. The higher RF total, the higher RF rank. Kalyoncuoglu-Matr (2011) used term "Criticality" defined as an event which has the possibility to cause a risk against patient safety. They proposed a risk analysis method named Criticality Risk Assessment (CRA) for diagnosing criticalities, the extension of their relevant risks and the major RFs contributing to their occurrence. In this method, for each criticality, separate evaluation is performed for contributing RFs. Contributing RFs are identified and rated by numbers one to ten. Functional Resonance Analysis Method (FRAM) is a method that models the mechanism of risk emergence through analysis of the system's normal operation. This method is on the basis of four underlying principles: equivalence of failure and success, approximate adjustment, emergence, and functional resonance (Guo *et al.*, 2023).

Frankly speaking, the above literature review on the risk-related methodologies shows that there is no well-defined specific model available for semi-quantitative evaluation of RFs. On the other hand, results of the current methods (for example, the FMEA) are very sensitive to minor variations on inputs. Hence, as the major aim of this paper, we focus on the semi-quantitative analysis of contributing RFs in a given system, and propose a robust methodology for RF ranking. Under the proposed methodology, two new methods are developed: a method called Risk Influential Factor Analysis (RIFA) for ranking RFs, and a method called Weight Estimation by Steady Trend (WEST) to estimate the weights of ranked RFs (in order to meet robust results, discussed in Section 4.1).

As a case study, the proposed methodology is employed for ranking RFs in Chemical Enhanced Oil Recovery (CEOR) that is under one of the major issues in oil engineering. Deeply describing the critical challenges in upstream petroleum engineering is out of scope of the current paper, but let's briefly state those challenges as follows:

– Enhanced Oil Recovery (EOR): It is recovering remaining oil after primary depletion, which is a technically complex operation. Related methods include water flooding, CO_2 injection, steam injection, and chemical flooding (i.e. CEOR). Main challenges through these methods are sweep efficiency, fluid compatibility, mobility control, and reservoir heterogeneity. Notably, many reservoirs still leave over half the oil underground.

– Reservoir characterization: Understanding the underground reservoir is one of the hardest problems because engineers cannot directly see the formation. Even with advanced technology, uncertainty remains high.
– Drilling in complex formations: Firstly, modern wells often pass through unstable or difficult rock formations. Secondly, maintaining proper pressure balance during drilling is critical. Thirdly, modern reservoirs often require highly deviated or horizontal wells. Extended-reach wells can extend several kilometers horizontally, making control difficult. Fourthly, drilling and completion operations can reduce reservoir productivity.
– Flow assurance problems: Maintaining smooth hydrocarbon flow from reservoir to surface is a major challenge. Additionally, weak formations may produce sand with hydrocarbons. Controlling sand without restricting production is difficult.
– Corrosion and material failure: Equipment operates in aggressive environments containing saltwater, CO_2, H_2S, high temperature, abrasive particles. This challenge leads to sulfide stress cracking, hydrogen embrittlement, pipeline corrosion, fatigue failure. Moreover, material selection becomes critical.
– Real-time data integration: Modern wells generate enormous real-time data streams. Relevant challenges include sensor reliability, data interpretation, automated decision-making, Artificial Intelligence (AI) model accuracy, and cybersecurity. Regarding this challenge, engineers must convert raw data into actionable operational decisions quickly.
– Unconventional reservoir complexity: Shale reservoirs behave differently from conventional reservoirs. The problems include nano-scale permeability, rapid decline rates, complex fracture networks, difficult reserve estimation, and parent-child well interference. Additionally, production forecasting remains uncertain.

The paper is structured as follows: Section 2.1 proposes a new idea for prioritization of RFs. Moreover, a novel method for weighting RFs is suggested in Section 2.2. The proposed methodology for RF analysis in group decision-making mode is offered in Section 2.3. Section 3 presents application of the proposed methodology in an empirical case study. Section 4 is to evaluate the proposed hybrid model. Finally, Section 5 summarizes the major findings of the paper, and points out some future research possibilities.

2. Materials and Methods

In this section, two new methods are developed, a method to prioritize RFs, and a method to estimate the weights of ranked RFs. The former is a method from risk management area, and the latter falls into Multiple Attribute Decision-Making (MADM) field. The course of action of the proposed methodology is explained at the end of this section.

2.1. *RIFA Method*

The proposed Risk Influential Factor Analysis (RIFA) is a proactive tool for evaluating the contributing RFs to an individual target risk or overall risk of a system. It is to assess the relative importance of different RFs in order to recognize RFs that are most in need of attention. Thereby, analyst concentrates on a risk/system, and performs the RIFA method. In Health, Safety and Environment (HSE) context, in most cases, a major accident is target risk. Major accident consists of an incident with severe impacts on human health, assets, and the environment (Abbassi *et al.*, 2022). A major accident usually has low frequency and high consequences which are not well supported by conventional statistical methods due to data scarcity (Khakzad *et al.*, 2014). Samples of major accidents are Macondo blowout and explosion, Chernobyl disaster, Coronaviruses contagion, etc.

The RIFA method employs three criteria to evaluate RFs. The criteria are a triple named "3C", i.e. contributivity, controllability, and causality. Each criterion is rated in a 1–9 scale. Number 9 depicts the most critical case, and 1 stands for the least critical situation. As equation (1), the RIFA method defines a metric called Risk Factor Priority Number (RFPN), for each RF, by using weighted geometric mean of the three scores given by SME. Accordingly, c1, c2, and c3 are relative importance of the criteria given by SME, i.e. the higher c1/c2/c3 indicates the more important contributivity/controllability/causality. According to common practice, these weights are non-negative and normalized to add up to one (i.e. $c1 + c2 + c3 = 1$). RFPN ranges from 1 to 9. RFs with higher RFPN indicate greater concerns to the system, and require more attention. Obviously, on the one hand, RFPN function originates in the common formula of Weighted Product Model (WPM) that is an alternative evaluation method in MADM (Hatefi, 2025). On the other hand, it follows the FMEA idea which is computed its index by multiplying three criteria entitled: severity of consequences (S), possibility of occurrence (O), and ease of detection (D) (Dhalmahapatra *et al.*, 2022; Chang *et al.*, 2014).

$$\mathrm{RFPN} = \mathrm{Contributivity}^{c1} \times \mathrm{Controllability}^{c2} \times \mathrm{Causality}^{c3}. \tag{1}$$

2.1.1. *Contributivity Criterion*

Contributivity is defined as the influence degree of RF to enforce materialization of an individual risk, or the overall risk impacting on the performance of a system. In respect to performance of a system, two famous concepts could be taken into account: operability and functionality. Often these terms are being used interchangeably by analysts. To avoid confusion, let's offer the following note. A system may include many sub-systems (units) working together to accomplish the system objectives. Functionality refers to the performance of each individual unit. Operability implies that the whole system properly acts; refers to the performance of all the system units together. As a matter of fact, operability is the ability to keep the whole system in a safe and reliable functioning condition. Anyway, while each unit has a specific function, without successful completion of individual tasks, the system operation would not be complete. Table 1 and Table 2 show the guidelines to rate the contributivity criterion, where 1 means having absolutely no significant contribution and 9 to be a substantial trigger. When rating contributivity of a given RF, analyst should assume that the RF under analysis is at the worst condition and the rest of RFs are kept at their best conditions.

Table 1
RF contributivity scale, regarding an individual risk.

Contributivity rating		Guidelines relating to occurrence of an individual target risk
Verbal expression	Score	
Absolutely contributive	9	RF increases risk probability to up to 0.9
Very highly contributive	8	RF increases risk probability to up to 0.8
Highly contributive	7	RF increases risk probability to up to 0.7
Relatively highly contributive	6	RF increases risk probability to up to 0.6
Moderately contributive	5	RF increases risk probability to up to 0.5
Relatively minimally contributive	4	RF increases risk probability to up to 0.4
Minimally contributive	3	RF increases risk probability to up to 0.3
Very minimally contributive	2	RF increases risk probability to up to 0.2
Absolutely not-contributive	1	RF increases risk probability to up to 0.1

Table 2
RF contributivity scale, regarding performance of a system.

Contributivity rating		Guidelines relating to performance of a system	
Verbal expression	Score	Influence on operability:	Influence on functionality:
Absolutely contributive	9	Highly destructive	Highly destructive
Very highly contributive	8	Highly destructive	Moderately destructive
High contributive	7	Highly destructive	Minimally destructive
Relatively high contributive	6	Moderately destructive	Highly destructive
Moderately contributive	5	Moderately destructive	Moderately destructive
Relatively low contributive	4	Moderately destructive	Minimally destructive
Minimally contributive	3	Minimally destructive	Highly destructive
Very minimally contributive	2	Minimally destructive	Moderately destructive
Absolutely not-contributive	1	Minimally destructive	Minimally destructive

2.1.2. *Controllability Criterion*

Controllability is the answer to this question: How much investment/time/energy needs to be consumed in order to control RF? By control and management of RF, we try to adjust its characteristics according the best situation. To control an RF, if we need a huge amount of energy, this actually means that no control actions can be done about RF, e.g. earthquake is an RF that can cause disruption of gas pipelines, but our control to prevent this natural hazard is really about zero. As another example, for gas pipe corrosion, type of gas is often very uncontrollable, because this is a systematic fact of the transportation pipeline system; on the contrary, humidity can be controlled by using appropriate coating, periodic inspections, and preventive maintenance system. Table 3 is to rate controllability. In this table, terms such as expensive, cheap, and so on, should be interpreted in relation to the cost of occurrence of target risk, or the cost of improper system performance due to RF. Anyway, the higher the controllability indicates the degree to which RF can be influenced by control actions.

2.1.3. *Causality Criterion*

Causality is a term extracted from cause-and-effect relationships among RFs. This criterion follows this fact that an RF alone can be alarming, but when it is combined with other

Table 3
RF controllability scale.

Controllability rating		Guideline
Verbal expression	Score	To control RF, the owner needs to consume:
Absolutely controllable	9	Almost zero investment/time/energy, i.e. no action is needed.
Very high controllable	8	Super cheap investment/time/energy.
High controllable	7	Cheap investment/time/energy.
Relatively high controllable	6	A little lower than normal investment/time/energy.
Moderately controllable	5	Normal investment/time/energy.
Relatively low controllable	4	A little higher than normal investment/time/energy.
Low controllable	3	Expensive investment/time/energy.
Very low controllable	2	Super expensive investment/time/energy.
Absolutely uncontrollable	1	Almost infinite investment/time/energy, i.e. it is impossible to control.

Table 4
RF causality scale.

Causality rating		Guidelines
Verbal expression	Score	RF exacerbates about:
Absolutely causative	9	$>90\%$ of the other RFs
Very high causative	8	80% of the other RFs
High causative	7	70% of the other RFs
Relatively high causative	6	60% of the other RFs
Moderately causative	5	50% of the other RFs
Relatively low causative	4	40% of the other RFs
Low causative	3	30% of the other RFs
Very low causative	2	20% of the other RFs
Absolutely not-causative	1	$<10\%$ of the other RFs

RFs, it may be destructive. Consequently, causality is an answer to this question: to what extent an RF can enforce other RFs? As an example, among heart attack RFs, stress is a major cause of other RFs such as lifestyle, poor sleep, and even diet. Table 4 exhibits the guidelines to rate the causality criterion.

2.2. *WEST Method*

According to the process of the proposed methodology (explained in Section 2.3), ranks of the RFs obtained by the RIFA method need to be converted into the weights. For this purpose, a branch of the attribute weighting methods entitled “surrogate weighting” can be used. The relevant methods have been coded as I/+SW by Hatefi (2023c), i.e. Integrated and Surrogate Weights. The related methods take ranks of n items as inputs, and convert them to weights. Firstly, priorities of the items are determined. Next, ranks $1, 2, \dots, n$ are assigned to the item of the first-ranked, second-ranked … and last-ranked. After that, the weights are estimated using a straightforward formula. The estimated weights need to be in accordance with the weight space as equation (2), in which ω_j is the weight of item by rank j.

$$\left\{(\omega_1, \omega_2, \dots, \omega_n) \,\middle|\, \omega_1 \geqslant \omega_2 \geqslant \dots \geqslant \omega_n, \sum_{j=1}^{n} \omega_j = 1, \omega_j \geqslant 0\right\}. \tag{2}$$

The proposed Weight Estimation by Steady Trend (WEST) is a new method from I/+SW family. The WEST method is founded on the elementary weights estimated by arithmetic progression and geometric progression. In what follows, firstly a brief background on most famous I/+SW methods is stated, then platforms of the WEST method are explained in next sub-sections.

2.2.1. *Background on Related MADM Methods*

There are many surrogate weight estimation formulas in the relevant literature (Hatefi *et al.*, 2023). Each method is build based upon a basic idea. Let us see some instances which are new or famous in the related literature. The underlying concept of Equal Weights method (EW) ($\omega_j = 1/n$) (Dawes and Corrigan, 1974) is this fact that if the DM has no reason for preferring one item over another, he/she can distribute the weights equally among all the items. Unit Vector method (UV) ($\omega_1 = 1$, $\omega_j = 0$, $j > 2$) assigns total weight only to the first-ranked item. The main idea behind this method originates in Pareto principle which say vital are few and trivial are many. The basic idea of Rank Sum method (RS) ($\omega_j = 2(n+1-j)/n(n+1)$) (Stillwell *et al.*, 1981) is the ranks should be reflected directly in the weights. Rank-Order Centroid method (ROC) ($\omega_j = \sum_{\mathrm{r}=j}^{n}(1/r)/n$) (Barron, 1992) assumes that the weights are uniformly distributed on the weight space, thus this method suggested the centre of the weight space. Notably, from I/+SW methods, the ROC method is known as a seminal model. There are some methods developed on the basis of the ROC method, such as Rank-Order Total method (ROT) ($\omega_j = 3(n+2-j)(n+1-j)/n(n+1)(n+2)$) (Liu *et al.*, 2020) which is a combination of the RS and the ROC methods, Improved ROC method (IROC) (Hatefi, 2023a), and Rank-Order Logarithm (ROL) $\left(\omega_j = \frac{\ln(j)-\ln(n+1)}{\ln(n!)-n\times\ln(n+1)}\right)$ (Hatefi, 2023b).

2.2.2. *Arithmetic Weights*

The DM's mentality about the weights may be distance-based, e.g. if he/she gives $\omega_1 = 0.8$ and $\omega_2 = 0.2$, he/she interprets that importance of the first-ranked item is 0.6 more than that of the second-ranked item. In such situation, arithmetic progression can be used to generate the weights. To this, a linear system as equation (3) is needed to be solved. In this system, distance between the weights of each two sequential items is a positive constant value ($= d$), i.e. we assume that the DM is steady in his/her judgments between each two sequential items.

$$\begin{cases} \sum_{j=1}^{n} \omega_j = 1, \\ \omega_j - \omega_{j+1} = d, \quad j = 1, 2, \dots, n-1. \end{cases} \tag{3}$$

By solving the above system, the formula is obtained as a linear equation (4):

$$\omega_j^A = \frac{1}{n} + \frac{d}{2}(n - 2j + 1), \quad j = 1, 2, \dots, n. \tag{4}$$

The weights for the most and the least important items guide us to obtain an upper bound for parameter d. For $j = 1$, we can write $\frac{1}{n} + \frac{d}{2}(n - 2 \times 1 + 1) \leqslant 1$, or $d \leqslant 2/n$. Additionally, for $j = n$, we have $\frac{1}{n} + \frac{d}{2}(n - 2 \times n + 1) \geqslant 0$, or $d \leqslant 2/n(n-1)$. Consequently, d has to be adjusted less than or equal to $2/n(n-1)$. This method reduces to the EW method provided that $d = 0$. Moreover, for $d = 2/n(n+1)$, it equals the RS formula.

2.2.3. *Geometric Weights*

The DM's mentality about the weights may be proportion-based, e.g. for $\omega_1 = 0.8$ and $\omega_2 = 0.2$, the DM expresses the first-ranked item is 4 times more important than the second-ranked item. In this case, geometric progression strikes us to calculate the weights. Accordingly, a linear system as the equation (5) should be solved. In this system, p ranges from 0 to 1. Like arithmetic series, we expect the DM to be steady in his/her judgments between each two sequential items.

$$\begin{cases} \sum_{j=1}^{n} \omega_j = 1, \\ \omega_{j+1}/\omega_j = p, \quad j = 1, 2, \dots, n-1. \end{cases} \tag{5}$$

The obtained weights would be a non-linear equation (6):

$$\omega_j^G = \frac{p^{j-1}}{\sum_{r=1}^{n} p^{r-1}} = \frac{p^{j-1} - p^j}{1 - p^n}, \quad j = 1, 2, \dots, n. \tag{6}$$

The above function reduces to the EW method, if $p = 1$. In addition, it approaches the UV method, if p approaches 0.

2.2.4. *The WEST Function*

The WEST method is a convex linear combination of the above two notions (arithmetic weights and geometric weights), as the equation (7). Parameter t is a number between 0 and 1, indicating the DM's tendency to distance-based or proportion-based outlook about the weights.

$$\omega_j^{\text{WEST}} = t\left(\frac{1}{n} + \frac{d}{2}(n - 2j + 1)\right) + (1-t)\left(\frac{p^{j-1} - p^j}{1 - p^n}\right), \quad j = 1, 2, \dots, n. \tag{7}$$

This formula contains three parameters d, p and t. Even so the DM can personally adjust the parameters, but the WEST method suggests default values for the parameters on the basis of well-founded concepts as follows.

According to many researchers such as Sureeyatanapas *et al.* (2018), Tversky *et al.* (1988), and Fischer and Hawkins (1993), steepest patterns of weight distribution are most likely to be consistent with the people's judgments. A function $S = \min_{j=1,\dots,n-1}\{\omega_j - \omega_{j+1}\}$ is proposed to measure the steepness. The larger S indicates more steepness reflecting more adaptation of the weights with people's judgments. In conclusion, maximization of S helps us to adjust a good value for parameters d and p. When arithmetic progression is used to produce the weights, the higher d causes the higher S, hence upper bound of parameter d is usually suggested, i.e. $2/n(n-1)$. The arithmetic progression weights by the most steepness are shown in Appendix A. As an example, for $n=3$, $d=1/3$ results in the maximum steepness. For geometric progression, to determine the best p value, for a given n mathematical model Max$S$ subject to equation (6) should be solved in which p and ω_j are decision variables. As an instance, for $n=4$ the mathematical model would be:

$$\begin{aligned}
&\mathrm{Max}S = \min\{\omega_1-\omega_2, \omega_2-\omega_3, \omega_3-\omega_4\},\\
&\omega_j = \frac{p^{j-1}-p^j}{1-p^4}, \quad j=1,2,3,4,\\
&0 \leqslant p \leqslant 1.
\end{aligned}$$

We solved the relevant mathematical models for $n=2$ to $n=15$. The best p value for $n=2$ to $n=15$ were 0.0001, 0.3660, 0.5437, 0.6445, 0.7090, 0.7538, 0.7867, 0.8118, 0.8317, 0.8477, 0.8610, 0.8721, 0.8816, and 0.8898, respectively. The geometric progression weights by the most steepness are represented in Appendix A.

To get the best value of t, we follow the idea of Zavadskas *et al.* (2012). We search a t value that minimizes variances of the WEST weights. As a matter of fact, the objective is to seek a t value resulting in minimum dispersion. This strategy assures maximal accuracy of estimations (Zavadskas *et al.*, 2012). According to equation (8), variances of the WEST function depend on variances of its components, i.e. equation (4) and equation (6).

$$\sigma^2\big(\omega_j^{\mathrm{WEST}}\big) = t^2\sigma^2\big(\omega_j^A\big) + (1-t)^2\sigma^2\big(\omega_j^G\big), \quad j=1,2,\dots,n. \tag{8}$$

The best values of t can be found when searching extreme of equation (8). Extreme of this function can be found when its derivative in regard to t is equated to zero (equation (9)).

$$2t\sigma^2\big(\omega_j^A\big) - 2\sigma^2\big(\omega_j^G\big) + 2t\sigma^2\big(\omega_j^G\big) = 0, \quad j=1,2,\dots,n. \tag{9}$$

We obtain equation (10). In conclusion, the best value of parameter t varies depending on variances of the weights regarding every particular n. It should be noted that in equation (10) a variance is divided by another variance, thereby we can use population variance or sample variance, so the results are identical.

$$\begin{aligned}
t_n &= \big(1+\sigma^2\big(\omega_j^A\big)/\sigma^2\big(\omega_j^G\big)\big)^{-1}\\
&= \left(1+\sigma^2\left(\frac{1}{n}+\frac{d}{2}(n-2j+1)\right)\Big/\sigma^2\left(\frac{p^{j-1}-p^j}{1-p^n}\right)\right)^{-1}, \quad n=1,2,\dots.
\end{aligned} \tag{10}$$

It should be noted that the best value of parameter t satisfies equation (11):

$$\frac{1}{\sigma^2(\omega_j^{\mathrm{WEST}})} = \frac{1}{\sigma^2(\omega_j^A)} + \frac{1}{\sigma^2(\omega_j^G)}, \quad n=1,2,\dots,n. \tag{11}$$

The WEST weights by the best t for different number of items ($n = 2$ to $n = 15$) are exhibited in Appendix A.

2.3. *The Proposed Methodology*

Figure 1 shows flowchart for implementing the RIFA-WEST methodology. The stages and steps are briefly described as follows:

Stage (A): Organize a panel of h SMEs ($k = 1, \dots, h$).

Stage (B): [Step I:] Assign a number between 1 and 5 to each SME. This number (denoted by d_k) shows level of expertise, on the basis of SME's knowledge, experiences, skills and outlooks around the RFs. This number is subjectively determined. A very professional SME is assigned 5, and a tyro SME receives 1. [Step II:] Normalize d_k by equation (12).

$$u_k = \frac{d_k}{\sum_{i=1}^{h} d_i}, \quad k = 1, 2, \dots, h. \tag{12}$$

Stage (C): [Step I:] Make a complete literature study, and draw up an initial RF list. For instance, published papers, books, related reports, and so on. [Step II:] SMEs benefit from the initial RF list to provide a final list of RFs. In fact, they are permitted to check RFs for recommending any corrective idea. Assume that N RFs ($\mathrm{RF}_1, \mathrm{RF}_2, \dots, \mathrm{RF}_n$) are finally identified.

The following stages (D) to (F) are taken by each individual SME:

Stage (D): [Step I:] Rate contributivity, controllability, and causality for each RF. [Step II:] Determine c1, c2, and c3. [Step III:] Calculate RFPN for each RF.

Step (E): Prioritize RFs in order of RFPNs, from the most important to the least important.
Stage (F): Use the WEST rule to convert ranks to the weights. Let's show the weights by w_{jk}, i.e. the weight determined for RF_j by SME number k.

Now, the individual results are combined through the following stages (G) and (H):

Stage (G): Combine the individual weights (received from h SMEs) by any valid method, e.g. by geometric mean formula. Anyway, as a recently suggested method, the proposed methodology advises to use the idea of Combined Compromise Solution method (CO-COSO) (Yazdani *et al.*, 2019). This combination is reached through six steps as equation (13) to equation (18). In equation (13) and equation (14), ω_{jk} depicts weight of jth RF given by kth SME.

$$S_j = \sum_{k=1}^{h} u_k \omega_{jk}, \quad j = 1, 2, \dots, n, \tag{13}$$

$$p_j = \sum_{k=1}^{h} \omega_{jk}^{u_k}, \quad j = 1, 2, \dots, n, \tag{14}$$

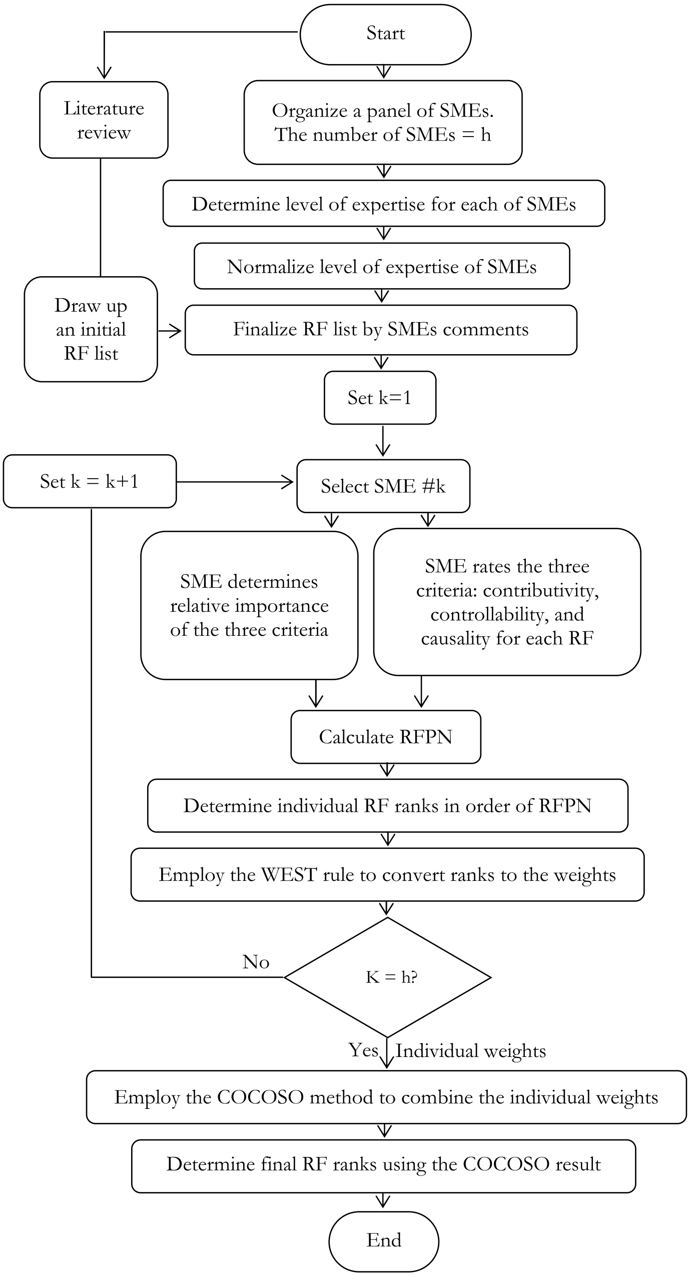

Fig. 1. Flowchart of the proposed RIFA-WEST methodology.

$$k_{ja} = \frac{S_j + p_j}{\sum_{i=1}^{n} S_i + p_i}, \quad j = 1, 2, \dots, n, \tag{15}$$

$$k_{jb} = \frac{S_j}{\min_{i=1,\dots,n} S_i} + \frac{p_j}{\min_{i=1,\dots,n} p_i}, \quad j = 1, 2, \dots, n, \tag{16}$$

$$k_{jc} = \frac{S_j + p_j}{\max_{i=1,\dots,n} S_i + \max_{i=1,\dots,n} p_i}, \quad j = 1, 2, \dots, n, \tag{17}$$

$$\mathrm{FS}_j = \frac{1}{3}(k_{ja} + k_{jb} + k_{jc}) + (k_{ja} \times k_{jb} \times k_{jc})^{1/3}, \quad j = 1, 2, \dots, n. \tag{18}$$

Stage (H): Prioritize RFs in order of the combined Final Score FS_j.

Table 5 is to show process of the proposed methodology, ensure each step is clarified with input, output and how input to output transformation happens.

3. Case Study

In this section, the proposed methodology is employed for general project of Chemical Enhanced Oil Recovery (CEOR) in a country with taking part of a panel of 12 SMEs. CEOR is one of the potential methods to increase the recovery efficiency in hydrocarbon fields. CEOR is a complex process which exhibits a number of risks and Risk Factors (RF). In what follows, the paper exhibits the results of identifying CEOR RFs, prioritizing them, and assigning numerical weights to them.

3.1. *An Introduction*

International Energy Agency (IEA), in 2018, published World Energy Outlook (WEO), which predicts an increment in world energy demand of about 25% by 2040. Fossil fuels, especially oil and gas, will continue to account for the majority of the supply to meet this growth in energy demand. That is why upstream oil and gas companies are still concentrating on enhancing the recovery factor from operational fields (Muggeridge *et al.*, 2014). Upstream oil and gas industry consists of exploration and production of oil and gas fields. For a new oil field with no or short production history, the natural pressure in the reservoir is normally high enough for the oil or gas to flow to the surface. As long as the pressure in the reservoir remains high enough, the production can continue with natural pressure, i.e. primary recovery. The average oil recovery rate from mature oilfields around the world under normal pressure of fields, for most hydrocarbon reservoirs is somewhere between 20% and 40% (Muggeridge *et al.*, 2014). In fact, normal recovery efficiency in Original Oil in Place (OOIP) is close to these numbers. This shows that there is a large potential for technologies to artificially increase the reservoir pressure (Abu-El-Ela *et al.*, 2014). As a matter of fact, as production continues, the reservoir pressure starts dropping at a certain time when the fluids are depleted. When the pressure drops down to the level that continuing production is not economical, owners/analysts need to take a decision whether to abandon the wells or to apply certain artificial lift strategies to increase the reservoir pressure. There are two major strategies (Vora *et al.*, 2021): Improved Oil Recovery (IOR) and

Table 5
Process of the proposed methodology.

Stage	Step	Title	Input	Transformation/tools	Output
A	–	Organize a panel of SMEs	A list of candidate experts	Screening based on knowledge, experiences, and skills	Established panel of SMEs
B	I	Determine level of expertise of SMEs	Panel of SMEs	Assign numbers between 1 and 5 to SMEs on the basis of knowledge, experiences, and skills of them	Level of expertise of SMEs (non-normalized)
B	II	Normalize level of expertise of SMEs	Level of expertise of SMEs (non-normalized)	Divide each level of expertise by total values	Level of expertise of SMEs (normalized)
C	I	Draw up an initial RF list	–	Literature study	Initial RF list
C	II	Make initial RF list	Initial RF list	Expert elicitation	Final RF list
D	I	Rate contributivity, controllability, and causality for each RF, by any SME individually	Final RF list	Tables 1 to 4 / Expert elicitation	Individual RF lists (h lists), characterized by the 3C criteria
D	II	Determine weight of the 3C criteria, by any SME individually	–	Expert elicitation	Weights of the 3C criteria (h vectors of weights)
D	III	Calculate RFPN for each RF, and for each SME, individually	Individual RF lists, characterized by the 3C criteria/Weights of the 3C criteria	Equation (1)	RFPNs for each SME (h lists of RFPNs)
E	–	Prioritize RFs, for each SME individually	RFPNs for each SME (h lists of RFPNs)	Sort according to RFPNs	Individual ranked RF lists (h lists)
F	–	Convert RF ranks to weights, for each SME individually	Individual ranked RF lists (h lists)	The WEST rule, i.e. equation (7)	Individual weighted RF (h lists)
G	–	Combine the RF weights	Individual weighted RF (h lists)	The COCOSO method, using equation (13) to equation (18)	Final weighted RF list
H	–	Prioritize RFs	Final weighted RF list	Sort according to RF weights	Final ranked RF list

Enhanced Oil Recovery (EOR). EOR strategies are used to recover mostly immobile oil that remains in the reservoir, while IOR strategies are employed to increase the recovery of mobile oil. Nowadays, various IOR/EOR technologies like water flooding; gas flooding, etc. are widely used in petroleum industry. One of these methods (the concentration point of the current paper), is known as Chemical EOR (CEOR). CEOR is an EOR technology in which a chemical combination is injected into the reservoir in order to increase sweep and/or displacement efficiency. CEOR processes can currently be considered as promising tertiary technologies for increasing oil recovery from depleted oil reservoirs (Flaaten, 2008). Nowadays, the number of CEOR programs has grown exponentially as the price

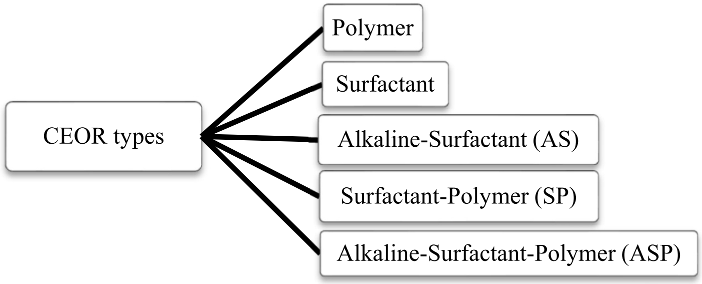

Fig. 2. CEOR types.

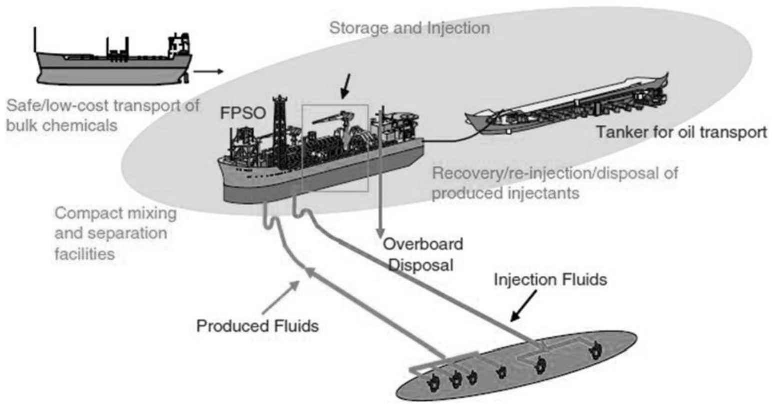

Fig. 3. Typical deep-water application of CEOR (Rany *et al.*, 2011).

of oil increases, and the cost of chemicals decreases. Typically, sandstone reservoirs are most frequently utilized for CEOR due to the higher permeability of sandstone compared to limestone reservoirs. There are many CEOR types (see Fig. 2).

Polymer flooding involves injecting polymer solution to decrease water mobility resulting in improved sweep efficiency. Surfactant flooding involves injecting surfactants that achieve low Interfacial Tension (IFT) with the displaced oil. The performed analyses have shown a chemical combination for injection is more productive. For instance, polymers are usually added to surfactants for mobility control, hence the name would be Surfactant-Polymer (SP) flood. SP flooding has advantage over the other EOR technologies because of its dual advantage of increasing both microscopic displacement efficiency and volumetric sweep efficiency (Flaaten, 2008). There are published reports around CEOR applications in real-world projects such as Daqing oilfield of China (Chang *et al.*, 2006), St Joseph field in the offshore Malaysia (Du *et al.*, 2011), and Angsi field located in the South China Sea (Othman *et al.*, 2007). Figure 3 is a schematic of a typical deep-water application of CEOR showing the complex interaction of various aspects of the process. This complexity can influence subsurface efficiency, logistics, injection, production, and environmental aspects. Offshore production facilities such as the floating production, storage, and offloading vessel shown in this figure are often quite crowded, with little deck space available for the equipment and storage required for CEOR. The remote location of many offshore production facilities can make shipment and storage of chemicals difficult and expensive (Rany *et al.*, 2011).

Processes in an oil and gas industry involve inherent risks, which should be kept under control for safe operation. IOR/EOR processes can have threats, e.g. adverse environmental impacts due to discharges to the marine environment and emissions to air (Vora *et al.*, 2021). Among these solutions, CEOR is a complex process which exhibits a number of risks and uncertainties, thus technical risk analysis must be included in a CEOR plan. In fact, this operation is subject to many risks which may cause failures in operational and functional performance. Finally, it should be noted that a successful CEOR implementation depends on the success and the ability in addressing all the relevant risks upfront (Chai *et al.*, 2011). In conclusion, in what follows, application of the proposed RIFA-WEST methodology for CEOR operation is presented. Notably, in all the assessment activities a panel of 12 SMEs has taken part.

3.2. *A Brief Review of the Related Literature*

The current case study is related to risk/RF ranking in IOR/EOR processes. Reviewing the relevant literature indicates that there are a few reported studies on risk ranking in IOR/EOR real-world situations. Dai *et al.* (2016) developed a multi-scale statistical model to apply CO2 accounting and risk analysis in an EOR environment at the Farnsworth Unit (FWU), Texas. Hatefi (2018) focused on the way of diagnosing and ranking RFs of a completed real-world gas injection project, i.e. a type of EOR methods. He employed a Nominal Group Technique (NGT) to establish a risk matrix structure, and to identify RFs. Vora *et al.* (2021) represented a review of potentially relevant Environmental/Ecological Risk Assessment (ERA) guidelines. They suggested an initial framework of an ERA model for understanding the environmental impacts from EOR solutions. Lee *et al.* (2021) developed a workflow for risk assessment and management, applied to the Southwest Regional Partnership on Carbon Sequestration (SWP) phase III demonstration project. This project is related to CO2-EOR, i.e. an oil production method in which oil recovery is enhanced by CO2 injection.

3.3. *The Identified CEOR RFs*

As mentioned before, CEOR can be technically complex with many RFs. Some key RFs are generic to CEOR development, such as the heterogeneity, chemical effectiveness, emulsion, issues in production of sales, specification oil, etc. However, there might be some RFs that are typical for a particular field, such as fractured injection, offshore environmental problems, large secondary gas cap, etc. In the current research we use the related literature (Flaaten, 2008; Rany *et al.*, 2011; Peyro, 2018); then the CEOR RFs are identified and categorized as:

- General

  - RF1: Chemical formulation
  - RF2: Produced fluids
  - RF3: Sweep efficiency
  - RF4: Injectivity
  - RF5: Scaling
  - RF6: Chemical supply and handling logistics
- Offshore
  - RF7: Logistics of handling large volumes of chemicals offshore
  - RF8: Platform space limited
  - RF9: High salinity in offshore
  - RF10: Large well spacing
  - RF11: Space and weight limitations on the deck
  - RF12: Limited disposal options
  - RF13: Seawater as the only available injection-water source
- Polymer flooding
  - RF14: Polymer yield
  - RF15: Polymer adsorption
  - RF16: Permeability reduction
  - RF17: High temperature
  - RF18: High salinity
  - RF19: Shear degradation
- Chemical combination
  - RF20: Securing a continuous supply of chemical
  - RF21: Chemical adsorption
  - RF22: Chemical performance
  - RF23: Localized heterogeneities
  - RF24: Impact of free gas on the process
  - RF25: Unconstrained fracture growth
  - RF26: Micro emulsion viscosity

3.4. *Weighting RFs*

A form (see Appendix B) was built and distributed among the 12 SMEs. Each of SMEs, individually assigned his/her relative importance about the RIFA criteria (contributivity, controllability, causality), and rated them. After that, the 26 RFs were ranked according to each SME, and then the WEST weights (in descending order: 0.0769, 0.0728, 0.0688, 0.0650, 0.0614, 0.0579, 0.0546, 0.0514, 0.0483, 0.0454, 0.0425, 0.0398, 0.0372, 0.0346, 0.0322, 0.0298, 0.0275, 0.0252, 0.0231, 0.0210, 0.0189, 0.0169, 0.0150, 0.0131, 0.0112, and 0.0094) were assigned to RFs. Table 6 displays the individual RF weights. For example, in view of SME1, RF19 (High temperature) is the first-ranked factor by weight 0.0769, whereas SME2 preferred to assign the biggest weight to RF22 (Chemical performance).

Having the individual weights, the COCOSO steps were performed as Table 7. For this purpose, the levels of expertise of 12 SMEs were adjusted as 3, 3, 3, 2, 3, 3, 3, 1, 1, 2, 2, and 2, respectively.

Table 6
Individual RF weights concerns with 12 SMEs.

RF	Weight1	Weight2	Weight3	Weight4	Weight5	Weight6	Weight7	Weight8	Weight9	Weight10	Weight11	Weight12
RF1	0.0094	0.0189	0.0131	0.0346	0.0483	0.0688	0.0346	0.0231	0.0398	0.0398	0.0546	0.0425
RF2	0.0579	0.0275	0.0210	0.0546	0.0131	0.0169	0.0189	0.0398	0.0169	0.0189	0.0112	0.0579
RF3	0.0346	0.0210	0.0346	0.0298	0.0210	0.0454	0.0298	0.0372	0.0131	0.0454	0.0210	0.0252
RF4	0.0372	0.0150	0.0483	0.0169	0.0189	0.0189	0.0112	0.0210	0.0514	0.0546	0.0252	0.0131
RF5	0.0150	0.0425	0.0112	0.0094	0.0169	0.0252	0.0769	0.0425	0.0425	0.0231	0.0346	0.0094
RF6	0.0231	0.0231	0.0579	0.0483	0.0094	0.0112	0.0169	0.0112	0.0252	0.0094	0.0454	0.0150
RF7	0.0425	0.0372	0.0372	0.0131	0.0112	0.0210	0.0322	0.0322	0.0112	0.0210	0.0425	0.0112
RF8	0.0398	0.0094	0.0614	0.0150	0.0231	0.0425	0.0094	0.0298	0.0298	0.0769	0.0150	0.0210
RF9	0.0728	0.0483	0.0322	0.0614	0.0688	0.0483	0.0514	0.0275	0.0322	0.0150	0.0769	0.0650
RF10	0.0298	0.0579	0.0546	0.0372	0.0614	0.0514	0.0372	0.0169	0.0210	0.0483	0.0298	0.0769
RF11	0.0189	0.0169	0.0514	0.0189	0.0150	0.0094	0.0579	0.0252	0.0614	0.0728	0.0275	0.0231
RF12	0.0252	0.0112	0.0769	0.0398	0.0346	0.0322	0.0483	0.0614	0.0094	0.0650	0.0514	0.0372
RF13	0.0169	0.0650	0.0425	0.0728	0.0579	0.0231	0.0398	0.0483	0.0275	0.0131	0.0579	0.0614
RF14	0.0483	0.0614	0.0398	0.0579	0.0728	0.0546	0.0252	0.0579	0.0650	0.0425	0.0483	0.0275
RF15	0.0322	0.0252	0.0728	0.0769	0.0546	0.0372	0.0728	0.0150	0.0189	0.0614	0.0728	0.0298
RF16	0.0454	0.0322	0.0454	0.0688	0.0514	0.0769	0.0688	0.0688	0.0231	0.0579	0.0614	0.0322
RF17	0.0112	0.0398	0.0231	0.0210	0.0650	0.0131	0.0614	0.0728	0.0150	0.0112	0.0398	0.0688
RF18	0.0546	0.0298	0.0169	0.0322	0.0769	0.0728	0.0454	0.0189	0.0728	0.0169	0.0094	0.0346
RF19	0.0769	0.0454	0.0650	0.0425	0.0252	0.0298	0.0210	0.0454	0.0346	0.0275	0.0169	0.0454
RF20	0.0275	0.0346	0.0252	0.0231	0.0398	0.0398	0.0231	0.0131	0.0579	0.0252	0.0688	0.0514
RF21	0.0688	0.0688	0.0150	0.0514	0.0298	0.0614	0.0425	0.0650	0.0454	0.0346	0.0322	0.0728
RF22	0.0210	0.0769	0.0094	0.0252	0.0275	0.0650	0.0650	0.0514	0.0769	0.0688	0.0231	0.0189
RF23	0.0514	0.0728	0.0298	0.0650	0.0372	0.0579	0.0275	0.0769	0.0688	0.0322	0.0650	0.0546
RF24	0.0614	0.0514	0.0688	0.0275	0.0454	0.0275	0.0131	0.0346	0.0483	0.0514	0.0131	0.0169
RF25	0.0650	0.0546	0.0275	0.0454	0.0425	0.0346	0.0546	0.0546	0.0546	0.0372	0.0372	0.0483
RF26	0.0131	0.0131	0.0189	0.0112	0.0322	0.0150	0.0150	0.0094	0.0372	0.0298	0.0189	0.0398

Final RF ranks are achieved based on final weights computed by the COCOSO process. Ranks represent that RF16 is the most critical factor, and RF26 is counted as the least important factor. The final ranking of the top ten RFs is determined as below:

$$\text{RF16} > \text{RF9} > \text{RF23} > \text{RF15} > \text{RF21} > \text{RF14} > \text{RF25} > \text{RF10} > \text{RF13} > \text{RF22}.$$

4. Analysis

4.1. *Robustness of the Proposed Methodology*

Robustness indicates the ability of an analytical method to maintain its outputs unaffected while slight variations are applied. To test the robustness of the proposed methodology, we discuss why the proposed methodology converts RFPNs to the WEST weights, and in fact why the methodology does not directly use RFPNs as the RF weights. To address the response, we use the case study data provided in the previous section.

In Table 8, regarding the case study discussed earlier, the RF ranks by the two methods (the WEST and RFPN) are shown. Firstly, this table represents that the RF ranks by the two methods are different. The rank vectors depict a 0.9921 Kendall's coefficient of correlation as equation (19) (Kendall and Gibbons, 1990). In this equation, n is the number of RFs, and v is the number of vectors to be compared, thus herein $v = 2$.

$$t = 12\frac{\sum_{j=1}^{n}\left(\left(\sum_{k=1}^{v} r_{kj}\right) - \frac{v(n+1)}{2}\right)^2}{v^2(n^3 - n)}. \tag{19}$$

Table 7
The calculation to get the final RF weights (stage G) and ranks (stage H).

ID	RF	S	P	ka	kb	kc	Weight	Rank
RF1	Chemical formulation	0.0347	9.0085	0.0382	2.7914	0.9574	1.7295	17
RF2	Produced fluids	0.0294	8.8802	0.0376	2.5105	0.9433	1.6103	21
RF3	Sweep efficiency	0.0308	8.9797	0.0380	2.5898	0.9539	1.6485	20
RF4	Injectivity	0.0267	8.8255	0.0374	2.3677	0.9372	1.5501	24
RF5	Scaling	0.0291	8.8248	0.0374	2.4852	0.9373	1.5965	22
RF6	Chemical supply and handling logistics	0.0255	8.7489	0.0370	2.2961	0.9289	1.5164	25
RF7	Logistics of handling large volumes of chemicals offshore	0.0278	8.8541	0.0375	2.4266	0.9403	1.5754	23
RF8	Platform space limited	0.0314	8.8829	0.0376	2.6122	0.9438	1.6505	19
RF9	High salinity in offshore	0.0516	9.3430	0.0396	3.6812	0.9946	2.0973	2
RF10	Large well spacing	0.0458	9.2622	0.0393	3.3820	0.9854	1.9767	8
RF11	Space and weight limitations on the deck	0.0320	8.9208	0.0378	2.6459	0.9478	1.6664	18
RF12	Limited disposal options	0.0411	9.1336	0.0387	3.1258	0.9713	1.8685	12
RF13	Seawater as the only available injection-water source	0.0431	9.1854	0.0389	3.2356	0.9770	1.9147	9
RF14	Polymer yield	0.0485	9.3286	0.0396	3.5232	0.9927	2.0358	6
RF15	Polymer adsorption	0.0498	9.2956	0.0394	3.5865	0.9894	2.0576	4
RF16	Permeability reduction	0.0534	9.3922	0.0399	3.7772	1.0000	2.1377	1
RF17	High temperature	0.0350	8.9711	0.0380	2.8018	0.9535	1.7309	16
RF18	High salinity	0.0404	9.0924	0.0385	3.0867	0.9669	1.8503	13
RF19	Shear degradation	0.0411	9.1553	0.0388	3.1299	0.9736	1.8716	11
RF20	Securing a continuous supply of chemical	0.0348	9.0599	0.0384	2.7994	0.9628	1.7363	15
RF21	Chemical adsorption	0.0489	9.2974	0.0394	3.5425	0.9895	2.0409	5
RF22	Chemical performance	0.0432	9.1294	0.0387	3.2352	0.9711	1.9104	10
RF23	Localized heterogeneities	0.0508	9.3562	0.0397	3.6432	0.9959	2.0838	3
RF24	Impact of free gas on the ASP process	0.0392	9.0890	0.0385	3.0262	0.9664	1.8267	14
RF25	Unconstrained fracture growth	0.0459	9.2936	0.0394	3.3887	0.9888	1.9815	7
RF26	Micro emulsion viscosity	0.0198	8.6553	0.0366	2.0000	0.9184	1.3917	26

Table 8
The RF ranks by the WEST weights and RFPNs.

	RF1	RF2	RF3	RF4	RF5	RF6	RF7	RF8	RF9	RF10	RF11	RF12	RF13
WEST	17	21	20	24	22	25	23	19	2	8	18	12	9
RFPN	15	12	18	23	21	25	24	20	2	8	19	12	11

	RF14	RF15	RF16	RF17	RF18	RF19	RF20	RF21	RF22	RF23	RF24	RF25	RF26
WEST	6	4	1	16	13	11	15	5	10	3	14	7	26
RFPN	6	4	1	17	10	13	16	5	7	3	14	9	26

The preliminary reason for using the WEST weights instead of RFPNs is normalizing the outputs in such a way that for all SMEs, among 26 RFs, the most important RF receives a weight of 0.0769 (i.e. the highest weight by the WEST method), and the least important RF gets a weight of 0.0094 (i.e. the lowest weight by the WEST method). Conversely, if we use RFPNs, the range is so variable. As an example, SME1 gives RFPN = 5.1768 to the most important RF, whereas this number for SME2 is 7.6525.

A sensitivity analysis experiment is designed to justify the robustness of the proposed method. In this experiment, the robustness of the methods is verified by changing the input data. For this purpose, we performed $N = 100$ rounds of the computer analysis, so the following procedure was repeated 100 times:

(I) A parameter called "No. of changed points" denoted by x is randomly generated. The range of this parameter is [1 26] because there are 26 RFs in the case study.

(II) For each SME and for each criterion (contributivity, controllability, causality), a number of x input data are changed from the current value to a new value. In order to carry out this movement, two parameters are randomly generated, the former is the size of movement (a number between 1 and 8), and the latter is the sign of movement ($+1$ or -1). For example, if the current value is 6, and the parameters are 4 and -1, thereby the new value for replacement would be $6 - 1 * (4) = 2$. If the calculated value is less than 1 or more than 9, then these bounds are used instead.

(III) Calculate new ranks of RFs by the WEST weights and by RFPNs.

(IV) Calculate the Kendall's correlation coefficients as the equation (19) for the two methods. For a given method, this coefficient is computed with regard to the initial RF ranks by SMEs and new RF ranks calculated in stage (III), i.e. the ranks before and after changing data in stage (II).

Table 9 represents the outputs of computer sensitivity analysis. The experiment was conducted with the use of a Visual Basic for application in the Excel programming language on a personal computer.

Even though Table 7 obviously displays the superiority of the WEST robustness over RFPN robustness in all the 100 rounds, we establish a hypothesis as the equation (20) to compare the Kendall WEST population mean and the Kendall RFPN population mean.

$$\begin{cases} h_0 : \mu_{\text{KendallWEST}} - \mu_{\text{KendallRFPN}} = 0, \\ h_1 : \mu_{\text{KendallWEST}} - \mu_{\text{KendallRFPN}} > 0. \end{cases} \tag{20}$$

Table 7 shows that the difference data (i.e. Kendall WEST minus Kendall RFPN) are paired. Indeed, there are two samples in which each datum in one sample is paired with one datum in another sample. Hence, we use the one-way paired t-student test. The t-student test statistic is calculated as 15.2620, and the critical range at 99.99% confidence level is t number greater than 3.165. Because $15.2620 > 3.165$, we reject null hypothesis, and deduce that there is absolutely significant difference between the two populations. As a matter of fact, in the proposed methodology, the WEST weights significantly cause higher robustness in the results than that of directly using RFPNs.

4.2. *A Comparative Analysis on the RIFA method*

The aim of the current part of the research is to address some features of the RIFA method compared to the classical FMEA method. Clearly, the two methods are different in application. The FMEA method is to prioritize risks, whereas the RIFA method is for prioritizing RFs. In spite of simplicity of the FMEA method, some FMEA drawbacks have been discussed by researchers (Ibarra *et al.*, 2024; Dhalmahapatra *et al.*, 2022; Ghoushchi *et al.*,

Table 9
The results of sensitivity analysis experiment (100 rounds).

Round	No. of changed points	Kendall WEST	Kendall RFPN
1	25	0.9860	0.8653
2	24	0.9826	0.9279
3	5	0.9949	0.9525
4	7	0.9973	0.9398
5	18	0.9880	0.9101
6	8	0.9918	0.9255
7	9	0.9850	0.9217
8	10	0.9884	0.9398
9	14	0.9839	0.8913
10	4	0.9945	0.9737
11	2	0.9966	0.9672
12	13	0.9884	0.9121
13	18	0.9863	0.8885
14	17	0.9761	0.8944
15	3	0.9949	0.9911
16	14	0.9904	0.9429
17	17	0.9819	0.8834
18	5	0.9942	0.9699
19	11	0.9771	0.8783
20	18	0.9843	0.8892
21	9	0.9867	0.8571
22	1	1.0000	0.9942
23	19	0.9856	0.8137
24	8	0.9956	0.9600
25	6	0.9908	0.9487
26	23	0.9850	0.9050
27	7	0.9918	0.9668
28	15	0.9843	0.9080
29	23	0.9774	0.8797
30	3	0.9935	0.9757
31	17	0.9737	0.8766
32	18	0.9901	0.8373
33	10	0.9966	0.8926
34	9	0.9880	0.9549
35	18	0.9863	0.8639
36	22	0.9778	0.8260
37	21	0.9863	0.9316
38	5	0.9949	0.9210
39	3	0.9949	0.9754
40	9	0.9897	0.9398
41	15	0.9815	0.9296
42	21	0.9781	0.7863
43	24	0.9791	0.8981
44	21	0.9853	0.8865
45	14	0.9764	0.9323
46	19	0.9904	0.9005
47	25	0.9785	0.8691
48	12	0.9867	0.9303
49	17	0.9880	0.9395
50	8	0.9884	0.9432
51	9	0.9860	0.9720
52	1	0.9959	0.9795
53	14	0.9836	0.8773
54	4	0.9942	0.9504
55	20	0.9935	0.8513
56	3	0.9956	0.9788
57	7	0.9925	0.9289
58	7	0.9942	0.9333
59	10	0.9949	0.9614
60	8	0.9887	0.9644
61	16	0.9894	0.7887
62	21	0.9860	0.7022
63	14	0.9956	0.9658
64	25	0.9815	0.8602
65	25	0.9891	0.9094
66	12	0.9850	0.8981
67	19	0.9815	0.8643
68	3	0.9962	0.9665
69	23	0.9802	0.8926
70	8	0.9921	0.9115
71	5	0.9942	0.9665
72	20	0.9826	0.8602
73	17	0.9853	0.9067
74	5	0.9945	0.9296
75	13	0.9863	0.8397
76	4	0.9935	0.9480
77	25	0.9788	0.9166
78	25	0.9815	0.8017
79	23	0.9904	0.8663
80	6	0.9874	0.9675
81	13	0.9935	0.9009
82	23	0.9860	0.8526
83	18	0.9894	0.8561
84	15	0.9754	0.9337
85	11	0.9860	0.9422
86	18	0.9891	0.9323
87	23	0.9860	0.8462
88	22	0.9839	0.8756
89	11	0.9819	0.9080
90	2	0.9915	0.9894
91	9	0.9928	0.9443
92	6	0.9863	0.9692
93	12	0.9952	0.8957
94	22	0.9880	0.8441
95	2	0.9966	0.9822
96	18	0.9860	0.9121
97	4	0.9952	0.9638
98	14	0.9832	0.8332
99	5	0.9925	0.9477
100	6	0.9904	0.9672

2020). In what follows, some characteristics of the RIFA method are described from the view of the most important shortcomings of the classical FMEA method:

- In the FMEA method, the relative importance of the risk criteria (occurrence, severity, detection) is not considered (Keskin and Ozkan, 2009). Moreover, the calculation formula for RPN (multiplication of the three criteria) is questionable, such as the same RPN value may be achieved by different combinations of its criteria scores. Conversely, the RIFA method uses the three parameters (c1, c2, c3) as the relative importance of the RF criteria (contributivity, controllability, causality). By this strategy, different combinations of the criteria score result in different RFPNs.
- A critical issue in the FMEA method is this fact that the relative importance of SMEs is ignored (Dhalmahapatra *et al.*, 2022). In comparison, the RIFA method uses a number (between 1 and 5) for each SME, indicating his/her level of expertise.
- In the FMEA method, the RPN value is discontinuous in the domain of 1 to 1000 (Wang *et al.*, 2020), while in many situations the RPN values are very lower than 1000. This drawback in the RIFA method has been resolved. In this method, RFPN ranges from 1 to 9 like its elementary criteria.
- In the FMEA method, the uncertainty of SME's judgments is not handled (Gargama and Chaturvedi, 2011), in such a way that the final results are very sensitive to the variation in criteria scores (Yang *et al.*, 2008). On the contrary, the proposed methodology benefits from the WEST method as a defensible robustness dimension. This characteristic is discussed and demonstrated in Section 4.1.

4.3. *A Comparative Analysis on the WEST Method*

As previously mentioned, the WEST method belongs to a family of attribute weighting methods entitled surrogate weighting by code I/+ SW (Hatefi, 2023c). There are many I/+ SW methods, some of them were reviewed in Section 2.2.1. A logical and acceptable approach to compare such methods is examining the match between the weights estimated by the methods and subjective weights achieved within real-world study-cases. Mean Absolute Difference (MAD) (equation (21)) is the index to measure the match. The method by lower MAD is better.

$$\mathrm{MAD} = \sum_{j=1}^{n} \left|\omega_j^{\text{the method}} - \omega_j^{\text{study}-\text{case}}\right| / n. \tag{21}$$

Fifteen real-life study-cases (see Table 10) were randomly derived from MADM papers. There was an attempt to have the cases from a variety of application fields, subjective or integrated weighting methods, and the number of attributes.

The WEST method was compared to six I/+SW methods, which are the EW, UV, RS, ROC, ROT, and ROL methods. Table 11 shows comparison results. In this table, for a given case, the first row stands for the MAD values, and the second row depicts ranks of the MAD values for the methods. To compare the methods, observing ranks received by the methods can be useful. Obviously, the WEST method, through all the instances, gets

Table 10
The real-life study-cases chosen from the MADM literature.

Case No.	Reference	Application field	Used method	n
1	Rao (2007)	Assessment of supplier performance	Analytical Hierarchy Process (AHP)	5
2	Tzeng *et al.* (2005)	Fuel selection for public transport	AHP	11
3	Gomes and Rangel (2009)	Rent of residential properties	Direct rating	8
4	Vafaeipour *et al.* (2014)	Implementation of solar projects	Step-Wise Weight Assessment Ratio Analysis (SWARA)	14
5	Ginevicius (2011)	Evaluation of effectiveness in a university	Factor Relationship (FARE)	12
6	Fayazbakhsh *et al.* (2009)	Material selection	Modified Digital Logic Method (MDLM)	9
7	Alemi-Ardakania *et al.* (2016)	Impact optimization of composites	Adjusted Mean Bar (AMB)	9
8	Ryan *et al.* (2001)	Patient tendencies for benefits after a change	Discrete Choice Experiments (DCE)	5
9	Ghorshi Nezhad *et al.* (2015)	Priority of high-tech industries	SWARA	7
10	Zizivic and Pamucar (2019)	Prioritizing railway level crossings for safety improvements	Level-Based Weight Assessment (LBWA)	8
11	Hashemi Petrudi *et al.* (2022)	Performance measurement in higher education	Best Worst Method (BWM)	7
12	Ramazani *et al.* (2014)	Evaluating accounting software	Analytical Network Process (ANP)	6
13	Mercan and Acıbuca (2025)	Identifying optimal beekeeping lands	Full Consistency Method (FUCOM)	9
14	Farajizadeh and Hatefi (2025)	Portfolio selection in oil exploration and production companies	BWM	10
15	Zizivic and Pamucar (2019)	Evaluating a car	Non-Decreasing Series at Criteria Significance Levels (NDSL)	5

a rank between 1 to 4, in such a way that in only 2 of 15 the rank is 4. On the contrary, this measure of judgment shows very weak results for the EW, UV, ROT, even ROC methods. Let's employ another index for making judgment. Based on the BORDA ranking rule, we calculate total ranks obtained from all the 15 instances to make judgement around the methods. This index and relevant overall ranks are shown at the two last rows in Table 11. This demonstrates relative comparability and good performance of the proposed WEST method over the other methods. From this point of view, the UV method acts as the worst performance. Considerably, the famous ROC method is placed at the fourth rank after the RS and ROL methods. In the table, the row entitled mean MAD confirms the above results.

5. Remarks and Conclusion

This paper firstly discussed that when dealing with risks, it is essential to distinguish between risk and RF. The paper showed that the relevant literature does not adequately concentrate on numerical assessment of RFs. The paper focused on analysis of RFs, and pro-

Table 11
The MAD values and ranks for the methods.

Case No.		EW	UV	RS	ROC	ROT	ROL	WEST
1	MAD	0.1368	0.2068	0.0598	0.0129	0.0278	0.0213	0.0344
	Rank	6	7	5	1	3	2	4
2	MAD	0.0399	0.1456	0.0166	0.0224	0.0251	0.0201	0.0118
	Rank	6	7	2	4	5	3	1
3	MAD	0.0563	0.1875	0.0181	0.0293	0.0333	0.0262	0.0121
	Rank	6	7	2	4	5	3	1
4	MAD	0.0148	0.1277	0.0188	0.0353	0.0367	0.0331	0.0188
	Rank	1	7	2	5	6	4	3
5	MAD	0.0163	0.1442	0.0229	0.0407	0.0425	0.0384	0.0234
	Rank	1	7	2	5	6	4	3
6	MAD	0.0310	0.1851	0.0212	0.0474	0.0469	0.0431	0.0250
	Rank	3	7	1	6	5	4	2
7	MAD	0.0334	0.1896	0.0205	0.0498	0.0488	0.0455	0.0270
	Rank	3	7	1	6	5	4	2
8	MAD	0.1036	0.2459	0.0236	0.0295	0.0230	0.0201	0.0088
	Rank	6	7	4	5	3	2	1
9	MAD	0.0367	0.2243	0.0273	0.0563	0.0585	0.0515	0.0362
	Rank	3	7	1	5	6	4	2
10	MAD	0.0245	0.2023	0.0318	0.0584	0.0596	0.0538	0.0383
	Rank	1	7	2	5	6	4	3
11	MAD	0.0467	0.2243	0.0189	0.0492	0.0514	0.0444	0.0291
	Rank	7	6	1	4	5	3	2
12	MAD	0.0628	0.2540	0.0251	0.0637	0.0613	0.0562	0.0410
	Rank	7	6	4	3	5	2	1
13	MAD	0.0720	0.1313	0.0521	0.0349	0.0486	0.0389	0.0470
	Rank	6	7	5	1	4	2	3
14	MAD	0.0630	0.1454	0.0340	0.0181	0.0248	0.0174	0.0279
	Rank	6	7	5	2	3	1	4
15	MAD	0.0972	0.2316	0.0395	0.0325	0.0329	0.0244	0.0257
	Rank	6	7	5	3	4	1	2
Mean MAD		**0.0522**	**0.1778**	**0.0269**	**0.0363**	**0.0388**	**0.0334**	**0.0254**
Total ranks		**68**	**103**	**42**	**59**	**71**	**43**	**34**
Overall rank		**5**	**7**	**2**	**4**	**6**	**3**	**1**

posed a general hybrid methodology called RIFA-WEST for semi-quantitative analysis of RFs. This methodology consists of the RIFA method which falls into risk management area, and the WEST method that belongs to decision-making science. Both the methods were developed in this paper, and are novel in the literature. Put simply, the methodology includes 8 stages as (A) organizing SMEs panel, (B) assigning level of expertise for any SME, (C) building RF list, (D) rating and combining the RF criteria using the RIFA method, (E) determining individual RF ranks, (F) converting ranks to weights using the WEST method, (G) aggregating the individual weights, and finally, (H) determining final RF ranks.

The RIFA can be used for evaluation of contributing RFs of an individual risk or overall risk of a system. In accordance, for application of the RIFA method, analyst may focus on an individual target risk, or overall risk of a unit/system/project. In practice, the RIFA method is RF-based version of the famous FMEA method. In the RIFA method, the three criteria (contributivity, controllability, causality) are involved to calculate an index called RFPN. Literature review represents that such a methodology has not been studied yet. Furthermore, the paper explained several advantages of the proposed methodology over the shortcomings of the classical FMEA method.

The WEST method is to estimate surrogate weights of factors influencing on analysis and decision-making. Such MADM methods are to convert any ranks to pre-defined weights. The paper showed that the WEST method is based on a justifiable and well-established idea. The method is a convex linear combination of arithmetic weights and geometric weights. Due to the fact that the WEST method belongs to the weight estimation family of the methods, it was compared to the relevant competitors (i.e. the EW, UV, RS, ROC, ROT, and ROL). According to the design of the comparison, the best method is the one that generates weights as close as possible to subjective weights received from experts. Correspondingly, the weights reported in 15 randomly selected real-world study-cases were taken. After that, an index called MAD was used, such that the lower MAD value indicates the better match between estimated weights and subjective weights. The mean MAD for the EW, UV, RS, ROC, ROT, ROL, and WEST methods were 0.0522, 0.1778, 0.0269, 0.0363, 0.0334, and 0.0254, respectively. In total, the results of this analysis depicts among these methods that the WEST method shows the best performance. By transforming MAD values to ranks, the results were obtained as EW(rank = 5), UV(rank = 7), RS(rank = 2), ROC(rank = 4), ROT(rank = 6), ROL(rank = 3), and WEST(rank = 1).

The paper took the concept of robustness into account, which means the ability of a method to maintain its outputs reliable when slight changes are applied. To have robust results, the proposed methodology combines the WEST method and the RIFA method. The paper also displayed that the ranking of RFs by applying the WEST weights is so robust compared to directly using RFPNs. For the purpose, the paper employs a t-test hypothesis to compare the Kendall WEST population mean and the Kendall RFPN population mean. The test statistic (15.2620) and critical range (3.165) clarified that there is an absolutely significant difference between the Kendall WEST population mean and the Kendall RFPN population mean. The paper concluded that the weights produced by the WEST method result in higher robustness than that of using RFPNs as the weights. We interpret that using the WEST weights acts as a way for backward uncertainty propagation of the proposed model. This type of uncertainty propagation helps to reduce uncertainties in the decision-making outcomes (Tabandeh *et al.*, 2022).

In regard to real-life grounding of the proposed methodology, let us express two facts. First, when assessing RFs in a real situation, analysts conventionally identify, list, and categorize them. If they wanted to make a deeper assessment, they may draw a diagram like cause and effect. All these jobs are entirely descriptive. Expressly, there is no existing tools for analysts to quantitatively perform RF assessment. From the perspective of this shortage, the proposed RIFA-WEST methodology can be very helpful. The second fact concerns the inclusion of the WEST method into the suggested methodology. In this method, SMEs just prioritize attributes rather than gives specific numerical values. Many researchers enumerate problems with receiving exact values from SMEs. According to Barron and Barrett (1996), eliciting the exact weights from SME may suffer on different counts, because the outcomes are very dependent on the elicitation method. By the way, Ginevicius (2011) believes the larger the number of attributes causes the lower the accuracy of their subjective evaluation. Also, it is much simpler for SME to give ranks of attributes rather than to give exact numbers (Alfares and Duffuaa, 2016). Therefore, taking the second fact into account, the proposed RIFA-WEST methodology is compatible with real-life circumstances.

Under a real-world case study about Chemical Enhanced Oil Recovery (CEOR) in a country, the proposed methodology was applied to finalize a RF register including 26 factors in four categories (general, offshore, polymer flooding, and chemical combination). As an important finding of the research, the below list of the CEOR items was formed. According to the famous Pareto principle, this list contains more than 70% of the sum of Final Scores (FS) gained by all the 26 factors. As a matter of fact, sum of FSs of this list is 25.8268 out of sum of FSs of 26 factors, i.e. 35.8293.

- Permeability reduction (FS = 2.1377)
- High salinity in offshore (FS = 2.0973)
- Localized heterogeneities (FS = 2.0838)
- Polymer adsorption (FS = 2.0576)
- Chemical adsorption (FS = 2.0409)
- Polymer yield (FS = 2.0358)
- Unconstrained fracture growth (FS = 1.9815)
- Large well spacing (FS = 1.9767)
- Seawater as the only available injection-water source (FS = 1.9147)
- Chemical performance (FS = 1.9104)
- Shear degradation (FS = 1.8716)
- Limited disposal options (FS = 1.8685)
- High salinity (FS = 1.8503)

Briefly speaking, the originality aspects of this research are: (I) suggesting the new RIFA method which has not been studied yet, (II) offering the new WEST method for estimation of RF weights, (III) suggesting a combination of RIFA and WEST methods, the former from risk management field, and latter from MADM branch, (IV) proposing a group decision-making methodology for RF analysis with robust results, and (V) conducting an integrated sensitivity and statistical analysis experiment to demonstrate the robustness of the proposed methodology.

A future investigation may focus on the development of the suggested methodology in different environments such as probabilistic and fuzzy. Except for this direction, it is also interesting to concentrate on the deep evaluation of inter-relationship effects of the RFs, i.e. the influence of one RF on the others, then, combining the results of this evaluation with the idea of the RIFA-WEST methodology.

At the end, the authors tend to remember an important issue for policy-makers of any risk management environments, among them project risk management, business risk management, technical risk management, health risk management, etc. In stages of risk management process, not only considering assessment of risks, but also inclusion of assessment of RFs are important. The RF assessment methodology proposed in this paper is a useful tool to enrich the stage of RF assessment in the overall process of risk management. Accordingly, incorporation of any RF assessment stage (consisting of a suitable tool, e.g. the proposed RIFA-WEST methodology) into the approved instructions, standards, and regulations are advised.

A. Appendix

Table 12
The estimated weights by the arithmetic progression, with the most steepness.

n	2	3	4	5	6	7	8	9	10	11	12	13	14	15
d	**1.0000**	**0.3333**	**0.1667**	**0.1000**	**0.0667**	**0.0476**	**0.0357**	**0.0278**	**0.0222**	**0.0182**	**0.0152**	**0.0128**	**0.0110**	**0.0095**
The weights	1.0000	0.6667	0.5000	0.4000	0.3333	0.2857	0.2500	0.2222	0.2000	0.1818	0.1667	0.1538	0.1429	0.1333
	0.0000	0.3333	0.3333	0.3000	0.2667	0.2381	0.2143	0.1944	0.1778	0.1636	0.1515	0.1410	0.1319	0.1238
		0.0000	0.1667	0.2000	0.2000	0.1905	0.1786	0.1667	0.1556	0.1455	0.1364	0.1282	0.1209	0.1143
			0.0000	0.1000	0.1333	0.1429	0.1429	0.1389	0.1333	0.1273	0.1212	0.1154	0.1099	0.1048
				0.0000	0.0667	0.0952	0.1071	0.1111	0.1111	0.1091	0.1061	0.1026	0.0989	0.0952
					0.0000	0.0476	0.0714	0.0833	0.0889	0.0909	0.0909	0.0897	0.0879	0.0857
						0.0000	0.0357	0.0556	0.0667	0.0727	0.0758	0.0769	0.0769	0.0762
							0.0000	0.0278	0.0444	0.0545	0.0606	0.0641	0.0659	0.0667
								0.0000	0.0222	0.0364	0.0455	0.0513	0.0549	0.0571
									0.0000	0.0182	0.0303	0.0385	0.0440	0.0476
										0.0000	0.0152	0.0256	0.0330	0.0381
											0.0000	0.0128	0.0220	0.0286
												0.0000	0.0110	0.0190
													0.0000	0.0095
														0.0000

Table 13
The estimated weights by the geometric progression, with the most steepness.

n	2	3	4	5	6	7	8	9	10	11	12	13	14	15
p	**0.0000**	**0.3660**	**0.5437**	**0.6445**	**0.7090**	**0.7538**	**0.7867**	**0.8118**	**0.8317**	**0.8477**	**0.8610**	**0.8721**	**0.8816**	**0.8898**
The weights	1.0000	0.6667	0.5000	0.4000	0.3333	0.2857	0.2500	0.2222	0.2000	0.1818	0.1667	0.1538	0.1429	0.1333
	0.0000	0.2440	0.2718	0.2578	0.2363	0.2154	0.1967	0.1804	0.1663	0.1541	0.1435	0.1342	0.1259	0.1186
		0.0893	0.1478	0.1661	0.1676	0.1623	0.1547	0.1465	0.1383	0.1307	0.1236	0.1170	0.1110	0.1056
			0.0804	0.1071	0.1188	0.1224	0.1217	0.1189	0.1150	0.1108	0.1064	0.1021	0.0979	0.0939
				0.0690	0.0842	0.0922	0.0957	0.0965	0.0957	0.0939	0.0916	0.0890	0.0863	0.0836
					0.0597	0.0695	0.0753	0.0784	0.0796	0.0796	0.0789	0.0776	0.0761	0.0744
						0.0524	0.0592	0.0636	0.0662	0.0675	0.0679	0.0677	0.0671	0.0662
							0.0466	0.0516	0.0550	0.0572	0.0585	0.0590	0.0591	0.0589
								0.0419	0.0458	0.0485	0.0503	0.0515	0.0521	0.0524
									0.0381	0.0411	0.0433	0.0449	0.0460	0.0466
										0.0348	0.0373	0.0392	0.0405	0.0415
											0.0321	0.0342	0.0357	0.0369
												0.0298	0.0315	0.0328
													0.0278	0.0292
														0.0260

Table 14
The estimated weights by the WEST method, with the best value of t.

n	2	3	4	5	6	7	8	9	10	11	12	13	14	15
t	**0.5000**	**0.4456**	**0.4239**	**0.4127**	**0.4060**	**0.4014**	**0.3982**	**0.3958**	**0.3939**	**0.3924**	**0.3911**	**0.3901**	**0.3892**	**0.3885**
The weights	1.0000	0.6667	0.5000	0.4000	0.3333	0.2857	0.2500	0.2222	0.2000	0.1818	0.1667	0.1538	0.1429	0.1333
	0.0000	0.2838	0.2979	0.2752	0.2487	0.2245	0.2037	0.1860	0.1708	0.1579	0.1466	0.1368	0.1283	0.1206
		0.0495	0.1558	0.1801	0.1807	0.1736	0.1642	0.1545	0.1451	0.1365	0.1286	0.1214	0.1149	0.1090
			0.0463	0.1042	0.1247	0.1306	0.1301	0.1268	0.1222	0.1172	0.1122	0.1073	0.1026	0.0981
				0.0405	0.0771	0.0934	0.1003	0.1023	0.1018	0.0999	0.0972	0.0943	0.0912	0.0881
					0.0355	0.0607	0.0738	0.0803	0.0832	0.0840	0.0836	0.0824	0.0807	0.0788
						0.0314	0.0499	0.0604	0.0664	0.0695	0.0710	0.0713	0.0709	0.0701
							0.0280	0.0422	0.0509	0.0562	0.0593	0.0610	0.0618	0.0619
								0.0253	0.0365	0.0437	0.0484	0.0514	0.0532	0.0542
									0.0231	0.0321	0.0382	0.0424	0.0452	0.0470
										0.0212	0.0286	0.0339	0.0376	0.0402
											0.0196	0.0258	0.0304	0.0337
												0.0182	0.0235	0.0275
													0.0170	0.0216
														0.0159

B. Appendix

Table 15
RIFA form.

Code	Title	Contributivity	Controllability	Causality
RF1	Chemical formulation			
RF2	Produced fluids			
RF3	Sweep efficiency			
RF4	Injectivity			
RF5	Scaling			
RF6	Chemical supply and handling logistics			
RF7	Logistics of handling large volumes of chemicals offshore			
RF8	Platform space limited			
RF9	High salinity in offshore			
RF10	Large well spacing			
RF11	Space and weight limitations on the deck			
RF12	Limited disposal options			
RF13	Seawater as the only available injection-water source			
RF14	Polymer yield			
RF15	Polymer adsorption			
RF16	Permeability reduction			
RF17	High temperature			
RF18	High salinity			
RF19	Shear degradation			
RF20	Securing a continuous supply of chemical			
RF21	Chemical adsorption			
RF22	Chemical performance			
RF23	Localized heterogeneities			
RF24	Impact of free gas on the ASP process			
RF25	Unconstrained fracture growth			
RF26	Micro emulsion viscosity			

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