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A fuzzy hierarchical analysis process for priority setting and resource allocation in carbon capture and storage technologies

Fahimeh Fattahipour [1*], Reza Azin [2]

1.Oil and Gas Research Centre, Persian Gulf University, Bushehr, Iran

2. Department of Petroleum Engineering, Faculty of Petroleum, Gas and Petrochemical Engineering, Persian Gulf University, Bushehr, Iran

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ABSTRACT

Implementing and developing carbon capture and storage (CCS) technologies can significantly impact the economic and environmental performance of oil and gas companies, creating at the same time various opportunities and threats for them. Given that resources—particularly financial, human, and technical—are indeed limited, it is essential for companies to evaluate the opportunities and threats associated with each CCS technology in order to allocate these resources effectively to research and development (R&D) projects. This research specifically focuses on the prioritisation and resource allocation, presenting a fuzzy multi-criteria group decision-making methodology that was successfully applied to assess the development opportunities for CCS technologies at Pars Special Economic Energy Zone (PSEEZ). In fact, the proposed methodology serves as a systematic and effective decision support tool, thereby enabling decision-makers to prioritise and select the most attractive technologies, where the attractiveness of each technology is defined by the associated opportunities and threats inherent in its acquisition and development.

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1. INTRODUCTION

Greenhouse gases (GHGs), mainly carbon dioxide (CO2), nitrous oxide (N2O), methane (CH4), and chlorofluorocarbons (CFCs), possess long atmospheric lifetimes and a high capacity to absorb infrared radiation, thereby causing global warming through the greenhouse effect, which has become a major worldwide environmental concern in recent decades. The combined warming impact of these gases is commonly expressed in terms of carbon dioxide equivalence (CO2e). For example, each molecule of CH4 and N2O contributes to global warming 27.0 and 273 times more than

* Corresponding Author Email: fahime.fattahipour@outlook.com

a molecule of CO_2, respectively, over a 100-year time horizon [1, 2].

Anthropogenic global warming is driven primarily by human activities, including energy consumption, fossil fuel combustion, industrial processes, electricity generation using fossil fuels, deforestation, land use, exploitation of fossil hydrocarbon resources, and emission of volatile organic hydrocarbons. According to [3], the energy sector is the largest contributor to GHG emissions, followed by agriculture, industrial processes, large-scale biomass burning, post-burn decay, peat decay, indirect N_2O emissions from non-agricultural emissions of oxides of nitrogen (NO_x) and ammonia (NH_3), waste, and solvent use. The contributions of CO_2, CH_4, and N_2O to GHG emissions worldwide are 90%, 9% and 1%, respectively. The growth in energy consumption is associated with the economic development, as the amount of energy supply has increased by 150% from 1971 to 2014, mainly provided by fossil fuels [4]. Accordingly, total energy-related CO_2 emissions increased by 0.8% in 2024, hitting an all-time high of 37.8 Gt. Consequently, atmospheric CO_2 concentrations reached a record 422.5 ppm in 2024, a level over 50% higher than in pre-industrial times [5].

Therefore, there is a significant challenge of GHG reductions versus economic growth facing countries with different levels of industrial development. Substantial CO_2 emissions worldwide must be mitigated to control global warming and limit the increase in global temperature. Key strategies include improving energy efficiency and productivity, replacing high-carbon fossil fuels (like coal) with lower-carbon ones (like natural gas), using renewable energy, enhancing natural carbon sinks in agriculture and forestry, developing carbon capture and utilisation (CCU) technologies, and deploying carbon capture and storage (CCS) technologies.

CO_2 has various applications, e.g., dry ice, supercritical extraction, neutralisation of wastewater, mineralisation of freshwater from desalination units, welding, and semiconductor cleaning. Additionally, it is used as a reactant in the production of urea, methanol, soda ash, polycarbonates, liquid fuels and chemicals like dimethyl ether (DME) through gas-to-liquid (GTL) processes, greenhouse culture, and algae culture. Alternatively, CO_2 can be injected into heavy and conventional oil reservoirs for enhanced oil recovery (EOR). The CCU and EOR approaches have inherent economic targets in addition to the environmental objectives.

Another option for carbon management through CCS is capturing the produced CO_2 and storing it in the deep underground formations, known as geological storage. In this approach, CO_2 may be stored in depleted oil and gas reservoirs as well as deep saline aquifers for extended periods. Once in contact with the saline aquifer, CO_2 diffuses and dissolves in brine and contributes to the geochemical reactions and converts into minerals that either precipitate or remain in solution. In this way, injected CO_2 is permanently removed from the atmosphere. A series of mechanisms, such as molecular diffusion, convection, thermodynamics, and geochemical reactions, are active in the geological storage of CO_2 into saline aquifers. A CCS project may involve capture, transport, storage, or a combination of two or three steps [6]. A detailed roadmap for CCS planning, implementation, and monitoring is discussed by Azin et al., [7].

As of early 2025, there were approximately 44 commercial-scale CCS facilities in operation worldwide, capturing over 50 million tonnes of CO_2 per year, seven of which were dedicated geological storage sites [8].

Compared to CCU, the geological storage of CO_2 does not provide direct economic benefits and is sometimes called “dedicated geological storage,” an approach mostly sponsored by governments rather than oil companies. On the other hand, according to global surveys, most CCS projects are EOR-targeted in the upstream oil and gas industry to be economically attractive while reducing GHGs. Furthermore, there are debates and doubts about the effectiveness of geological storage in mitigating global warming and climate change [9]. The key issues raised include the possibility of leakage and re-emission of CO_2 after injection, the costs of CCS (which affect the price of produced goods and services, e.g., electricity), and the technology's perceived low potential compared with the vast volume of CO_2 emissions.

However, this technique becomes attractive in cases where there are available facilities and depleted sinks neighbouring the CO_2 emission sources. For example, depleted geological oil and gas formations with sufficient closure, storage capacity, and a proven seal located near power plants are ideal options for the rapid transfer and storage of CO_2. Extensive data on these formations and the host area are provided by oil companies, covering different engineering aspects including depth, caprock integrity, tectonic setting, seismicity, fault strength, freshwater, and geothermal gradient. The information obtained during the exploration, appraisal, production, and monitoring of oil and gas reservoirs makes these prospects well-defined when considered for CCS. Moreover, the wells drilled for oil and gas production, along with the pipeline and compressor facilities constructed for hydrocarbon delivery from reservoirs to oil and gas plants, are often available in the area and can be used for CO_2 storage without the need for high capital expenditure (CAPEX).

On the other hand, the construction and development of CCU technologies often require significant investment and advanced technology, usually provided by licensors, making them difficult to access in developing countries. Decision-makers in oil and gas companies thus face the complex task of allocating resources in a manner that balances both organisational goals and environmental objectives. Ranking and prioritising carbon management scenarios can therefore provide a basis for making trade-offs and effectively distributing available resources among CCS projects.

The challenge of prioritising technologies and allocating resources in the energy sector is frequently addressed through multi-criteria decision-making (MCDM) frameworks. As reviewed by Kumar et al., [10], these methodologies are essential for navigating the complexities of sustainable energy development. The field is continuously evolving, and novel approaches such as the Spherical Fuzzy Analytic Hierarchy Process have been developed for specific renewable energy applications [11]. This body of research confirms the suitability of fuzzy AHP-based models for evaluating complex energy technologies. Building upon this established foundation, our study employs a fuzzy AHP framework to address the unique challenges of prioritising CCS technologies.

This study, focusing on the evaluation of technology attractiveness, provides a resource allocation methodology in which the attractiveness of a specific technology reflects the threats and opportunities associated with its acquisition or development. This methodology consists of a multi-criteria optimisation framework for resource allocation based on the technology attractiveness. In particular, the framework employs eight key criteria: (1) Contribution to carbon emission reduction; (2) Applicability to carbon-emitting sources; (3) Potential for cross-industry application; (4) Interdependency with other CCS technologies; (5) Overall environmental performance; (6) Implementation timeline; (7) Economic performance; and (8) Potential for successful localisation.

Two primary questions are addressed in this study. First, based on the different decision-making criteria for the prioritisation of technologies (which are not necessarily compatible), how can we properly extract the relative importance assigned by each member of the decision-making group to each technology in criteria? Second, how can we merge the individual judgements into a single group decision? To address these questions, a decision support framework is developed. The proposed methodology, as a systematic and effective decision support tool, enables decision-makers to select and prioritise the most attractive technologies. We have successfully applied this methodology to evaluate the opportunities for the development of CCS technologies in Pars Special Economic Energy Zone (PSEEZ).

The remainder of this paper is organised as follows. Sections 2 and 3 provide a brief overview of the mathematical foundations of the methodology, focusing on fuzzy theory and hierarchical analysis, respectively. Section 4 details the fuzzy multi-criteria algorithm employed to determine the optimal resource allocation policy. Section 5 presents a case study to illustrate the validity of the proposed algorithm. Finally, Section 6 concludes the paper and outlines directions for future research.

2. Fuzzy Theory

When decision-makers' evaluations are not crisp in the assessment process, fuzzy theory can be utilised to adequately capture uncertainties and represent vague concepts expressed in natural language within a mathematical framework. Fuzzy theory, first introduced by Zadeh in 1965, provides a powerful mathematical tool for handling the uncertainty inherent in subjective assessment processes [12]. In other words, this theory is useful for dealing with human-centred systems in which decision-makers express their evaluations as linguistic variables, since crisp data are inappropriate for modelling such situations. A linguistic variable is a variable whose values are not crisp numbers, but rather words or sentences in a natural or artificial language representing imprecise concepts [13].

Linguistic variables play a fundamental role in complex decision problems and can be converted into fuzzy numbers using fuzzy theory. Column 1 of Table 1 lists the linguistic variables utilised in the proposed methodology.

In one of the earliest studies on decision-making in a fuzzy environment, van Laarhoven and Pedrycz [14] define a triangular fuzzy number (TFN) as a special case of a fuzzy number ã on R (=(-∞,+∞)) if its membership function $\mu_{\tilde{a}}: R \rightarrow [0,1]$ that specifies the degree to which any element x in R belongs to the fuzzy set ã, is equal to:

$$\mu_{\tilde{a}}(x) = \begin{cases} \dfrac{x - a^{(L)}}{a^{(M)} - a^{(L)}}, & x \in (a^{(L)}, a^{(M)}] \\ \dfrac{x - a^{(U)}}{a^{(M)} - a^{(U)}}, & x \in (a^{(M)}, a^{(U)}) \\ 0, & otherwise \end{cases} \quad (1)$$

where the lower number $a^{(L)}$ is the smallest possible value, the middle number $a^{(M)}$ is the most likely value, and the upper number $a^{(U)}$ is the greatest possible value for the uncertain quantity ã. The triangular fuzzy number ã , given by Equations (1), can be equivalently denoted by a triple of real numbers in the following equivalent forms:

$$\tilde{a} = \left(a^{(L)}, a^{(M)}, a^{(U)}\right) \equiv \begin{pmatrix} a^{(L)} \\ a^{(M)} \\ a^{(U)} \end{pmatrix}^T, \quad a^{(L)} \le a^{(M)} \le a^{(U)}. \quad (2)$$

Definition 2.1. Based on the results of van Laarhoven and Pedrycz [14], the operations of addition, multiplication, inverse, and logarithm are computed as follows, respectively:

$$\tilde{a} \oplus \tilde{b} = \left(a^{(L)} + b^{(L)}, a^{(M)} + b^{(M)}, a^{(U)} + b^{(U)}\right) \quad (3)$$

$$\tilde{a} \otimes \tilde{b} \approx \left(a^{(L)}.b^{(L)}, a^{(M)}.b^{(M)}, a^{(U)}.b^{(U)}\right) \quad (4)$$

$$\tilde{a}^{-1} \approx \left(\frac{1}{a^{(U)}}, \frac{1}{a^{(M)}}, \frac{1}{a^{(L)}}\right) \quad (5)$$

$$ln\tilde{a} \approx \left(ln\, a^{(L)}, ln\, a^{(M)}, ln\, a^{(U)}\right) \quad (6)$$

Definition 2.2. The distance between ã and b̃ is calculated by the vertex method, [15]:

$$d\left(\tilde{a}, \tilde{b}\right) = \sqrt{\frac{1}{3}\left((a^{(L)} - b^{(L)})^2 + (a^{(M)} - b^{(M)})^2 + (a^{(U)} - b^{(U)})^2\right)} \quad (7)$$

Table 1. Linguistic variables and corresponding TFNs

Linguistic variable	Triangular fuzzy number
Very High (VH)	(0.7,0.9,1.0)
High (H)	(0.5,0.7,0.9)
Medium (M)	(0.3,0.5,0.7)
Low (L)	(0.1,0.3,0.5)
Very Low (VL)	(0.0,0.1,0.3)

Definition 2.3. A triangular fuzzy number

$$\tilde{a} = \left(a^{(L)}, a^{(M)}, a^{(U)}\right)$$

is positive if $a^{(L)} \geq 0$, [16].

3. Hierarchical analysis

Multi-criteria decision making (MCDM) is a field of operational research that involves analysing decision alternatives in complex scenarios characterised by multiple, often conflicting, objectives and criteria [10]. MCDM methods can determine a ranking of alternatives even when the decision criteria are measured on differing scales [17]. The analytic hierarchy process (AHP) is an MCDM approach for assessing and prioritising decision alternatives based on the judgements of decision-makers [11]. In this approach, first developed by Saaty [18], the elements of a decision-making problem are structured hierarchically to derive priorities via pairwise comparisons. Pairwise comparisons are used to systematically weigh the criteria according to the decision-maker's preferences and subsequently to evaluate the different decision alternatives against these criteria. This process results in selecting the best decision alternative or an optimal mix thereof.

In Saaty's traditional Analytic Hierarchy Process, pairwise comparisons of the elements are performed using a 9-point scale. This scale, presented in Table 2, consists of linguistic variables ranging from "Equal" to "Absolute" [18]. Assuming that p_{ij} represents the preference degree of the i th element to the j th element and satisfies $p_{ji}=1/p_{ij}$,$i,j \in \{1,2,\ldots,d\}$, the hierarchical analysis arranges the pairwise comparisons into an d×d positive reciprocal matrix $P=[p_{ij}]$, where d indicates the number of elements being compared.

If $P=[p_{ij}]$ be a positive reciprocal matrix, then P is consistent if and only if the following condition is satisfied [18], for each

$$1 \leq i, j, k \leq d:$$

$$p_{ij} \times p_{jk} = p_{ik}. \quad (8)$$

However, in real situations, because of the random process of pairwise comparisons, we cannot expect the matrix P to be consistent even if the comparisons are done very carefully. Therefore, a consistency test shall be carried out to ensure the validity and conformity of the comparisons. The hierarchical analysis adopts the following value as the consistency index (CI) to measure the deviation from entire consistency within the pairwise comparisons [19]:

$$CI(d) = (\lambda_{max} - d)/(d-1)\,, \quad (9)$$

where λ_{max} indicates the maximum eigenvalue of the matrix P.

Considering the consistency index is dependent on the dimension of the matrix, d, Saaty & Vargas [20] propose the consistency ratio (CR), which is defined as the ratio of the CI(d) to the random index (RI(d)) to provide an independent measure of inconsistency:

$$CR(d) = CI(d)/RI(d)\,, \quad (10)$$

where RI(d) represents the average consistency index over a sample of size 500 of random entries of the same dimension positive reciprocal matrices, which are constructed using the 9-point scale (see Table 3).

Table 2. The Saaty scale and its description

Intensity of importance	Definition
1	Equal importance
3	Weak importance of one over another
5	Essential or strong importance
7	Demonstrated importance
9	Absolute importance
2, 4, 6, 8	Intermediate values between the two adjacent judgements

Table 3. The average random consistency index

Dimension of Matrix	1	2	3	4	5	6	7	8	9	10
Random Consistency Index	.00	.00	.58	.90	1.12	1.24	1.32	1.41	1.45	1.49

For each d×d pairwise comparison matrix, CR(d)=0 is a necessary and sufficient condition for consistency [18], and otherwise, for inconsistent matrices, the value of CR should be less than or equal to 10 percent to make inconsistency acceptable [19].

4. Set up the evaluation methodology

Based on the Fuzzy Analytic Hierarchy Process (FAHP), the proposed methodology provides a rational framework for technology attractiveness assessment, prioritisation, and resource allocation in fuzzy environments. The methodology comprises a 13-step process, outlined below, designed to elicit group judgements on the relative importance of the criteria and the performance of the alternatives:

Step 1. Identify the decision alternatives from a set of potential solutions.

Step 2. Select an expert group comprising researchers and policymakers.

Step 3. Determine each expert's decision weight.

This weight is assigned by the project manager based on the expert's depth of knowledge regarding the alternatives. An expert's decision weight indicates their relative importance within the group and is expressed using the linguistic variables. Following normalisation, the normalised decision weights calculated are:

$$\tilde{\lambda}_i(k) := \left(\sum_{k=1}^{m} \gamma_i^{(M)}(k)\right)^{-1} \tilde{\gamma}_i(k), i \in \{1,2,\dots,l\}. \quad (11)$$

In this context, $\tilde{\gamma}_i$ (k) is the decision weight of the k th expert in evaluating the i th alternative.

Step 4. Identify the decision criteria for evaluating the alternatives.

Step 5. Collect the experts' judgements in the form of linguistic variables.

Each member of the expert group independently performs pairwise comparisons for two purposes: to judge the relative importance of the evaluation criteria, and to assess the alternatives against each criterion. These judgements are expressed using the linguistic variables presented in Column 2 of Table 4.

Step 6. Convert the linguistic variables into triangular fuzzy numbers.

To mathematically process the subjective judgements, all linguistic variables are converted into triangular fuzzy numbers (TFNs). The variables for the experts' decision weights are converted according to Table 1, while the variables from the individual pairwise comparisons are converted according to Table 4.

Step 7. Construct the individual fuzzy pairwise comparison matrices.

For each member of the expert group, an indi

Table 4. The FUZZY scale of relative importance intensity and its description

Intensity of importance	Linguistic variables
$\tilde{1} = (1,1,1)$	Equal importance
$\tilde{2} = (1,2,3)$	Intermediate values between equal importance and weak importance
$\tilde{3} = (2,3,4)$	Weak importance of one over another
$\tilde{4} = (3,4,5)$	Intermediate values between weak importance and strong importance
$\tilde{5} = (4,5,6)$	Essential or strong importance
$\tilde{6} = (5,6,7)$	Intermediate values between strong importance and demonstrated importance
$\tilde{7} = (6,7,8)$	Demonstrated importance
$\tilde{8} = (7,8,9)$	Intermediate values between demonstrated importance and absolute importance
$\tilde{9} = (8,9,9)$	Absolute importance

vidual fuzzy pairwise comparison d×d matrix, $P=[\tilde{p}_{ij}]$, is constructed. In this matrix, the element $\tilde{p}_{ij}$ represents the judgement of the relevant expert on the preference of the i th element over the j th element with respect to a specific criterion, and satisfies $\tilde{p}_{ij}\geq 0$, $\tilde{p}_{ji}=\tilde{p}_{ij}^{(-1)}$, $i,j\in\{1,\ldots,d\}$. The consistency of each matrix is then checked; a Consistency Ratio (CR) of less than 0.10 is required to ensure the validity of the judgements.

Step 8. Estimate the relative importance assigned by each expert to each alternative with respect to each criterion.

Suppose, $\tilde{a}(ir,j,k)$ denotes the judgement of the k th expert on the preference of the i th alternative over the r th alternative with respect to the j th criterion and satisfies $\tilde{a}(ir,j,k)\geq 0$, $\tilde{a}(ri,j,k)=\tilde{a}^{(-1)}(ir,j,k)$, $i,r\in\{1,\ldots,l\}$, $j\in\{1,\ldots,n\}$, and $k\in\{1,\ldots,m\}$. With this assumption, each l×l pairwise comparison matrix of alternatives is represented in the form of $[\tilde{a}(ir,j,k)]$, where l indicates the number of alternatives being compared.

Let $\tilde{a}_{ij}(k)$, $i\in\{1,2,\ldots,l\}$, denotes the assigned relative importance by the k th expert to the i th alternative with respect to the j th criterion. This value is then estimated using the pairwise comparisons collected from the corresponding expert. Clearly, without loss of generality, we can assume

$$\sum_{i=1}^{l} a_{ij}^{(M)}(k)=1. \quad (12)$$

that

According to definitions of $\tilde{a}(ir,j,k)$, $\tilde{a}_{ij}(k)$ and $\tilde{a}_{rj}(k)$ for certain values of $j\in\{1,\ldots,n\}$, and $k\in\{1,\ldots,m\}$, each pairwise comparison $\tilde{a}(ir,j,k)$, $i,r\in\{1,\ldots,l\}$,can approximate the ratio between two

$$\tilde{a}(ir,j,k)\approx \tilde{a}_{ij}(k)\oslash \tilde{a}_{rj}(k), \forall i,r\in\{1,\ldots,l\}. \quad (13)$$

fuzzy weights $\tilde{a}_{ij}(k)$ and $\tilde{a}_{rj}(k)$; i.e.

Nevertheless, it is obvious that if the equation $\tilde{a}(ir,j,k)=\tilde{a}_{ij}(k)\oslash\tilde{a}_{rj}(k)$,holds for all $i,r\in\{1,\ldots,l\}$, then the l×l pairwise comparison matrix $[\tilde{a}(ir,j,k)]$ must be consistent. As a result, considering the probability of inconsistency of matrix $[\tilde{a}(ir,j,k)]$ in most real situations, the following inequality may be true for some $i,r\in\{1,\ldots,l\}$,

$$\tilde{a}(ir,j,k)\neq \tilde{a}_{ij}(k)\oslash \tilde{a}_{rj}(k), \quad (14)$$

Mathematically, we can combine and rewrite the relations (13) and (14) to the general form

$$\tilde{a}(ir,j,k)=\tilde{\varepsilon}(ir,j,k)\otimes \tilde{a}_{ij}(k)\oslash \tilde{a}_{rj}(k), \text{or}$$
$$\tilde{a}(ir,j,k)\otimes \tilde{a}_{rj}(k)\oslash \tilde{a}_{ij}(k)=\tilde{\varepsilon}(ir,j,k), \forall i,r\in\{1,\ldots,l\}, \quad (15)$$

where $\tilde{\varepsilon}(ir,j,k)$ as a perturbation factor dependent on the errors of judgement, is a positive triangular fuzzy number.

From Equations (13) and (15), it is simply concluded that the value of $\tilde{\varepsilon}(ir,j,k)$, $\forall i,r\in\{1,\ldots,l\}$, in general, should be close to $\tilde{1}$. Accordingly, for certain values of $j\in\{1,\ldots,n\}$,and $k\in\{1,\ldots,m\}$, we must find the fuzzy weights such that the value of

$$\prod_{i=1}^{l}\prod_{r=1}^{l}\tilde{\varepsilon}(ir,j,k),$$

be as close to $\tilde{1}$ as possible. The following optimisation model formulates this problem:

$$\begin{aligned}&\text{minimise } d\left(\ln\left(\prod_{i=1}^{l}\prod_{r=1}^{l}\tilde{\varepsilon}(ir,j,k)\right),\tilde{0}\right)\\ &\text{subject to} \sum_{i=1}^{l} a_{ij}^{(M)}(k)=1, \text{and } a_{ij}^{(L)}(k)\geq 0, \forall i\in\{1,\ldots,l\}.\end{aligned} \quad (16)$$

The optimal solution $(\tilde{a}_{1j}(k),\tilde{a}_{2j}(k),\ldots,\tilde{a}_{lj}(k))$, $j\in\{1,2,\ldots,n\}$, $k\in\{1,2,\ldots,m\}$, of the above problem is given as follows [16]:

$$a_{pj}^{(L)}(k)=\min_{i=1,\ldots,l}\left\{\frac{\left(\prod_{r=1}^{l}a^{(M)}(ir,j,k)\right)^{\frac{1}{l}}}{\left(\prod_{r=1}^{l}a^{(L)}(ir,j,k)\right)^{\frac{1}{l}}}\right\}\times\frac{\left(\prod_{r=1}^{l}a^{(L)}(pr,j,k)\right)^{\frac{1}{l}}}{\sum_{i=1}^{l}\left(\prod_{r=1}^{l}a^{(M)}(ir,j,k)\right)^{\frac{1}{l}}}, \forall p\in\{1,\ldots,l\} \quad (17)$$

$$a_{pj}^{(M)}(k)=\frac{\left(\prod_{r=1}^{l}a^{(M)}(pr,j,k)\right)^{\frac{1}{l}}}{\sum_{i=1}^{l}\left(\prod_{r=1}^{l}a^{(M)}(ir,j,k)\right)^{\frac{1}{l}}}, \forall p\in\{1,\ldots,l\} \quad (18)$$

$$a_{pj}^{(U)}(k)=\max_{i=1,\ldots,l}\left\{\frac{\left(\prod_{r=1}^{l}a^{(M)}(ir,j,k)\right)^{\frac{1}{l}}}{\left(\prod_{r=1}^{l}a^{(U)}(ir,j,k)\right)^{\frac{1}{l}}}\right\}\times\frac{\left(\prod_{r=1}^{l}a^{(U)}(pr,j,k)\right)^{\frac{1}{l}}}{\sum_{i=1}^{l}\left(\prod_{r=1}^{l}a^{(M)}(ir,j,k)\right)^{\frac{1}{l}}}, \forall p\in\{1,\ldots,l\}. \quad (19)$$

Step 9. Estimate the assigned relative importance by each expert to each criterion.

For a certain value of k∈{1,…,m}, let [c̃(ir,k)] be an n×n pairwise comparison matrix of criteria. Among which c̃(ir,k) represents the judgement of the k th expert on the intensity of importance of the i th criterion over the r th criterion, ∀i, r∈{1,…,n}. According to matrix [c̃(ir,k)], with the same argument as in the previous step, we derive the fuzzy weight assigned by the k th expert to the i th criterion, denoted as

$$\tilde{c}_i(k) = \left(c_i^{(L)}(k), c_i^{(M)}(k), c_i^{(U)}(k)\right),$$

for all i∈{1,2,…,n}.

Step 10. Calculate the fuzzy weight assigned by each expert to each alternative based on all criteria.

For a certain value of k∈ {1,…,m},by considering that ($\tilde{c}_1$ (k),$\tilde{c}_2$ (k),…,$\tilde{c}_n$(k))and,($\tilde{a}_{1j}$ (k),$\tilde{a}_{2j}$ (k),…,$\tilde{a}_{lj}$ (k)), j∈{1,2,…,n}, are the vectors of fuzzy weights, the following equation holds:

$$\sum_{i=1}^{l}\sum_{j=1}^{n} c_j^{(M)}(k) \times a_{ij}^{(M)}(k) = 1, \quad (20)$$

and therefore, we propose the following fuzzy average as a formula for calculating the individual judgements regarding the weight of each alternative in criteria:

$$\tilde{a}_i(k) = \sum_{j=1}^{n} \tilde{c}_j(k) \otimes \tilde{a}_{ij}(k) \quad (21)$$

where $\tilde{a}_i$ (k), i∈{1,…,l}, is an estimate of the assigned importance value to the i th alternative with respect to all criteria together by the k th expert.

Step 11. Defuzzify each expert's decision weight and judgements.

Defuzzification is the process of converting a fuzzy quantity into a precise, or crisp, value [21]. While several methods exist in the literature, this study employs the centre of gravity (COG) method due to its high accuracy. The COG method is defined by the following algebraic expression [22]:

$$e(\tilde{a}) = \int x\mu_{\tilde{a}}(x)dx \Big/ \int \mu_{\tilde{a}}(x)dx\,. \quad (22)$$

For all k∈{1,2,…,m} and i∈{1,2,…,l}, this equation is used to defuzzify the expert's decision weight and judgements as e($\tilde{\lambda}_i$ (k)) and e($\tilde{a}_i$ (k)), respectively. Here, $\tilde{\lambda}_i$ (k) represents the decision weight of the k th expert in evaluating the i th alternative, while $\tilde{a}_i$ (k) is the assigned fuzzy weight given by the k th expert to the i th alternative.

Step 12. Combine individual judgements into a single group decision.

The geometric mean is employed to aggregate the individual judgements from all experts, yielding a single, representative group decision for each alternative. The geometric mean of the defuzzified individual judgements is calculated using the following expression:

$$a_i = \prod_{k=1}^{m} e\left(\tilde{a}_i(k)\right)^{e\left(\tilde{\lambda}_i(k)\right)/\sum_{k=1}^{m} e\left(\tilde{\lambda}_i(k)\right)}$$

$$, i \in \{1,2,\dots,l\} \quad (23)$$

where a_i is the assigned importance value to the i th alternative with respect to all criteria together by the expert group.

Step 13. Normalise the aggregated group weights.

Finally, the aggregated group weights are normalised to ensure they sum to one, creating a final priority vector. The normalised weight of the i th alternative, w_i ,is calculated as follows:

$$w_i = \frac{a_i}{\sum_{i=1}^{l} a_i}, i \in \{1,2,\dots,l\}. \quad (24)$$

5. Case study: Pars Special Economic Energy Zone

A comprehensive review of the literature, combined with interviews and expert consultations, facilitated the identification of key CCS technologies in Iran, as presented in Table 5. Furthermore, an analysis of the attributes influencing the attractiveness of these technologies established several decision-making criteria, which are summarised in Table 6.

Table 5. The key CCS technologies description

Technology	Description
Solvent Absorption	CO2 Capture Technologies
Sorbents	
Membrane Absorption	
Compression	CO2 Compression Technologies
Pipelines	CO2 Transport Technologies
Railway and Road Trucks	
Enhanced Oil Recovery (EOR)	CO2 Geological Storage Technologies
Enhanced Gas Recovery (EGR)	

Table 6. Criteria for CCS technologies attractiveness assessment

Criterion	Description
c_1	The contribution of technology in reducing carbon emission
c_2	Applicability of technology in the field of carbon emission
c_3	Applicability of technology in industries beyond carbon emission
c_4	Number of dependent CCS technologies
c_5	Environmental performance of the technology
c_6	Required time for technology implementation
c_7	Economic performance of technology
c_8	Likelihood of success in technology localisation

By considering the identified key CCS technologies and the aforementioned decision criteria, we set up the appropriate questionnaires and asked the relevant experts to fill them out, among which the questionnaire is a systematic way of gathering and organising the opinions of several experts. In line with Step 2 of the proposed methodology (detailed in Section 4), the expert panel consisted of 61 individuals purposefully selected from Iran's oil and gas industry, government, and associated research institutes. The panel included 5 senior executives and policymakers, 16 mid-level managers, 23 specialists (from both industry and academia), and 17 senior engineers working in refineries and petrochemical plants.

The designed questionnaire consisted of two main categories of questions. The first category was concerned with the pairwise comparison of the criteria's relative importance, while the second was for determining the relative importance of the CCS technologies with respect to each criterion. Through these questionnaires, expert group members independently expressed their judgements on the alternatives and criteria, using the linguistic variables presented in Column 2 of Table 4.

Subsequently, Steps 6 to 12 were implemented to derive a single group judgement for each CCS technology, with the results detailed in Row 2 of Table 7. While these findings were sufficient for prioritising the key CCS technologies, the group judgements were then normalised using Equation

Table 7. Group decisions regarding the importance of CCS technologies

	solvent	*sorbent*	*membrane*	*compression*	*pipeline*	*truck*	*EOR*	*EGR*
Group judgements	0.141	0.141	0.096	0.135	0.104	0.046	0.147	0.135
Weights	0.149	0.149	0.101	0.143	0.110	0.049	0.155	0.143
Share from resources (%)	14.911	14.939	10.128	14.274	11.000	4.909	15.523	14.316
Rank	3	2	7	5	6	8	1	4

(24) to facilitate resource allocation, yielding the final weights for each technology (Table 7, Row 3). From these weights, the percentage share of available resources for each CCS technology was determined (Table 7, Row 4). Finally, the technologies were ranked by comparing their final weights (Table 7, Row 5).

6. Conclusions and future work

This paper addressed the priority setting and resource allocation for key CCS technologies. The study developed a fuzzy multi-criteria group decision-making methodology to help stakeholders prioritise and select the most attractive technologies. The proposed methodology handles potentially incompatible decision-making criteria by first extracting the relative importance assigned by each member of the decision-making group. Subsequently, it merges these individual judgements into a single group decision. This methodology was successfully applied to evaluate the opportunities for the development of CCS technologies in the Pars Special Economic Energy Zone (PSEEZ).

Although CCS technologies are recognised as a vital solution for addressing climate change, their development in Iran has been slow. This can be attributed to several barriers, including low public acceptance, financial instability, and the lack of a long-term strategic vision for CCS. Furthermore, Iran lacks a clear and reliable legal framework for implementing and monitoring these technologies. Therefore, advancing the development of CCS technologies first requires identifying key implementation barriers and formulating strategies to overcome them. The following are some recommendations for the effective implementation of CCS.

- Develop a long-term vision for CCS and identify the actions required to achieve it.
- Establish a clear policy for CO2 reduction, including a detailed CCS roadmap, to define the technology's expected role.
- Create an adequate legal framework with clear and stable regulatory, organisational, and financing structures.
- Identify CO2 sources suitable for CCS.
- Estimate the costs associated with the large-scale implementation of CCS.
- Establish a mechanism for penalising CO2-emitting sources.

Although the recommendations provided can help overcome key barriers to the commercial deployment of CCS, sustained and comprehensive R&D remains essential. These research activities are vital for both the effective implementation of carbon mitigation technologies and for ensuring their economic viability. Furthermore, close coordination between policymakers, industry, and the scientific community is necessary to define clear strategies for attracting investment and facilitating the large-scale deployment of CCS systems.

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مقاله تحقیقاتی

اولویت‌بندی و تخصیص منابع برای فن‌آوری‌های جذب و ذخیره‌سازی کربن با استفاده از فرآیند تحلیل سلسله مراتبی فازی

فهیمه فتاحی‌پور [۱*]، رضا آذین [۲]

۱.مرکز پژوهشی نفت و گاز، دانشگاه خلیج فارس، بوشهر، ایران

۲.گروه مهندسی نفت، دانشکده مهندسی نفت، گاز و پتروشیمی، دانشگاه خلیج فارس، بوشهر، ایران

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نظریه فازی؛

تصمیم‌گیری گروهی

چندمعیاره.

*عهده‌دار مکاتبات؛

رایانامه:

fahime.fattahipour@outlook.com

تلفن:

چکیده

پیاده‌سازی و توسعه فن‌آوری‌های جذب و ذخیره‌سازی کربن (CCS) می‌تواند بر عملکرد اقتصادی و زیست‌محیطی شرکت‌های نفت و گاز تأثیر بگذارد و فرصت‌ها و تهدیدهای مختلفی را برای این شرکت‌ها ایجاد کند. با توجه به این واقعیت و هم‌چنین با توجه به محدودیت منابع به ویژه در حوزه‌های مالی، انسانی و فنی، به منظور توزیع مناسب منابع موجود در پروژه‌های تحقیق و توسعه (R&D) در حوزه نفت و گاز، ارزیابی فرصت‌ها و تهدیدهای مرتبط با هر فن‌آوری CCS برای شرکت‌ها ضروری است. این پژوهش با تمرکز بر اولویت‌بندی و تخصیص منابع، یک روش تصمیم‌گیری گروهی چندمعیاره فازی ارائه می‌دهد. روش پیشنهادی، برای ارزیابی فرصت‌های توسعه فن‌آوری‌های CCS در سازمان منطقه ویژه اقتصادی انرژی پارس، با موفقیت اجرا شده است. این روش به عنوان یک ابزار پشتیبانی تصمیم‌گیری سیستمی و مؤثر، تصمیم‌گیرندگان را قادر می‌سازد تا فناوری‌ها را بر اساس جذابیتشان، که منعکس‌کننده فرصت‌ها و تهدیدهایی است که با کسب و توسعه آن‌ها به وجود می‌آیند، اولویت‌بندی و انتخاب کنند.

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