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Supplier selection in the oil & gas industry: A comprehensive approach for Multi-Criteria Decision Analysis

Amir Karbassi Yazdi [a,*], Peter Fernandes Wanke [b], Thomas Hanne [c], Farshid Abdi [d], Amir Homayoun Sarfaraz [d]

[a] Department of Industrial Management, South Tehran Branch, Islamic Azad University, Tehran, Iran
[b] Business Analytics and Economics Research Unit, COPPEAD Graduate Business School, Federal University of Rio de Janeiro, Rio de Janeiro, Brazil
[c] Institute for Information Systems, University of Applied Sciences and Arts Northwestern Switzerland, Switzerland
[d] Department of Industrial Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran

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ABSTRACT

The focus of this paper is on selecting suppliers in the Oil and Gas (O&G) industry by developing a comprehensive approach for Multi-Criteria Decision Analysis (MCDA) based on alternative methods capable of assessing different aspects of supplier selection uncertainty in terms of utility functions and criteria related to efficiency. The O&G industry has a key role in the public sector of various countries such as Iran with its revenues being of prime importance to develop infrastructure facilities such as for healthcare, education, and transportation. This comprehensive approach walks through various stages for selecting Critical Success Factors (CSFs), ranking suppliers, and for setting partial weighting alternatives. While CSFs are selected using a traditional Delphi approach, the partial supplier rankings are defined based on Complex Proportional Assessment (COPRAS) utility functions together with criteria weights derived from Step-wise Weight Assessment Ratio Analysis (SWARA) for each CSF. As it concerns information reliability of utility and efficiency functions of both methods obtained via expert preferences or perceptions, Z-numbers are used to address the intrinsic fuzziness level inherent to each analytical stage. Iran's economy depends on revenues from oil and other related production, which means that by earning more income from this industry, most of its economic indicators such as GDP and employment rate should increase significantly, thus leading to economic growth. Various countries put plans in place related to production for increasing their social economics. One of these plans is focused on suppliers since they have a high impact on providing essential items such as equipment, HR, and transportation, so by choosing the best suppliers in all fields, costs will decrease and consequently revenue will increase. This research points out how to rank O&G industry suppliers using MCDA methods in an uncertain environment. An example based on actual data from an Iranian O&G company is provided to show the applicability of the approach proposed. Results suggest that the complexity of O&G operations on selecting suppliers can be adequately handled by information reliability techniques applied to traditional economic concepts such as utility- and efficiency-related factors, particularly in business environments characterized by a trade embargo.

1. Introduction

The petroleum industry in Iran is experiencing an investment and modernization boom after the end of the Western oil embargo a few years ago [1]. This increased foreign demand and a scenario of higher investments and innovation in the Iranian oil and gas (O&G) industry has not only raised the bar in terms of supplier requirements to achieve higher production levels and competitiveness, but it has also forced producers to meet customer expectations in a scenario of heavy price and demand uncertainty [2]. Nurturing long-term relationships across a supply chain is often a cumbersome task [3] in which developing novel alternative approaches for continuous evaluation of Critical Success Factors (CSFs) in productive arrangements is deemed necessary as a way to better discriminate supplier choices in a situation of uncertainty [4].

Iran was the fourth largest oil producer in the world in 2001 and it is estimated that its oil resources contribute to 10% of all global oil

* Corresponding authorDepartment of Industrial Management, South Tehran Branch, Islamic Azad University, Tehran, Iran.
E-mail addresses: st_a_karbassiyazdi@azad.ac.ir (A.K. Yazdi), peter@coppead.ufrj.br (P.F. Wanke), thomas.hanne@fhnw.ch (T. Hanne), farshidabdi@azad.ac.ir (F. Abdi), a_sarfaraz@azad.ac.ir (A.H. Sarfaraz).

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reserves. Besides, 16% of the gas in the world is located in Iran. Iran's economy depends on many factors, but the oil & gas industry drives most of Iran's GDP. Various other industries benefit greatly from this industry such as healthcare, education, and transportation, hence this industry can be beneficial for socio-economic planning in the country. The revenue from selling oil was US$ 71.5 billion in 2010. Besides, this industry is public and most suppliers were in the public sector as well, but now some private companies are entering into this market to compete with the public companies.

The O&G sector has a crucial role in the economy of Iran and other countries with both state and private companies pursuing low-cost production and on-time delivery targets [5,6]. Iran's GDP has increased dramatically during recent years, which is calculated based on the O&G industry.

Petroleum production depends on many factors such as equipment, expert staff, and high investments with companies attempting to choose the best suppliers based on the supply chain management (SCM) concept in order to decrease their costs, increase revenue, and provide better products or services. Income from petroleum fell steadily from 2010 to 2017 for many reasons, so focusing on selecting suppliers can lead to decreasing both fixed and variable costs in this industry and subsequently increasing revenue. In summary, a focus on selecting the best suppliers improves O&G income.

Refineries require specific equipment to convert crude oil into gasoline, diesel, kerosene, etc. This equipment can be either acquired from local or foreign suppliers, which are supposed to provide the best mix of technology, quality, prices, and after-sales support [7], so ranking and prioritizing suppliers is a crucial task that may present strong economic impacts on O&G producers [8,9].

Multi-Criteria Decision Analysis (MCDA) is a continuously growing research field with different approaches being continuously developed and combined for coping with underlying uncertainty in defining, ranking, and weighting criteria for selecting a business partner [10,11]; B. [12–16]. One of the modeling approaches for dealing with situations under uncertainty or vagueness are Z-numbers, which are based on fuzzy logic and provide a robust way of handling the selection process [17]. Therefore, this paper contributes to the MCDA literature by using Z-numbers together with recently developed approaches such as Complex Proportional Assessment (COPRAS) and other established methods such as Delphi to capture and model vagueness throughout the steps for defining criteria, ranking, and weighting. Thus far this is the first time these models have been combined together using the Z-numbers technique to capture information reliability as previous studies on supplier selection have focused rather on fuzzy applications of different MCDA methods to capture data vagueness.

The reason for considering vagueness for data analysis is first that the price of oil has strong fluctuations most of the time, while another reason relates to political issues, which are usually not well predictable. As O&G production can take on the role of a strategic weapon, countries may change their decision from day to day based on national interests, and these decisions may strongly affect factors such as cost and transportation. Another reason for using fuzzy-based methods is to help decision makers (DMs) depict their preferences using linguistic variables. The significant difference between this paper and previous research in the supplier selection field is that previous approaches have translated data into fuzzy numbers/sets and subsequently converted them into crisp numbers without any inference on their reliability. The Z-numbers technique overcomes this shortcoming by addressing the reliability of the fuzzy sets used in the research based on granular information also provided by the decision makers.

Results from a supplier selection case in the Iranian O&G industry indicate that using the novel Z-numbers technique as an analytical cornerstone has yielded better discriminatory power and accuracy in comparison to other approaches taken individually. Particularly in this research, Z-numbers help with discriminating well-known economic concepts embedded in COPRAS for assessing a utility function in order to discriminate supplier alternatives and Step-wise Weight Assessment Ratio Analysis (SWARA), to determine the relative efficiency of criteria, and to rank their importance. The successful application of this comprehensive and innovative MCDA approach for selecting suppliers in a real O&G industry problem in Iran suggests some evidence in terms of validity and robustness in comparison to other techniques. The question of this research points out which factors are effected when selecting suppliers in the field of O&G, and based on these factors, which of these suppliers should be selected based on hybrid MCDA methods in an uncertain environment. Since O&G has a key role in Iranian economics, domestic and foreign suppliers have provided many elements used in extraction, production, and transportation. Using an MCDA methodology can help Iran's O&G industry to not only find the best suppliers based on the most important factors, but also to create a competitive environment among domestic and foreign suppliers to increase the quality of services and goods, resulting in lower prices. This work allows the O&G industry to reduce the final production cost and to increase profits by selecting suitable suppliers.

Many suppliers work in diverse fields of the O&G industry with suppliers in a specific field being distinguished by their individual attitudes and other business aspects. A special focus should be put on selecting suppliers from other Persian Gulf countries because of low transport cost. The equipment used in the O&G industry in Iran is rather old and needs to be renewed. Because of the Iran and Libya Sanctions Act (ILSA) and other sanctions against Iran and especially the O&G industry, Iran has restricted access to many types of equipment, so it needs to decrease all costs in order to increase revenue despite these sanctions. As mentioned above, there are both public and private companies in this sector and the aim of this research is to find out which of these companies have the best performance considering a number of criteria that are analyzed by hybrid Multiple Attribute Decision-Making (MADM) methods in an uncertain environment. In the past, other similar CSFs were considered for selecting a supplier in the O&G industry, but recently the sanctions have made the old version for selecting suppliers obsolete and a new approach is needed. Though in previous studies researchers have considered the company's viewpoint, the CSFs for selecting suppliers in the O&G industry are very different depending on the particular situation. In this paper, similar to other research, not only are essential factors related to financial and production aspects considered, but also R&D factors and other related factors. Many MCDA methods such as Analytical Hierarchy Process (AHP), Weighted Point Matrix, ELECTRE, Data Envelop Analysis (DEA), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), FAHP, FTOPSIS, and entropy have been used for ranking O&G suppliers in previous papers [18–23]. The most crucial difference of this research to previous studies is that of prioritizing suppliers using the SWARA and COPRAS methods. The results and computation of these methods are more accurate compared to previous research. Besides, using Z-numbers in this research helps increase the reliability of results compared to other fuzzy tools used in previous papers.

Although many types of researches have been done for selecting suppliers in diverse industries, the main research questions (RQ) of this paper point to a new supplier selection method in the O&G industry, which are as follows:

- ✓ RQ1: What are the supplier selection CSFs in the O&G industry?
- ✓ RQ2: What is the best model for selecting suppliers in the O&G industry using hybrid MCDA methods in an uncertain environment?
- ✓ RQ3: How does this model help provide a better social-economic planning?

The contribution of this paper is that first the factors that affect supplier selection are extracted from previous studies to ensure that the most important factors are chosen. Then a Delphi method is used for customizing these factors for Iran's O&G industry. As the COPRAS method used for ranking suppliers is based on a decision matrix, it needs weights of the criteria considered, which are obtained from the SWARA method. The merits of SWARA are that ranking factors depend on preferences from DMs and this method is more user-friendly and simple compared to other methods [24]. Another contribution of this paper is that although there are many tools based on uncertainty such as fuzzy tools for ranking factors, they cannot measure the reliability of data compared to approaches using Z-numbers.

The rest of this paper is structured as follows. Section 2 focusses the methodological background, while the Multiple-Criteria Decision Analysis (MCDA) is considered with a focus on the SWARA and the COPRAS methods. On the other hand, analysis of an uncertain environment and issues of information reliability are considered by discussing fuzzy sets and Z-numbers, tackling the venues of computing with words [17]. Section 3 deals with the literature review and the research gap. The research methodology is further detailed in Section 4, while data analysis and a discussion of results are presented in Section 5. The conclusions and managerial implications are shown in Section 6.

2. Review of methods applied

Section 2.1 describes two different MCDA methods that have been combined to tackle the problem of selecting and/or assessing business partners in various industries and contexts, while aspects of uncertainty are addressed within the context of fuzzy sets and Z-numbers in Section 2.2.

2.1. Multi-Criteria Decision Analysis (MCDA) methods

Due to space restrictions, we cannot provide a broad overview of Multi-Criteria Decision Analysis (MCDA) methods, but refer to the respective literature, see e.g. Gal et al. [25] or Hanne [26]. Instead, we focus on the two approaches used within the study conducted. Although the set of methods used and the combined approaches developed are quite heterogeneous, as well as their application fields, it is noteworthy that the relatively recent SWARA method is still understudied in terms of its roles and benefits for weighting criteria within the ambit of the comprehensive MCDA methodology [27]. It is possible to affirm, however, that one of its significant distinctions from other tools relies on its rational dispute resolution procedure that assesses the trade-offs among different important criteria in a step-wise manner where their ultimate relative weights are computed in hierarchical pairwise comparisons of criteria, thus helping establish relative efficiency levels among the criteria [28]. Section 2.2 is devoted to the computational aspects of the COPRAS method for developing criteria ranks based on SWARA weights, which are taken as cornerstones.

2.1.1. SWARA method

SWARA is a general tool that is used for calculating criteria weights within the ambit of performance measurement as well as the respective resulting importance levels [27]. It is one of the few MCDA methods that is based on a rational dispute resolution method [29]. Analogously to other MCDA methods, however, experts also have critical roles in terms of decision-making inputs. The preferences of experts are obtained first, then the average expert judgements are computed. Subsequently, the comparative importance of each criterion is calculated next with the results being ranked in descending order. Finally, the weight of a given criterion is calculated based on the relative importance of the next most important criterion [28]. The SWARA method is duly described next.

Step 1: Sort criteria from the highest to the lowest importance.

Step 2: As the preference indicator of the first criterion is 0, then the decision-maker preferences for the second most important criterion are expressed. This is repeated until the least important criterion is reached. These preferences are based on comparing this specific criterion with the first criterion with their pairwise relative importance denoted by S_j being computed, which shows the ratio of this comparison.

Step 3: Set up pairwise efficiency criteria $K_j$using (1). Pairwise means that the importance of each factor j is expressed in comparison with the first, most important factor.

$$K_j = \begin{cases} 1, j = 1 \\ S_j + 1, j > 1 \end{cases} \tag{1}$$

Step 4: Compute relative weights (q_j) based on sorted pairwise efficiency concerning the importance criterion ranking:

$$q_j = \begin{cases} 1 \quad j = 1 \\ \dfrac{K_{j-1}}{K_j} \quad j > 1 \end{cases} \tag{2}$$

Step 5: Compute final weights as $W_j = \frac{q_j}{\sum_{k=1}^{n} q_k}$, where W_j denotes the weight of each criterion j.

2.1.2. COPRAS method

COPRAS was introduced more than two decades ago by Zavadskas & Kaklauskas [30]. Since then several approaches have been published on possible alternative ways for combining SWARA and COPRAS (e.g. Refs. [31–33], SWARA and Fuzzy COPRAS [34,35], and COPRAS and other MCDA methods [36–40]. The next lines briefly present the major steps of the COPRAS method:

Step 1: Create a decision-making matrix X containing m criteria and n alternatives. Note that frequently in MCDA, rows correspond to alternatives whereas columns correspond to criteria, see e.g. Yazdani, Alidoosti & Zavadskas [35]:

$$X = \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} \dots i = 1, 2, \dots n; j = 1, 2, \dots, m \tag{3}$$

Step 2: Normalize the decision matrix X by computing:

$$\overline{x_{ij}} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \tag{4}$$

Then the decision matrix will be:

$$\overline{X} = \begin{pmatrix} \overline{x}_{11} & \dots & \overline{x}_{1n} \\ \vdots & \ddots & \vdots \\ \overline{x}_{m1} & \cdots & \overline{x}_{mn} \end{pmatrix} \tag{5}$$

Step 3: Compute the weighted normalized decision matrix by means of:

$$\widehat{x_{ij}} = \overline{x}_{ij} \times w_{ij}; i = 1, 2, \dots, n; j = 1, 2, \dots, m \tag{6}$$

Therefore,

$$\widehat{X} = \begin{pmatrix} \widehat{x}_{11} & \dots & \widehat{x}_{1n} \\ \vdots & \ddots & \vdots \\ \widehat{x}_{m1} & \cdots & \widehat{x}_{mn} \end{pmatrix}; i = 1, 2, \dots, n; j = 1, 2, \dots, m \tag{7}$$

Step 4: Sum up the criteria values to be maximized, denoted as P_i:

$$P_i = \sum_{j=1}^{k} \overline{x_{ij}} \tag{8}$$

Step 5: Sum up the smaller criteria values to be minimized, denoted as R_i:

$$R_i = \sum_{j=k+1}^{k} \overline{x_{ij}} \tag{9}$$

Then the number of criteria that should be minimized is given by the difference m-k.

Step 6: Minimize $R_i$observing eq. (8):

$$R_{\min} = \min_i R_i; i = 1, 2, \dots, n \tag{10}$$

Step 7: Compute the relative significance of each alternative $Q_i$as given:

$$Q_i = P_i + \frac{R_{\min}\sum_{i=1}^{n} R_i}{R_i \sum_{i=1}^{n} \frac{R_{\min}}{R_i}} \tag{11}$$

Step 8: Identify the optimal alternative i given by K, as illustrated:

$$K = \max_i Q_i;\ i = 1, 2, \ldots, n \tag{12}$$

Step 9: Prioritize alternatives in a descending order.

Step 10: Determine the utility degree N of each subsequent alternative i, given as:

$$N_i = \frac{Q_i}{Q_{\max}} \times 100\% \tag{13}$$

2.1.3. Weighted aggregated sum-product assessment (WASPAS) method

The WASPAS method is an MADM method introduced by Zavadskas, Turskis, Antucheviciene, & Zakarevicius (2012). The first step of this method to create a decision matrix as shown in Eq. (14).

$$x = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{14}$$

m indicates the number of alternatives, and n is the number of criteria.

Two different variants of the WASPAS method are considered: the Weighted Sum Model (WSM) and the Weighted Product Model (WPM). The next step is normalizing the data based on Eqs. (7) and (8).

For benefit criteria (to be maximized)

$$\overline{x}_{ij} = \frac{x_{ij}}{max_i x_{ij}} \tag{15}$$

For cost criteria (to be minimized)

$$\overline{x}_{ij} = \frac{min_i x_{ij}}{x_{ij}} \tag{16}$$

$\overline{x}_{ij}$ represents the normalized value of x_{ij}.

The WSM method can be applied for calculating the additive optimality scores. The importance of the ith alternative is calculated by Eq. (17).

$$Q_i^{(1)} = \sum_{j=1}^{n} \overline{x}_{ij} w_j \tag{17}$$

Thew_j value represents the weight of the jth criterion.

According to a multiplicative model (WPM), Eq. (18) is used for the ith alternative's total score computation.

$$Q_i^{(2)} = \prod_{j=1}^{n} \left(\overline{x}_{ij}\right)^{w_j} \tag{18}$$

The calculation of a generalized criterion of weighted aggregation based on the additive and the multiplicative method is shown in Eq. (19).

$$Q_i = 0.5Q_i^{(1)} + 0.5Q_i^{(2)} = 0.5\sum_{j=1}^{n} \overline{x}_{ij} w_j + 0.5\prod_{j=1}^{n} \left(\overline{x}_{ij}\right)^{w_j} \tag{19}$$

In the *WASPAS* method, Eq. (19) can be changed to Eq. (20) for a more accurate calculation of the rankings.

$$Q_i = \lambda Q_i^{(1)} + (1-\lambda) Q_{(i)}^{2} = \lambda \sum_{j=1}^{n} \overline{x}_{ij} w_j + (1-\lambda)\prod_{j=1}^{n} \left(\overline{x}_{ij}\right)^{w_j} \tag{20}$$

$(\lambda = 0, 0.1, \ldots, 1)$

The value of Q is considered for ranking alternatives based on this equation. The alternative with the highest Q value is the most important one, and the alternative with the smallest value of Q is the least essential (Zavadskas et al., 2012).

2.1.4. Technique for Order of Preference by similarity to ideal solution (TOPSIS)

Step 1: Create a decision matrix.

$$x = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{21}$$

m indicates the number of alternatives, and n is the number of criteria.

Step 2: Normalize the decision matrix. This normalization of value $r_{ij}$is computed as follows:

$$r_{ij} = x_{ij} \sqrt{\sum_{i-1}^{m} x_{ij}^2} \text{i} = 1,\ 2,\ \ldots,\ \text{m and j} = 1,\ 2,\ \ldots,\ \text{n} \tag{22}$$

Step 3: Calculate the weighted normalized decision matrix. Weights are used for multiplication with the normalized values v_{ij} as follows:

$$v_{ij} = r_{ij} \times w_j \text{i} = 1,\ 2,\ldots,\ \text{m and j} = 1,\ 2,\ \ldots,\ \text{n} \tag{23}$$

where w_j is the weight of the jth criterion or attribute and $\sum_{j=1}^{n} w_j = 1$.

Step 4: The ideal (A^*) and negative ideal (A^-) solutions are determined by the following equations.

$$A^* = \left\{ \left(\max_i v_{ij} \middle| j \in C_b \right), \left(\min_i v_{ij} \middle| j \in C_c \right) \right\} = \left\{ v_j^* \middle| j = 1, 2, \ldots, m \right\} \tag{24}$$

$$A^- = \left\{ \left(\min_i v_{ij} \middle| j \in C_b \right), \left(\max_i v_{ij} \middle| j \in C_c \right) \right\} = \left\{ v_j^- \middle| j = 1, 2, \ldots, m \right\} \tag{25}$$

Step 5: Compute the separation measures by using the m-dimensional Euclidean distance. These separation measures of each alternative are from the positive ideal solution and the negative ideal solution as follows:

$$S_i^* = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^*\right)^2}, j = 1, 2, \ldots, m \tag{26}$$

$$S_i^- = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^-\right)^2}, j = 1, 2, \ldots, m \tag{27}$$

Step 6: Find the relative closeness to the ideal solution. The relative closeness of the alternative $A_i$with respect to A^* is defined as follows:

$$RC_i^* = \frac{S_i^-}{S_i^* + S_i^-}, i = 1, 2, \ldots, m \tag{28}$$

Step 7: Rank the preference order. The RC values specify the preferability ranking of the alternatives.

2.1.5. VIseKriterijumska optimizacija I kompromisno resenje (VIKOR)

Step 1: Run Equations 21–23.

Step 2: Calculate the maximum group utility S and the minimum individual regret to the opponent R. f is the criterion function.

$$S_i = \sum_{j=1}^{n} W_j \times \frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \tag{29}$$

$$R_i = \max\left[W_j \times \frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \right] \tag{30}$$

Step 3: Compute the indicator of VIKOR.

$$Q_i = v\left[\frac{s_i - s^*}{s^- - s^*}\right] + (1-v)\left[\frac{R_i - R^*}{R^- - R^*}\right] \quad) \tag{31}$$

$$S^* = \min S_i;\ S^- = \max S_i \tag{32}$$

$$R^* = \min R_i;\ R^- = \max R_i \tag{33}$$

The acceptable advantage is $Q(A_2) - Q(A_1) \geq \frac{1}{m-1}$.

2.2. Decision-making in an uncertain environment

Information reliability is the source of decision-making, and in this regard, defining a *Z*-number is strictly related to the reliability aspect of a piece of information. *Z*-numbers are formed by two components: $Z = (A, B)$. The first one, *A*, is a fuzzy set of possible values that a variable, *X*, is allowed to take [17]. The second component, *B*, is a linguistic measure of the reliability of the former. In this section, the concept of a *Z*-number is introduced and methods for its computation are proposed by means of fuzzy numbers. Differently from fuzzy or grey numbers, a Z-number allows the assessment of the reliability levels of each piece of information [41].

2.2.1. Fuzzy sets

Fuzzy sets are a concept often used for handling vagueness in decision-making as they allow to access how data reliability could be obfuscated by the uncertainty that cannot be described in statistical terms (error, randomness, etc.). Fuzzy sets were introduced by Zadeh [42] and many papers have since been published about them, not only building new layers into the fuzzy logic theory, but also developing alternative kinds of fuzzy sets [43–46]. One of the relatively recent methods for fuzzy sets are Z-numbers. Z-numbers are to be used when the possible real numbers of an outcome can be constrained by some linguistic reliability degree [17]; 2011b). When the reliability and possibility of a given dataset are determined, then Z-numbers can be transformed into fuzzy numbers without loss of information [41]. Putting it in other words, a Z-number represents the vagueness of a possible outcome, thus incorporating the granularity of speech into real numbers [47].

2.2.2. Z-numbers

Fuzzy numbers and sets were first defined by Zadeh [42] with different modelling approaches emerging since then. One particular definition is with respect to Triangular Fuzzy Numbers (TFNs), which are depicted as (a, m, b), where a is the lowest number, m is the middle number, and b is the highest number. The TFN membership is given as follows:

$$\widetilde{\mu}_A = \begin{cases} \dfrac{x-a}{m-a}, a \leq x \leq m \\ \dfrac{b-x}{b-m}, m \leq x \leq b \\ 0, otherwise \end{cases} \tag{34}$$

Consider $\widetilde{A}$ and $\widetilde{B}$ as two distinct TFNs with their product being given by t-norm operators $\widetilde{\mu}_A(x) and \widetilde{\mu}_B(y) = \widetilde{\mu}_A(x) \times \widetilde{\mu}_B(y)$[42]. It is noteworthy that a Z-number can also be represented by a TFN. Considering that Z = (A, B), membership functions can be assigned to eq. (34) such as $\widetilde{A} = (x, u_{\widetilde{A}} | x \in [0,1],\ \widetilde{B} = (x, u_{\widetilde{B}} | x \in [0,1])$. The information reliability of a Z-number modelled as a pair of TFNs can be converted into a crisp number using the following formula [41]:

$$\alpha = \frac{\int x\mu_\beta dx}{\int \mu_\beta dx} \tag{35}$$

In (35), αrepresents the cut-off value, ranging between 0 and 1, upon which information reliability is assessed [42]. Subsequently, the weighted Z-number can be computed as follows:

$$\widetilde{Z}^\alpha = \left\{ \left(x, \mu_{\widetilde{A}^\alpha} | \mu_{\widetilde{A}^\alpha}(x) = \alpha\mu_{\widetilde{A}^\alpha}(x), X \in [0,1]\right\} \tag{36}$$

Several authors have provided triangular fuzzy scales to represent the granularity of different linguistic variables through different kinds of fuzzy numbers [15,48–50]. Of particular interest are the scales developed by Yazdi & Haddadi due to the fact that they are built upon the natural numbers from 1 to 9, thus allowing a better discrimination of results (A.K. [51]. Tables 1 and 2 align the variable rules in linguistics with their respective information reliabilities represented in terms of TFNs.

3. Literature review

In this subsection, previous recent studies are clustered in terms of MCDA approaches and methodological affinity regardless of the plethora of study objects about selecting suppliers so that the managerial and/or economical counterpart of their major assumptions can be clearly apprehended in terms of decision-making strengths and limitations. This will help in positioning the approach proposed in light of the current body of MCDA literature applied to supplier selection, thus clarifying the research gap tackled by this research. Previous studies such as Sabaei, Erkoyuncu, & Roy [52] and Liu, Zhao, Li, & Liu [53,54] have compiled the previous research that focused on MCDA methods applied to the supplier selection problem. The next subsections present a segmented update on this subject.

3.1. AHP/ANP-based approaches

The Analytic Hierarchical Process (AHP) converts pairwise criteria evaluations into eigenvalues that can be used as weights for discriminating possible alternatives (T. L. [55]. These endogenously defined eigenvalues allow comparing *a priori* incomparable criteria measured very often in distinct dimensions in a consistent way. Therefore, AHP is reputed as a flexible MCDA method that can be either used in a stand-alone fashion or in conjunction with other methods for supplier selection problems, providing the weights for each criterion [56–59]. The most prominent justifications for using AHP were found to be when there is a small sample size and a high level of weight consistency (R. W. [60].

Table 1
Linguistic variable rules (A.K [51]].

Linguistic terms	TFN support for A
Extremely Dissatisfied	(1,1,2)
Very Dissatisfied	(1,2,3)
Moderately Dissatisfied	(2,3,4)
Slightly Dissatisfied	(3,4,5)
Neither Satisfied nor Dissatisfied	(4,5,6)
Slightly Satisfied	(5,6,7)
Moderately Satisfied	(6,7,8)
Very Satisfied	(7,8,9)
Extremely Satisfied	(8,9,9)

Table 2
- Linguistic variable information reliability.

Linguistic terms	TFN support for B
Extremely low	(0.15, 0.25, 0.35)
Very low	(0.25, 0.3, 0.35)
Moderately low	(0.3, 0.35, 0.4)
Slightly low	(0.35, 0.4, 0.45)
Moderate	(0.4, 0.45, 0.5)
Slightly high	(0.45, 0.5, 0.55)
Moderately high	(0.5, 0.55, 0.6)
Very high	(0.6, 0.65, 0.7)
Extremely high	(0.65, 0.7, 0.75)

Table 3
Compilation of recent MCDA applications in supplier selection problems.

	Aloini, Dulmin, Farina, Mininno, & Pellegrini [77]	Büyüközkan & Görener [87]	Pongsathornwiwat, Huynh, Theeramunkong, & Jeenananta [46]	Wu & Barnes [84]	Later on, Wu & Barnes [61]	Zhou, Wang, Lim, He, & Li [68]	Büyüközkan, Güleryüz, & Karpak [63]	. Rao, Xiao, Goh, Zheng, & Wen [85]
MOORA								
QFD								
IFH								
LINMAP								
TOPSIS								
Fuzzy AHP								
Fuzzy TOPSIS								
Best-Worst Method								
DEMATEL								
Neutrosophic Sets								
FIAHP								
IFAD								
MAIRCA								
MABAC								
MULTIMOORA								
COPRAS								
Rough EDAS								
Fuzzy type 2								
ELECTRE II								
Multi-attribute Auction								*
GRA								*
VIKOR		*						
Multi-objective Programming					*			
Fuzzy VIKOR						*		
AEW						*		
IF-ANP							*	
Fuzzy DEMATEL						*	*	
ANP					*			
Artificial Neural Network				*				
Dempster-Shafer Theory			*					
AHP		*						
IF-TOPSIS	*							

For instance, Büyüközkan & Görener [48] developed a model for matching business partners for product development by combining AHP with the VIKOR technique. They used 13 criteria to evaluate partner development levels. Since VIKOR (*Vlse Kriterijumsk Optimizacija Kompromisno Resenje*) is an MCDA method that is based on a decision matrix, it needs criteria weights, which were derived from preliminary AHP computation. Wu & Barnes [61] tackled the issue of selecting green partners within supply chains by developing a hybrid model combining Analytic Network Process (ANP) and multi-objective programming for controlling negative environmental criteria. Analogously, but using fuzzy logic, Wan, Xu, & Dong [62] implemented ANP and ELECTRE II (*ELimination Et Choix Traduisant la REalité*) in an uncertain environment for selecting suppliers. Fuzzy weights were obtained using ANP with suppliers subsequently being ranked using ELECTRE II based on these weights. Under a more sophisticated fuzzy logic modeling, Büyüközkan & Göçer [63] illustrated how experts can select suppliers based on intuitionistic fuzzy axiomatic design (IFAD). Intuitionistic fuzzy-AHP was used to compute weights and rank five suppliers with respect to different quality and cost criteria.

3.2. DEMATEL-based approaches

The method Decision Making Trial and Evaluation Laboratory (DEMATEL) is considered effective for identifying cause-effect chain components in a complex system (E [64]; Emilio [65,66]. It deals with evaluating interdependent relationships among criteria by dividing them into a cause group and an effect group. In comparison to other MCDA methods, the possible disadvantages of DEMATEL are as follows [67]: (i) the ranking of alternatives is based only on interdependent relationships among themselves with relevant criteria frequently being ignored; (ii) the relative weights of experts are not endogenously determined; and (iii) partial rankings cannot be derived based on a subset of criteria and alternatives as long as a strong dependence is supposed to exist among different criteria. For instance, Zhou, Wang, Lim, He, & Li [68] indicated how business partners for sustainable recycling in small and medium enterprises could be selected by combining Anti-Entropy Weights (AEW), fuzzy-DEMATEL, and fuzzy-VIKOR. Analogously, Büyüközkan, Güleryüz, & Karpak [69] designed new intuitionistic fuzzy-DEMATEL and intuitionistic fuzzy-ANP for selecting business partners. As regards the treatment of information reliability levels, Abdel-Basset, Manogaran, Mohamed, & Chilamkurti [70] designed a hybrid approach based on neutrosophic sets and DEMATEL for selecting suppliers. Neutrosophic sets are a generalization of fuzzy sets and intuitionistic fuzzy sets, becoming a helpful tool for handling indeterminate and inconsistent pieces of information that exist in the real world [71]. Criteria weights are based on truth, indeterminacy, and falsity membership functions [72]. Finally, Yazdani, Hashemkhani Zolfani, & Zavadskas [73] applied DEMATEL and Quality Function Deployment (QFD) for selecting green suppliers. In the first step, the DEMATEL method was used for determining the relational structure among different criteria with QFD being subsequently applied for finding the degree of relationship (weights) among suppliers and customer requirements.

3.3. TOPSIS-based approaches

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method is based on the concept of positive and negative ideal solutions that may exist in the Euclidean space and that are built upon different criteria, but different from VIKOR, a compromise solution is

Wan, Xu, & Dong [62]	Stević, Pamučar, Vasiljević, Stojić, & Korica, ([88]	(Büyüközkan & Göçer, ([63]	Abdel-Basset et al. [70],	Gupta & Barua, ([80]	Hamdan & Cheaitou [81],	Jain et al. [78],	Qin et al. [86],	Zhao et al. [83],	Yazdani et al., ([73]	Venkatesh et al. [79],
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not required [74–76]. For instance, Aloini, Dulmin, Farina, Mininno, & Pellegrini [77] studied the issue of selecting business partners to improve innovation levels by using an intuitionistic fuzzy-TOPSIS approach. On the other hand, Jain, Sangaiah, Sakhuja, Thoduka, & Aggarwal [78] implemented fuzzy AHP and TOPSIS for selecting suppliers in the Indian automobile industry. Fuzzy AHP was used first for computing weights, then TOPSIS was used to rank alternative suppliers. Similarly, Venkatesh, Zhang, Deakins, Luthra, & Mangla [79] illustrated a fuzzy AHP-TOPSIS approach for selecting suppliers in humanitarian aid supply chains. Gupta & Barua [80] showed how to select suppliers for small and medium enterprises by using a hybrid Best-Worst Method (BWM) for weight computation and fuzzy-TOPSIS for alternative hierarchies. A similar approach was developed by Hamdan & Cheaitou [81], but AHP was used instead of BWM.

3.4. VIKOR-based and other approaches

Similarly to DEMATEL and TOPSIS, weights should be exogenously defined in VIKOR [82]. Using fuzzy logic for weight definition in VIKOR differs from its joint use with other MCDA methods such as AHP with Zhao, You, Liu, & Wu [83] depicting how suppliers can be selected by proposing a hybrid intuitionistic fuzzy-VIKOR method.

Other approaches usually focus on the issue of information reliability regardless of the MCDA method, which sometimes is not employed at all. For instance, Pongsathornwiwat, Huynh, Theeramunkong, & Jeenananta (2016) studied the problem of assessing business partner performance across a tourism supply chain network. While the authors employed the Dempster-Shafer theory[1] on the evidence collected with respect to partner satisfaction, linguistic variables were incorporated into the model to allow decision-making under different degrees of reliability. Wu & Barnes [84] depicted how partner selection could be made operational in an agile supply chain environment by means of the joint use of fuzzy sets and an artificial neural network. Their research was conducted in 84 Chinese energy companies. Rao, Xiao, Goh, Zheng, & Wen [85] illustrated how suppliers can be selected using Grey Relational Analysis (GRA) model and multiple attribute auctions. And lastly, Qin, Liu, & Pedrycz [86] implemented an interval type-2 fuzzy group decision making for selecting suppliers by the extended Linear Programming for Multidimensional Analysis of Preference (LINMAP) technique.

3.5. Research gap

A systematic review on using MCDA methods for handling supplier selection problems reveals not only a heterogeneous scenario where it is not possible to claim whether a specific method is preferable over others given a particular set of circumstances, but also a variety of alternative methodological approaches where a creative effort is placed by authors to combine different techniques for handling uncertainty (vagueness or randomness), dealing with objective functions and constraints, and capturing decision-maker perceptions while defining weighting schemes with respect the ideal positive and negative benchmarks for comparing

[1] This is a particular type of information theory that combines evidences obtained from different sources together with the degree of belief with respect to each evidence available [138].

and ranking alternatives. Table 3 departs from Chai et al. [11] and presents a compilation of recent MCDA methods used in supplier selection.

In fact, Chai et al. [11] proposed a framework for classifying the various methodological approaches used in the supplier selection problem. These approaches can be categorized into metaheuristic methods, exact methods, pure MCDA methods, and hybrid combinations of MCDA with uncertainty methods. Especially in the last category, very often the reasons, strengths, and weaknesses of each method used in hybrid combinations of MCDA for handling uncertainty are not properly discussed. In this research, it is deemed necessary to put into perspective the specifics of the O&G industry in terms of selecting suppliers for achieving efficient, effective, low-cost, and reliable production and distribution processes of a scarce and crucial commodity negotiated every day on stock markets worldwide. In this respect, COPRAS, differently from other MCDA methods, helps establish a partial utility degree for each criterion related to selecting suppliers [89]; Edmundas Kazimieras Zavadskas et al., 2007). Readers should recall that utility functions are a well-known economic concept applied in MCDA [90]. Precisely utility is an important concept that measures preferences over a set of alternatives and criteria, representing the satisfaction that DMs attribute for choosing a specific supplier in terms of given CSFs [91,92]. This approach is the form most simply and easily understood by experts since it does not require any stronger restrictions on the preference structures than on the aggregation formula, straightforwardly

Table 4
Details of the decision makers.

Expert No.	Years of Experience	Education Level
1	27	PhD.
2	28	MA
3	30	MSc
4	24	MA
5	21	MS.
6	27	BSc
7	22	PhD.
8	24	PhD.
9	29	MA
10	30	BSc

Table 5
Supplier selection CSFs.

Authors	CSFs
[110]	Customer loyalty, Culture, Customer value, Customer satisfaction
[111,112]	Flexibility, Technical capability, Quality, Cost
[113]	Cost, Quality
[114]	Cost, Finance
[115]	Organizational size, Technical capability, Technical experts
[116]	Compatibility, Flexibility
(Y. [117]	Positive image, R&D
[118]	Novelty, Quality, Independence
[119]	New products, Reputation
(Y. [53]	Exchange of knowledge, Trust, Communication
[120]	Commitment, Technology, Competency
[121]	Economy, Reputation
[122]	Political stability, Geographic location
[123]	Project expectation, Geographic location, Quality
[124]	Willingness, Market
[125]	Complementarity, Strategy, Relation

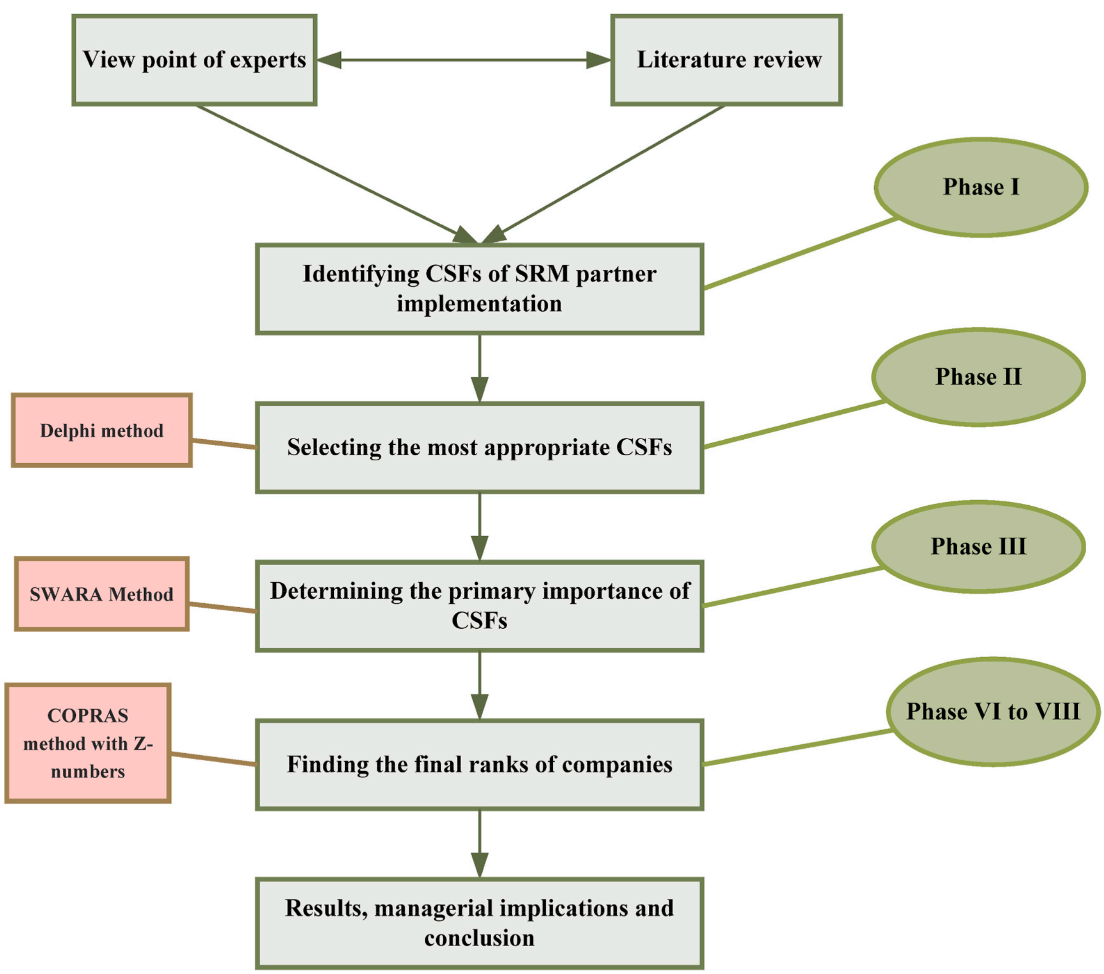

Fig. 1. Phases of approach proposed.

Table 6
Importance assigned to each CSF.

CSFs	Expert1	Expert2	Expert3	Expert4	Expert5	Expert6	Expert7	Expert8	Expert9	Expert10
Customer loyalty	3	2	3	4	5	3	2	4	5	3
Customer value	2	3	5	3	2	4	3	5	4	3
Customer satisfaction	4	5	3	2	2	3	2	4	5	3
Positive image	4	5	4	5	4	3	2	4	5	5
Independence	3	4	2	5	3	4	3	2	3	2
New products	5	4	5	4	2	5	3	4	5	5
Exchange of knowledge	5	4	4	5	2	3	3	5	4	5
Commitment	5	4	5	5	4	3	2	5	3	5
Organizational size	2	3	3	5	3	4	2	2	5	4
Communication	2	3	5	4	2	3	5	4	2	2
Novelty	5	5	4	5	4	4	3	2	5	3
Quality	5	4	5	4	4	5	3	3	5	2
Cost	5	5	4	4	4	2	3	5	4	5
Economy	2	3	2	3	2	4	5	2	3	3
Political stability	2	3	3	4	2	5	3	5	2	3
Reputation	5	4	5	4	5	4	3	5	2	3
Flexibility	5	5	4	4	2	3	5	4	4	5
Culture	3	5	2	2	3	4	5	3	5	2
Project expectation	5	2	3	3	2	4	5	2	3	2
R&D	5	4	5	4	4	2	3	5	5	4
Technical capability	5	4	5	4	5	3	2	4	5	5
Technical experts	5	4	4	5	4	5	5	2	3	5
Willingness	2	3	3	4	2	5	3	2	3	2
Complementarity	3	2	3	2	3	4	5	2	3	5
Compatibility	5	4	5	4	5	5	2	3	5	4
Trust	3	3	2	5	3	5	4	5	4	5
Competency	3	2	3	2	3	2	5	4	5	2
Geographic location	2	3	3	2	5	4	5	2	3	3
Market	2	2	2	3	5	3	5	4	2	3
Finance	2	3	2	4	5	2	3	2	5	3
Relation	5	4	5	5	4	4	3	5	4	2
Strategy	3	2	2	3	2	5	4	2	3	5
Technology	5	4	5	5	4	5	4	2	3	5

Table 7
Results from the CSF filtering.

Factors	Average	Result
Customer loyalty	3.4	Reject
Customer value	3.4	Reject
Customer satisfaction	3.3	Reject
Positive image	4.1	Accept
Independence	3.1	Reject
New products	4.2	Accept
Exchange of knowledge	4	Accept
Commitment	4.1	Accept
Organizational size	3.3	Reject
Communication	3.2	Reject
Novelty	4	Accept
Quality	4	Accept
Cost	4.1	Accept
Economy	2.9	Reject
Political stability	3.2	Reject
Reputation	4	Accept
Flexibility	4.1	Accept
Culture	3.4	Reject
Project expectation	3.1	Reject
R&D	4.1	Accept
Technical capability	4.2	Accept
Technical experts	4.2	Accept
Willingness	2.9	Reject
Complementarity	3.2	Reject
Compatibility	4.2	Accept
Trust	3.9	Reject
Competency	3.1	Reject
Geographic location	3.2	Reject
Market	3.1	Reject
Finance	3.1	Reject
Relation	4.1	Accept
Strategy	3.1	Reject
Technology	4.2	Accept

Table 8
Weights computed using the SWARA method for each filtered CSF.

CSFs	Pairwise relative importance	Pairwise efficiency	Relative weights	Final weights
Positive image	–	1	1	0.242
New products	0.34	1.34	0.746	0.182
Exchange of knowledge	0.13	1.13	0.66	0.162
Commitment	0.46	1.46	0.45	0.111
Novelty	0.27	1.27	0.356	0.086
Quality	0.31	1.31	0.271	0.065
Cost	0.62	1.62	0.167	0.04
Reputation	0.41	1.41	0.119	0.028
Flexibility	0.29	1.29	0.092	0.022
R&D	0.12	1.12	0.082	0.0199
Technical capability	0.28	1.28	0.064	0.015
Technical experts	0.35	1.35	0.047	0.011
Compatibility	0.61	1.61	0.029	0.007
Relation	0.49	1.49	0.0198	0.0048
Technology	0.12	1.12	0.0177	0.0042

establishing the relation between criteria and partial value function amounts for each supplier alternative, which must be performed by the experts [93–95]. The simplicity of the usually assumed additive aggregation makes the utility function approach particularly appealing. Only relatively minor assumptions are needed and these are primarily related to defining criteria and to interpreting partial value functions and weights often considered as scaling constants [96] indirectly subject to the discretion of the DMs.

As regards to weight definition, SWARA, differently from other MCDA methods, is particularly useful as long as it computes the preferences for each criterion as a relative efficiency score in comparison to the most important one [27]. This being the case, SWARA helps in

Table 9
Z-numbers for the CSFs considered for each possible supplier.

Supplier	Positive image	New products	Exchange of knowledge	Commitment	Novelty	Quality
Type	+	+	+	+	+	+
1	(1,1.25,1.5)	(5.6,6.4,7.2)	(6.64,7.47,7.47)	(4.45,5.18,5.92)	(5.6,6.4,7.2)	(2.68,3.35,4.02)
2	(4.45,5.18,5.92)	(5.6,6.4,7.2)	(6.64,7.47,7.47)	(2.68,3.35,4.02)	(1,1.25,1.5)	(0.6,0.8,1)
3	(2.68,3.35,4.02)	(1,1.25,1.5)	(0.6,0.8,1)	(2.68,3.35,4.02)	(1.18,1.77,2.36)	(0.54,1.08,1.62)
4	(5.6,6.4,7.2)	(6.64,7.47,7.47)	(4.45,5.18,5.92)	(5.6,6.4,7.2)	(2.68,3.35,4.02)	(1,1.25,1.5)
5	(5.6,6.4,7.2)	(6.64,7.47,7.47)	(4.45,5.18,5.92)	(0.6,0.8,1)	(0.54,1.08,1.62)	(0.5,0.5,1)
6	(4.45,5.18,5.92)	(5.6,6.4,7.2)	(0.6,0.8,1)	(2.68,3.35,4.02)	(1,1.25,1.5)	(1.18,1.77,2.36)
7	(1,1.25,1.5)	(2.68,3.35,4.02)	(0.6,0.8,1)	(6.64,7.47,7.47)	(5.6,6.4,7.2)	(4.45,5.18,5.92)
8	(1,1.25,1.5)	(4.45,5.18,5.92)	(5.6,6.4,7.2)	(0.6,0.8,1)	(0.54,1.08,1.62)	(1.18,1.77,2.36)
9	(2.68,3.35,4.02)	(0.6,0.8,1)	(4.45,5.18,5.92)	(5.6,6.4,7.2)	(6.64,7.47,7.47)	(0.54,1.08,1.62)

assigning efficiency levels for each partial utility function derived in COPRAS for each supplier in light of different CSFs. Similarly, efficiency also has its grounds as a well-known economic concept for measuring or capturing relative performance differences between two units of analysis [97]. It is worth noting that both utility and efficiency functions within MCDA convert preference variables often expressed in ordinal scales into a metric support where relative differences for each supplier-CSF can actually be computed [98,99].

There is, however, a remaining issue regarding the reliability of these relative differences if they are computed based on ordinal preference scales subject to expert vagueness. As presented in Table 1, some researchers address vagueness in MCDA using intuitionistic fuzzy methods, fuzzy sets, or rough numbers, which do not capture the expert impressions on how reliable their assigned preferences are, but only focus on the inherent threshold vagueness. Z-numbers address this shortcoming by convoluting two fuzzy sets into rescaled efficiency levels for each supplier utility function.

In various MCDA methods, consistency can be measured as a rate that expresses how reliable the results are. Decision matrix based MCDA methods such as TOPSIS, VIKOR, COPRAS, and Additive Ratio Assessment (ARAS) cannot measure consistency rates, so they should be supported by a method from the first category for computing the required weights. The resulting hybrid method not only leads to prioritized criteria, but it also covers the weaknesses of decision-matrix methods that cannot measure consistency rates [100,101]; A.K. [102,103]. Therefore, this research focuses on using a hybrid method. This also better supports the difficulties of DMs in specifying their preferences in a sufficiently reliable way. Fuzzy numbers based on linguistic variables can help DMs in determining their preferences easily [104]. As discussed above, Z-numbers are one kind of fuzzy numbers that has more merits than other kinds of fuzzy numbers.

Therefore, this research proposes to fill a literature gap left by previous studies by handling information reliability issues of two critical economic concepts usually considered by experts concerning selecting suppliers: partial utility function of each alternative and relative efficiency of each criterion. To the best of our knowledge, this is the first time a link between economic concepts and information reliability has been established within the ambit of a hybrid MCDA applied to supplier selection problems based on different CSFs.

The main gap of this research is that in previous papers, diverse MCDA methods were used in both certain and uncertain environments, and in those, that have the same homogeneous environment for selecting suppliers both in the internal and external environment. Since this research is located in Iran, the environment is quite different from similar companies in other countries due to the US sanctions against its basic industries. Therefore, finding suppliers based on the specific environment is a hard problem that required not only considering common factors, but also other factors specific to this situation. In addition, the cost of supply services and materials are very high for Iranian companies.

4. Research methodology

4.1. Case study

Nine mostly larger companies were considered in our study that represent more than 65% of the O&G market in Iran. We tried to cover all supplier selection CSFs considering previous study results and also experts interviewed, thus we can claim that this model is generalized for supplier selection in Iran's O&G industry. The references for each CSF are illustrated in Appendix 1. The Delphi method was initially used to filter these CSFs based on the aggregated importance attributed by experts to each CSF. In this research, ten experts were chosen in accordance with the prescriptions presented in previous publications [105–107].

4.2. Expert participants

There are many definitions of the concept of decision makers (DMs). One of these definitions pointed out that DMs make the decision by choosing one solution among several alternatives. Methods supporting DMs are considered as prescriptive. Many people work in the O&G industry in Iran, but within the scope of our study, we considered only highly qualified participants who fully understand most O&G industry SCM fields such as extraction, refinement, transportation, supply equipment, and so on.

Moreover, the participants were expected to have conducted successful projects during their work experience with a project success rate of more than 80% and have undergone more than 1000 h of SCM training and related courses in the academic environment on SCM in the O&G industry. Under these constraints, we found 10 DMs in Iran for participating in our study who were prepared to answer the questionnaires during the winter of 2019. They are managers and decision-makers in respective companies dealing with procurement activities. Table 4 shows information about the DMs.

4.3. Approach proposed

This supplier selection problem in the Iranian O&G industry is addressed by a 4-phase approach as depicted in Fig. 1. It is noteworthy that although several MCDA approaches are combined, analogously to previous studies, this is the first time that Z-number modelling is used as a cornerstone of a joint use of Delphi, SWARA, and COPRAS throughout different stages or phases so that information reliability regarding different CSFs can be properly assessed. Besides, MCDA applied research on the supplier selection problem in the O&G industry is scarce [108,109]. Hence, the aim is to contribute not only to the MCDA literature, but also to practitioners so that O&G managers can make better decisions regarding supplier selection in an uncertain environment with higher reliability.

These phases are described next.

Phase 1. Determine the CSFs through a literature review and

Cost	Reputation	Flexibility	R&D	Technical capability	Technical experts	Compatibility	Relation	Technology
–	+	+	+	+	+	+	+	+
(0.54,1.08,1.62)	(0.6,0.8,1)	(1.18,1.77,2.36)	(0.5,0.5,1)	(2.68,3.35,4.02)	(1,1.25,1.5)	(6.64,7.47,7.47)	(5.6,6.4,7.2)	(0.6,0.8,1)
(5.6,6.4,7.2)	(2.68,3.35,4.02)	(0.54,1.08,1.62)	(0.5,0.5,1)	(1.18,1.77,2.36)	(1,1.25,1.5)	(2.68,3.35,4.02)	(0.6,0.8,1)	(4.45,5.18,5.92)
(0.5,0.5,1)	(5.6,6.4,7.2)	(6.64,7.47,7.47)	(4.45,5.18,5.92)	(1,1.25,1.5)	(2.68,3.35,4.02)	(0.6,0.8,1)	(0.54,1.08,1.62)	(0.6,0.8,1)
(1.18,1.77,2.36)	(0.54,1.08,1.62)	(0.5,0.5,1)	(0.6,0.8,1)	(2.68,3.35,4.02)	(1,1.25,1.5)	(5.6,6.4,7.2)	(4.45,5.18,5.92)	(1.18,1.77,2.36)
(1.18,1.77,2.36)	(1,1.25,1.5)	(2.68,3.35,4.02)	(0.5,0.5,1)	(0.6,0.8,1)	(2.68,3.35,4.02)	(1,1.25,1.5)	(1.18,1.77,2.36)	(0.54,1.08,1.62)
(0.54,1.08,1.62)	(0.5,0.5,1)	(2.68,3.35,4.02)	(0.6,0.8,1)	(4.45,5.18,5.92)	(5.6,6.4,7.2)	(6.64,7.47,7.47)	(0.5,0.5,1)	(0.6,0.8,1)
(1.18,1.77,2.36)	(0.54,1.08,1.62)	(0.5,0.5,1)	(2.68,3.35,4.02)	(0.6,0.8,1)	(1,1.25,1.5)	(2.68,3.35,4.02)	(5.6,6.4,7.2)	(4.45,5.18,5.92)
(6.64,7.47,7.47)	(5.6,6.4,7.2)	(2.68,3.35,4.02)	(0.6,0.8,1)	(4.45,5.18,5.92)	(6.64,7.47,7.47)	(1.18,1.77,2.36)	(0.54,1.08,1.62)	(0.5,0.5,1)
(0.6,0.8,1)	(6.64,7.47,7.47)	(4.45,5.18,5.92)	(1.18,1.77,2.36)	(0.6,0.8,1)	(0.5,0.5,1)	(0.54,1.08,1.62)	(6.64,7.47,7.47)	(5.6,6.4,7.2)

interviews with experts. In this research, 33 CSFs were found after confirming them by interviewing 10 experts who assigned the importance of each CSF by means of a Likert scale ranging from 1 (less important) to 5 (most important). These results are presented in Table 6. For gathering data, first a questionnaire was designed in which all CSFs were evaluated based on the DM preferences. The weights were later assigned using the SWARA method by the DMs asserting their preference and their average was considered for evaluation. In the ZCOPRAS method, the preferences are obtained by using the aggregated weights from the DMs. For doing so, the mode is determined after collecting responses from the DMs such as the preference value mentioned most often. Then the DMs were informed about this result including the reason for choosing this preference value for reaching a unique preference. After the CSFs were customized and the weights determined with the SWARA method, the questionnaire for using the COPRAS method was designed. In the questionnaire, alternatives (suppliers) were ranked by the customized CSFs based on a 9-point Likert scale. For both steps involving the DMs, the questionnaires were sent to them by email, which were returned back to the researchers (see Table 7).

Phase 2. Filter the CSFs by defining a cut-off value for the average relative importance of each CSF. CSFs below this cut-off value should be rejected. In this research we considered 4 as the cut-off value for the average importance of each CSF, yielding 15 most important ones as presented in Table 6.

Phase 3. Rank the CSFs using the SWARA method to compute their respective weights. Results for this phase are given in Table 8. The population of this research is identical with the SWARA method and the COPRAS method.

Phase 4. Select suppliers by using COPRAS based on the Z-numbers technique to address information reliability of each success factor criterion. Based on the viewpoint of the decision-makers, their preferences were assigned to each partner based on CSFs, which were based on Z-numbers to capture information reliability under uncertainty.

Table 10
CSF defuzzification.

Supplier	Positive image	New products	Exchange of knowledge	Commitment	Novelty	Quality	Cost	Reputation	Flexibility	R&D	Technical capability	Technical experts	Compatibility	Relation	Technology
1	1.25	6.4	7.19	5.18	6.4	3.35	1.08	0.8	1.77	0.66	3.35	1.25	7.47	6.4	0.8
2	5.18	6.4	7.19	3.35	1.25	0.8	6.4	3.35	1.08	0.66	1.77	1.25	3.35	0.8	5.18
3	3.35	1.25	0.8	3.35	1.77	1.08	0.66	6.4	7.47	5.18	1.25	3.35	0.8	1.08	0.8
4	6.4	7.19	5.18	6.4	3.35	1.25	1.77	1.08	0.66	0.8	3.35	1.25	6.4	5.18	1.77
5	6.4	7.19	5.18	0.8	1.08	0.66	1.77	1.25	3.35	0.66	0.8	3.35	1.25	1.77	1.08
6	5.18	6.4	0.8	3.35	1.25	1.77	1.08	0.66	3.35	0.8	5.18	6.4	7.47	0.66	0.8
7	1.25	3.35	0.8	7.47	6.4	5.18	1.77	1.08	0.66	3.35	0.8	1.25	3.35	6.4	5.18
8	1.25	5.18	6.4	0.8	1.08	1.77	7.19	6.4	3.35	0.8	5.18	7.47	1.77	1.08	0.66
9	3.35	0.8	5.18	6.4	7.19	1.08	0.8	7.19	5.18	1.77	0.8	0.66	1.08	7.47	6.4

Table 11
Decision-making matrix.

Supplier	Positive image	New products	Exchange of knowledge	Commitment	Novelty	Quality	Cost	Reputation	Flexibility	R&D	Technical capability	Technical experts	Compatibility	Relation	Technology
1	1.25	6.4	7.19	5.18	6.4	3.35	1.08	0.8	1.77	0.66	3.35	1.25	7.47	6.4	0.8
2	5.18	6.4	7.19	3.35	1.25	0.8	6.4	3.35	1.08	0.66	1.77	1.25	3.35	0.8	5.18
3	3.35	1.25	0.8	3.35	1.77	1.08	0.66	6.4	7.47	5.18	1.25	3.35	0.8	1.08	0.8
4	6.4	7.19	5.18	6.4	3.35	1.25	1.77	1.08	0.66	0.8	3.35	1.25	6.4	5.18	1.77
5	6.4	7.19	5.18	0.8	1.08	0.66	1.77	1.25	3.35	0.66	0.8	3.35	1.25	1.77	1.08
6	5.18	6.4	0.8	3.35	1.25	1.77	1.08	0.66	3.35	0.8	5.18	6.4	7.47	0.66	0.8
7	1.25	3.35	0.8	7.47	6.4	5.18	1.77	1.08	0.66	3.35	0.8	1.25	3.35	6.4	5.18
8	1.25	5.18	6.4	0.8	1.08	1.77	7.19	6.4	3.35	0.8	5.18	7.47	1.77	1.08	0.66
9	3.35	0.8	5.18	6.4	7.19	1.08	0.8	7.19	5.18	1.77	0.8	0.66	1.08	7.47	6.4
Criterion Type	Max	Max	Max	Max	Max	Max	Min	Max	Max	Max	Max	Max	Max	Max	Max
Weight	0.242	0.182	0.162	0.111	0.086	0.065	0.04	0.028	0.022	0.02	0.015	0.011	0.007	0.0048	0.0042

Table 12
Normalized decision-making matrix.

Supplier	Positive image	New products	Exchange of knowledge	Commitment	Novelty	Quality	Cost	Reputation	Flexibility	R&D	Technical capability	Technical experts	Compatibility	Relation	Technology
1	0.037	0.145	0.186	0.140	0.215	0.198	0.048	0.028	0.066	0.045	0.149	0.048	0.227	0.208	0.035
2	0.154	0.145	0.186	0.090	0.042	0.047	0.284	0.119	0.040	0.045	0.079	0.048	0.102	0.026	0.228
3	0.100	0.028	0.021	0.090	0.059	0.064	0.029	0.227	0.278	0.353	0.056	0.128	0.024	0.035	0.035
4	0.190	0.163	0.134	0.173	0.113	0.074	0.079	0.038	0.025	0.054	0.149	0.048	0.194	0.168	0.078
5	0.190	0.163	0.134	0.022	0.036	0.039	0.079	0.044	0.125	0.045	0.036	0.128	0.038	0.057	0.048
6	0.154	0.145	0.021	0.090	0.042	0.104	0.048	0.023	0.125	0.054	0.230	0.244	0.227	0.021	0.035
7	0.037	0.076	0.021	0.201	0.215	0.306	0.079	0.038	0.025	0.228	0.036	0.048	0.102	0.208	0.228
8	0.037	0.117	0.165	0.022	0.036	0.104	0.319	0.227	0.125	0.054	0.230	0.285	0.054	0.035	0.029
9	0.100	0.018	0.134	0.173	0.242	0.064	0.036	0.255	0.193	0.121	0.036	0.025	0.033	0.242	0.282
Criterion Type	Max	Max	Max	Max	Max	Max	Min	Max	Max	Max	Max	Max	Max	Max	Max
Weight	0.242	0.182	0.162	0.111	0.086	0.065	0.04	0.028	0.022	0.02	0.015	0.011	0.007	0.0048	0.0042

Table 13
Weighted normalized decision matrix.

Supplier	Positive image	New products	Exchange of knowledge	Commitment	Novelty	Quality	Cost	Reputation	Flexibility	R&D	Technical capability	Technical experts	Compatibility	Relation	Technology
1	0.0090	0.0264	0.0301	0.0155	0.0185	0.0129	0.0019	0.0008	0.0014	0.0009	0.0022	0.0005	0.0016	0.0010	0.0001
2	0.0373	0.0264	0.0301	0.0100	0.0036	0.0031	0.0114	0.0033	0.0009	0.0009	0.0012	0.0005	0.0007	0.0001	0.0010
3	0.0241	0.0052	0.0033	0.0100	0.0051	0.0041	0.0012	0.0064	0.0061	0.0071	0.0008	0.0014	0.0002	0.0002	0.0001
4	0.0461	0.0296	0.0217	0.0191	0.0097	0.0048	0.0031	0.0011	0.0005	0.0011	0.0022	0.0005	0.0014	0.0008	0.0003
5	0.0461	0.0296	0.0217	0.0024	0.0031	0.0025	0.0031	0.0012	0.0027	0.0009	0.0005	0.0014	0.0003	0.0003	0.0002
6	0.0373	0.0264	0.0033	0.0100	0.0036	0.0068	0.0019	0.0007	0.0027	0.0011	0.0035	0.0027	0.0016	0.0001	0.0001
7	0.0090	0.0138	0.0033	0.0223	0.0185	0.0199	0.0031	0.0011	0.0005	0.0046	0.0005	0.0005	0.0007	0.0010	0.0010
8	0.0090	0.0213	0.0268	0.0024	0.0031	0.0068	0.0128	0.0064	0.0027	0.0011	0.0035	0.0031	0.0004	0.0002	0.0001
9	0.0241	0.0033	0.0217	0.0191	0.0208	0.0041	0.0014	0.0071	0.0042	0.0024	0.0005	0.0003	0.0002	0.0012	0.0012

Table 14
Supplier scores: sum of weighted criterion values, i.e. normalized weighted scores for benefit factors (P) and cost factors (R).

Supplier	P_i	R_i
1	0.120933663	0.001918295
2	0.119069616	0.011367673
3	0.074150736	0.001172291
4	0.138964843	0.003143872
5	0.112995271	0.003143872
6	0.099913264	0.001918295
7	0.096770138	0.003143872
8	0.086871654	0.01277087
9	0.110330814	0.001420959

Table 15
Final ranking of alternatives, overall importance scores Q, and relative significance of each alternative N.

Partner	Q_i	N_i	Ranking
1	0.126539177	88.87104551	2
2	0.120015547	84.28936677	3
3	0.083323396	58.51972041	9
4	0.142385157	100	1
5	0.116415585	81.76104003	5
6	0.105518778	74.10799003	6
7	0.100190452	70.36579819	7
8	0.087713651	61.60308629	8
9	0.117898258	82.80235132	4

4.4. CSFs from previous research

For customizing the supplier selection CSFs, most of them were gathered from previous studies and interviews with experts. Table 5 lists the customized supplier selection CSFs by author.

4.5. Software

For data computation for all methods including Delphi, SWARA, and ZCOPRAS, the MS Excel software version 2016 was used and SPSS V.22 for sensitive analysis.

5. Results

5.1. Data analysis of supplier selection

The first step of this research was finding CSFs customized for the O&G industry, so suitable CSFs were first extracted from previous papers and interviews with experts then evaluating them using questionnaires. DMs allocated their preferences by values between 1 and 5. When the average DM score for each CSFs was less than 4, the respective CSF was eliminated, otherwise it was accepted.

After obtaining the results indicated, 17 factors were eliminated. The reason for this high elimination rate is that according to many specific factors in the O&G industry in Iran, various CSFs taken from other studies are not useful for the case under consideration.

The SWARA method was used for determining weights based on Eqs. (1) and (2).

Table 9 presents the DM preferences for each supplier based on Z-numbers. The names of the suppliers are not included explicitly in this table and further results shown because of the confidentiality they required.

The respective defuzzification results for the Z-numbers from Table 9 are given in Table 10 based on Eq. (15).

The decision matrix shown in Table 11 was created as the matrix of defuzzified values. The CSFs were first divided into two categories: beneficial (to be maximized) and non-beneficial (to be minimized).

The normalized decision matrix is shown in Table 12. The numbers of each column were summed up for creating the decision matrix, which were subsequently used as the respective denominators to compute the normalized values.

The weighted normalized decision matrix is illustrated in Table 13. In this table, the weights of each CSF, which were obtained from SWARA, are multiplied with the respective column values.

The summation of the weighted normalized decision matrix is presented in Table 14.

Ranking of alternatives are displayed in Table 15.

The result shows that among these nine companies, the companies that have the highest turnover and are the largest in size have the highest priority because first they have larger budgets to purchase state-of-the-art software and also routinely train their staff at renowned foreign companies, so their staff are up-to-date and can help their organizations to transfer their knowledge to their companies. In a larger company, tasks can be better divided and be more specific for each person than in smaller companies. Moreover, the highest priority company is the oldest one. It means that the oldest company has worked a long time in this field and has a good knowledge about these issues. This result shows that some characteristics have a strong effect on the opinion of experts. Some of the suppliers presented similar performance results. This reveals that the characteristics and the preferences that experts assign to each CSFs are closely related.

5.2. Correlation among CSFs

The Grey method [126] was used in this section for analyzing whether there is any correlation among these CSFs or not, because if correlations exist among the CSFs, this may cause a strong effect on the result.

First, consider that there are m alternatives with n criteria specified as $Y_i = (y_{i1}, y_{i2}, \ldots \vdots y_{ij}, \ldots, y_{in})$.

The degree of importance of alternative i is represented by Y_i based on criteria 1, …,n. Then Y_i must be transferred to$X_i = (x_{i1}, x_{i2}, \ldots \vdots x_{ij}, \ldots, x_{in})$ by normalization according to (37) – (39).

There may be three types of criteria:.

$$x_{ij} = \frac{y_{ij} - \min(y_{ij})}{\max(y_{ij}) - \min(y_{ij})} \text{the bigger is better} \tag{37}$$

$$x_{ij} = \frac{\max(y_{ij}) - y_{ij}}{\max(y_{ij}) - \min(y_{ij})} \text{the smaller is better} \tag{38}$$

$$x_{ij} = \frac{|y_{ij} - y^*|}{max\{\max(y_{ij}) - y^*, y^* - \min(y_{ij})\}} \text{when the value close to y* is better} \tag{39}$$

Based on the above equations, the first table is dimensionless (Eqs. (37)–(39)) and then further normalized based on Eqs. 40–43. The dimensionless matrix is denoted as N and each entry of the matrix leads to the Grey Relational Analysis (GRA) coefficients indicated by G_{ij}^*.

For benefit criteria, G_{ij}^* is calculated using (40) and (41).

$$G_{ij}^* = \left[\frac{\underline{G_{ij}}}{G_j^{max}}, \frac{\overline{G_{ij}}}{G_j^{max}} \right] \tag{40}$$

$$G_j^{max} = max\left\{\overline{G_{ij}}\right\} \tag{41}$$

For cost criteria, G_{ij}^* is calculated using (42) and (43).

$$G_{ij}^* = \left[\frac{G_j^{min}}{\overline{G_{ij}}}, \frac{G_j^{min}}{\underline{G_{ij}}}\right] \tag{42}$$

$$G_j^{min} = \min_{1 \le i \le m}\left\{\underline{G_{ij}}\right\} \tag{43}$$

The coefficient of GRA is then computed using (44) and (45):

$$\gamma\left(x_{oj}, x_{ij}\right) = \frac{\Delta min - r\Delta max}{\Delta_{ij} - r\Delta max} \tag{44}$$

$$\Delta_{ij} = x_{oj} - x_{ij} \tag{45}$$

Hence, Δmin and Δmax are the smallest and largest amount of Δ_{ij}. r is a distinguished coefficient [127]; Y. [128].

Based on the decision-making matrix (Table 11), the (dimensionless) preferences of DMs regarding each supplier (GRA) are shown based on the factors considered.

For a dimensionless version of the data from Table 11, Table 17 is calculated using Eq (37)–(39). Table 18 is then obtained by normalizing this data using Eqs. (40)–(43) (matrix N) (see Table 19).

In the last table, the results from the grey relational analysis are computed by Eqs. (44) and (45). When this correlation is less than 0.5, it means there are no strong correlations among these CSFs.

Δmin is the minimum value of each factor, Δmax is the maximum value of each factor, rΔmin and rΔmax are then obtained by multiplying these values with a coefficient of $r = 0.5$.

Many scientists believe that a coefficient of $r = 0.5$ is the best indicator for this measurement (T. C. [129,130].

The result indicates that there is no strong relationship among these CSFs because all CSF coefficients are less than 0.5.

5.3. Sensitivity analysis

In this section, the results of this paper are compared with those of other methods, which can be divided into two categories. Two older decision-making techniques based on a decision matrix such as TOPSIS and VIKOR and a newer technique such as WASPAS as explained in Sections 2.1.3, 2.1.4, and 2.1.5 are used with the sensitivity analysis indicating how similar the result from this paper is to other methods. The computation results are shown in Table 20.

After finding the order of alternatives, they are compared to each other based on the Spearman Coefficient for determining their similarity. This correlation coefficient indicates the similarity of two rankings. The coefficients are between −1 and 1 and values close to 1 show that two rankings are very similar. We have tested the hypothesis that there is a correlation between the result of ZCOPRAS and ZTOPSIS using the Spearman test. If the p-value of the comparison is less than 0.05, there is a significant relationship between each other. Otherwise, the hypothesis is rejected. SPSS version 22 was used for this calculation and the results are given in Table 21.

The result indicates that our method suggested is very similar to those of the ZWASPAS method as the resulting rankings are actually identical, but there is no evidence as to a similarly strong relationship between the results of ZCOPRAS and those of ZVIKOR and ZTOPSIS.

6. Conclusions

6.1. Managerial implications

The O&G industry is one of the most prominent industrial sectors in Iran. The revenue of this sector contributes significantly to the infrastructure of Iran such as in healthcare, education, and transport, hence selecting the best suppliers in this industry is crucial. In the past, all suppliers were governmental, but now private companies enter the market, which complicates the supplier selection process. In particular, a balance between public and private suppliers appears promising, but is hampered because public sectors tend to work with public companies. As pointed out above, the CSFs needed for supplier evaluation are customized in our study based on expert input. In the first step, 33 factors were extracted based on previous studies and interviews with experts. Afterwards, only 15 factors were accepted for evaluating suppliers based on the DM preferences. The reason for most of the factors being rejected is that the O&G industry in Iran has a specific situation, and hence factors used in other countries or industries cannot be used in the case considered. The SWARA method was then used for calculating weights required for COPRAS/ZCOPRAS for prioritizing suppliers. In response to RQ1, the prioritized CSFs resulting from the SWARA method indicate that among these CSFs, a positive image was the most important factor, meaning that when the supplier has a positive image in all aspects such as on-time delivery, quality, cost, discounts, and so on, customers want to close a contract with them. The least important factor was technology. A possible reason for this is that most of the suppliers have a suitable technology and can build or provide the equipment required. In response to RQ2, suppliers are ranked by the ZCOPRAS based on these CSFs. Z-numbers are used because the decision problem considered is vague and uncertain. The merit of this method compared with other methods is that it considers the reliability of data adequately. The ZCOPRAS method based on these CSFs and DM preferences ranks the suppliers. Due to the special situation, the paper cannot reveal the names of the suppliers because they did not accept mentioning their names as they believe that the information about these suppliers must be confidential. Among the 9 suppliers considered, Supplier 4 received the highest priority and Supplier 3 was the least important. Answering RQ1 and 2 also helped the DMs to answer RQ3. By finding suitable CSFs and customizing them for the O&G industry and a subsequent application of hybrid MCDA methods, suppliers were prioritized by these CSFs. DMs of this industry can ensure that both fixed and variable costs will be decreased and revenues can be increased, which allows the government to make a plan to increase the level of social economics such as healthcare, employment rate, or education.

The factors Positive image and Exchange of knowledge have a high priority in both the study by S.-I. Wu & Hung [131] and our study, however in this paper the New products factor was ranked as a high priority while receiving a low priority in the research by S.-I. Wu & Hung [131]. In the research by Kannan & Tan [132]; the priority of the New products and Exchange of knowledge factors were similar to our research, but our results are in conflict with those of Cheraghi, Dadashzadeh, & Subramanian [133] regarding factors of New products and Positive image. The results of Cheraghi et al. [133], for the Relation and Technology factors are similar to our results.

Table 17
Grey Relational Analysis (GRA) decision matrix.

	Positive image	New products	Exchange of knowledge	Commitment	Novelty	Quality	Cost	Reputation	Flexibility	R&D	Technical capability	Technical experts	Compatibility	Relation	Technology
A1	0.05	0.87	1.00	0.65	0.87	0.56	0.01	0.03	0.12	0.08	0.56	0.04	1.00	0.83	0.04
A2	0.77	0.87	1.00	0.36	0.04	0.05	0.87	0.38	0.01	0.08	0.18	0.04	0.36	0.03	0.77
A3	0.44	0.04	0.03	0.36	0.12	0.02	0.05	0.87	1.00	1.00	0.06	0.36	0.03	0.01	0.04
A4	1.00	1.00	0.68	0.83	0.38	0.06	0.12	0.01	0.05	0.05	0.56	0.04	0.83	0.65	0.14
A5	1.00	1.00	0.68	0.03	0.01	0.08	0.12	0.04	0.36	0.08	0.05	0.36	0.04	0.12	0.01
A6	0.77	0.87	0.03	0.36	0.04	0.18	0.01	0.05	0.36	0.05	1.00	0.83	1.00	0.05	0.04
A7	0.05	0.38	0.03	1.00	0.87	1.00	0.12	0.01	0.05	0.56	0.05	0.04	0.36	0.83	0.77
A8	0.05	0.68	0.87	0.03	0.01	0.18	1.00	0.87	0.36	0.05	1.00	1.00	0.12	0.01	0.06
A9	0.44	0.03	0.68	0.83	1.00	0.02	0.03	1.00	0.65	0.18	0.05	0.05	0.01	1.00	1.00
min	1.25	0.8	0.8	0.8	1.08	0.66	0.66	0.66	0.66	0.66	0.8	0.66	0.8	0.66	0.66
max	6.4	7.19	7.19	7.47	7.19	5.18	7.19	7.19	7.47	5.18	5.18	7.47	7.47	7.47	6.4
max-min	5.15	6.39	6.39	6.67	6.11	4.52	6.53	6.53	6.81	4.52	4.38	6.81	6.67	6.81	5.74
star	5.4	6.19	6.19	6.47	6.19	4.18	6.19	6.19	6.47	4.18	4.18	6.47	6.47	6.47	5.4

Table 18
Normalized matrix.

	Positive image	New products	Exchange of knowledge	Commitment	Novelty	Quality	Cost	Reputation	Flexibility	R&D	Technical capability	Technical experts	Compatibility	Relation	Technology
A1	0.046	0.872	1.000	0.646	0.872	0.562	0.013	0.032	0.119	0.081	0.562	0.039	1.000	0.835	0.037
A2	0.774	0.872	1.000	0.363	0.040	0.048	0.872	0.380	0.012	0.081	0.184	0.039	0.363	0.031	0.774
A3	0.435	0.040	0.032	0.363	0.124	0.019	0.055	0.872	1.000	1.000	0.060	0.363	0.031	0.012	0.037
A4	1.000	1.000	0.675	0.835	0.380	0.060	0.124	0.013	0.053	0.048	0.562	0.039	0.835	0.646	0.143
A5	1.000	1.000	0.675	0.031	0.013	0.081	0.124	0.040	0.363	0.081	0.048	0.363	0.039	0.119	0.015
A6	0.774	0.872	0.032	0.363	0.040	0.184	0.013	0.055	0.363	0.048	1.000	0.835	1.000	0.053	0.037
A7	0.046	0.380	0.032	1.000	0.872	1.000	0.124	0.013	0.053	0.562	0.048	0.039	0.363	0.835	0.774
A8	0.046	0.675	0.872	0.031	0.013	0.184	1.000	0.872	0.363	0.048	1.000	1.000	0.119	0.012	0.063
A9	0.435	0.032	0.675	0.835	1.000	0.019	0.032	1.000	0.646	0.184	0.048	0.053	0.012	1.000	1.000

Table 19
Grey coefficients.

	Positive image	New products	Exchange of knowledge	Commitment	Novelty	Quality	Cost	Reputation	Flexibility	R&D	Technical capability	Technical experts	Compatibility	Relation	Technology
A1	0.954	0.128	0.000	0.354	0.128	0.438	0.987	0.968	0.881	0.919	0.438	0.961	0.000	0.165	0.963
A2	0.226	0.128	0.000	0.637	0.960	0.952	0.128	0.620	0.988	0.919	0.816	0.961	0.637	0.969	0.226
A3	0.565	0.960	0.968	0.637	0.876	0.981	0.945	0.128	0.000	0.000	0.940	0.637	0.969	0.988	0.963
A4	0.000	0.000	0.325	0.165	0.620	0.940	0.876	0.987	0.947	0.952	0.438	0.961	0.165	0.354	0.857
A5	0.000	0.000	0.325	0.969	0.987	0.919	0.876	0.960	0.637	0.919	0.952	0.637	0.961	0.881	0.985
A6	0.226	0.128	0.968	0.637	0.960	0.816	0.987	0.945	0.637	0.952	0.000	0.165	0.000	0.947	0.963
A7	0.954	0.620	0.968	0.000	0.128	0.000	0.876	0.987	0.947	0.438	0.952	0.961	0.637	0.165	0.226
A8	0.954	0.325	0.128	0.969	0.987	0.816	0.000	0.128	0.637	0.952	0.000	0.000	0.881	0.988	0.937
A9	0.565	0.968	0.325	0.165	0.000	0.981	0.968	0.000	0.354	0.816	0.952	0.947	0.988	0.000	0.000
Δmin	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Δmax	0.954	0.968	0.968	0.969	0.987	0.981	0.987	0.987	0.988	0.952	0.952	0.961	0.988	0.988	0.985
rΔmin	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
rΔmax	0.477	0.484	0.484	0.485	0.494	0.490	0.494	0.494	0.494	0.476	0.476	0.481	0.494	0.494	0.493
Δmin + rΔmax	0.477	0.484	0.484	0.485	0.494	0.490	0.494	0.494	0.494	0.476	0.476	0.481	0.494	0.494	0.493

Table 20
Ranking alternatives by different methods.

ZCOPRAS	ZTOPSIS	ZVIKOR	ZWASPAS
Alt.4	Alt.4	Alt.4	Alt.4
Alt.1	Alt.2	Alt.2	Alt.1
Alt.2	Alt.5	Alt.5	Alt.2
Alt.9	Alt.1	Alt.6	Alt.9
Alt.5	Alt.6	Alt.9	Alt.5
Alt.6	Alt.9	Alt.1	Alt.6
Alt.7	Alt.7	Alt.3	Alt.7
Alt.8	Alt.8	Alt.7	Alt.8
Alt.3	Alt.3	Alt.8	Alt.3

Table 21
Spearman Coefficients of the MCDA methods considered.

ZCOPRAS	ZTOPSIS	ZVIKOR	ZWASPAS
Sig	0.47	0.7	0
Relationship	No	No	Yes

6.2. *Novel approach*

This research proposed a novel hybrid MCDA approach for handling the supplier selection problem in the Iranian O&G industry. By combining recent MCDA techniques, it was possible to treat the information reliability issues with respect to expert preferences in terms of well-known economic concepts such as utility functions for each selection criterion (CSF). Although weights have to be exogenously defined for the COPRAS method, partial utility functions could be derived based upon Likert scales collected from several experts. These weights were computed using the SWARA method where a relative efficiency criterion rank was established for each CSF. Another innovative aspect of this research is related to using Z-numbers to model information reliability, thus helping discriminate the SWARA crisp relative efficiency values (weights) applied to the COPRAS partial utility functions.

6.3. *Limitations and future research*

Limitations of this research are that of the geographical extent of experts, which was caused by time and cost aspects of data gathering, and that most of the experts who filled in the questionnaires did not have knowledge about MCDA methods, so some training was required in advance.

Future studies should compare how these economic concepts relate to other intrinsic characteristics of different MCDA methods such as positive and negative ideal solutions (TOPSIS), compromise solutions (VIKOR), cause-effect structures (DEMATEL), and dimensionless pairwise comparisons (AHP) by means of a robust analysis where results are compared and cross-checked against each other with the idea being to explore the economic counterparts of these intrinsic characteristics. Another research stream may be related to using alternative tools for handling information reliability such as neutrosophic sets and entropic weights so that the relative importance of the utility function for supplier selection and criteria of relative efficiency (CSFs) could be better apprehended in terms of expert preferences. As the experts involved did not have a good knowledge of MCDA methods, their preference elicitation had to be done with care and for this reason approaches based on fuzzy numbers were applied. In this kind of method, verbal information is used instead of exact numbers. For future studies, researchers can use other types of fuzzy methods such as hesitant fuzzy sets, picture fuzzy sets, and Pythagoras fuzzy sets. Afterwards the results should be compared with those of Z-numbers and further conclusions regarding data reliability will be needed.

Appendix I. References for CSFs

Factors	References
Customer loyalty	[131]
Customer value	[134]
Customer satisfaction	[68]
Positive image	[131]
Independence	[131]
New products	[131,132]
Exchange of knowledge	[131,132]
Commitment	[46]
Organizational size	[131]
Communication	[46]
Novelty	[46]
Quality	[46]
Cost	[84,131]
Economy	[46]
Political stability	[46]
Reputation	[46]
Flexibility	[46]
Culture	[46,135]
Project expectation	[136]
R&D	[136]
Technical capability	[136]
Technical experts	[137]
Willingness	[84,137]
Complementarity	[137]
Compatibility	[87,137]
Trust	[87]
Competency	[87]
Geographic location	[87]
Market	[84,87]
Finance	[77,87,136]
Relation	[77]
Strategy	[77]
Technology	[77]

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