Decision Making: Applications in Management and Engineering

Journal homepage: www.dmame-journal.org
ISSN: 2560-6018, eISSN: 2620-0104

A Fuzzy AHP–MARCOS Integrated Model for Cost Control Strategy Selection in Upstream Oil Operations

Ming Zhu[1*], Ming Kuang[1], Meng Zhao[2], Xiang Wang[1]

[1] PetroChina Research Institute of Petroleum Exploration & Development, Beijing 100083, China
[2] KunLun Digital Technology Co., Ltd, Beijing 102206, China

ARTICLE INFO

Article history:
Received 19 February 2024
Received in revised form 10 May 2024
Accepted 12 May 2024
Available online 30 June 2024

Keywords:
Cost control, strategy, oil, FAHP, MARCOS, decision support, upstream oil operations

ABSTRACT

International oil companies (IOCs) are under growing pressure to control costs amid increasing operational complexity and market volatility. This paper presents a structured model to help identify the most effective cost control strategies for the upstream segment. This approach integrates the Fuzzy Analytic Hierarchy Process (FAHP) and the Measurement of Alternatives and Ranking according to the Compromise Solution (MARCOS) to evaluate the relative importance of various criteria and prioritize alternatives based on these weighted factors, respectively. This integrated approach ensures a balanced consideration of expert insights and quantitative assessment under uncertain conditions. The results demonstrated that alternative A7 (Optimization of Supply Chain and Procurement) was the best-ranked alternative in the final ranking, while A5 (Integrated Planning of Drilling and Production Activities) ranks lowest. On the other hand, criterion C1 exerted the largest influence with the highest weight, followed by C2, C4, and C3, with C5 receiving the least significance. The results have shown that the developed model is highly applicable and can be extended to similar decision-making problems.

1. Introduction

The upstream oil industry is a critical sector within the global energy market, responsible for exploring, extracting, and initially processing crude oil and natural gas [1-3]. Oil companies operate in increasingly complex environments, which are characterized by fluctuating prices, risks, regulatory pressures, and growing environmental concerns. Therefore, efficient cost management has become essential for maintaining competitiveness and ensuring long-term profitability [4]. The selection of an optimal cost control strategy is pivotal in enhancing operational efficiency, minimizing waste, and aligning cost management with corporate goals [5-8]. This paper explores the development of an optimal model for selecting cost control strategies within the upstream business of IOCs, considering various criteria (potential for cost reduction, risk reduction, ease of implementation, required investment, and time to realize benefits). By integrating decision-making tools and quantitative approaches, the proposed model aims to guide oil companies in selecting the most effective

* *Corresponding author.*
E-mail address: mingzhu@petrochina.com.cn
https://doi.org/10.31181/dmame7120241432

strategies to mitigate operational costs, improve resource allocation, and maintain a competitive edge in a volatile market. The model relies on the application of FAHP and MARCOS for criteria weight calculation and ranking, respectively [9-11].

FAHP integrates both qualitative and quantitative approaches. Unlike the traditional Analytic Hierarchy Process (AHP), FAHP allows the classification of evaluation factors into three levels: target (to choose the best solution), criterion (relevant for the evaluation of the solution), and factor levels (alternatives, i.e., solutions for achieving the objective). In contrast, unlike the traditional AHP, which restricts classification to just target and factor levels, FAHP addresses the limitations effectively, such as its subjectivity, as well as the one-sidedness of Fuzzy Comprehensive Evaluation (FCE) [12]. On the other hand, MARCOS evaluates each alternative by comparing it against both the optimal (ideal) and the least desirable (anti-ideal) reference scenarios. It determines each option's utility based on its closeness to these two benchmarks. The next step involves alternative ranking based on their utility values. This method emphasizes the selection of the most beneficial alternative by simultaneously accounting for its closeness to the optimal solution and its remoteness from the least preferred option. A fundamental feature of the MARCOS technique lies in the early incorporation of both ideal and anti-ideal alternatives into the decision-making matrix. This early inclusion improves the precision of utility calculations and supports an even-handed comparison across all options. Additionally, the MARCOS method offers a novel methodology for defining utility functions and aggregating evaluations, thereby effectively addressing complex decision-making scenarios with numerous alternatives and criteria, while maintaining result stability [13].

The study is structured below. Section 2 presents a comprehensive literature review, followed by a detailed problem description in Section 3. The proposed methodology, including the implementation steps, is outlined in Section 4. A quantitative case study is provided in Section 5, along with the results. Finally, Section 6 offers conclusions and recommends directions for future research.

2. Literature Review

Akenbor and Agwor [14] conducted an investigation into how standard costing influences cost management practices within Nigeria's oil and gas sector, using both primary and secondary data from questionnaires and stock exchange reports, respectively. The findings indicated that greater use of standard costing improves the management efficiency of material, labor, and overhead costs, highlighting its importance in accounting practices. Similarly, Akpe et al. [15] examined the formulation and implementation of cost management strategies within the context of engineering projects in the oil and gas industry, emphasizing their critical role in ensuring project viability amid volatile market conditions. It highlights methodologies such as project cost estimation, real-time cost tracking, risk management, and advanced technologies, while also discussing challenges like price fluctuations and scope changes along with solutions to enhance financial performance. Similarly, cost control strategies for offshore production companies have been investigated by Sylvester et al. [16], focusing on optimizing petroleum production costs during the field development phase. It identifies key cost components such as labor, equipment, maintenance, and logistics, with preventive maintenance identified as the most effective strategy in minimizing costs and enhancing efficiency.

Gu [17] investigated the management of engineering costs across the entire life cycle of large-scale chemical projects by standardizing processes and lowering costs at all stages. By adopting the Life-Cycle Cost (LCC) analysis and developing an all-factor LCC model, the study provides valuable insights for optimizing cost management and supporting investment decisions in large-scale chemical projects. Guo and Zhang [18] presented a model for evaluating cost management control systems in petroleum enterprises under various market scenarios, categorizing cost control methods into five strategic grades. By using expert scoring and a formula-based approach, the model determines the effectiveness of the cost management system, with a positive score indicating a beneficial contribution to strategy, as demonstrated in the case of Daqing Oilfield Company Limited.

Egbumokei et al. [19] examined the importance of strategic supplier management in the energy and oil & gas sectors, emphasizing its role in project delivery optimization, risk reduction, and innovation promotion through strong supplier partnerships. It highlights the integration of technology, data analytics, and risk mitigation strategies, demonstrating the improvement of cost control, project timelines, and sustainability outcomes by effective supplier management. Egbumokei et al. [20] examined the challenges of strategic contract management in the drilling industry and focused on complex relationships, regulatory compliance, and cost control, while offering solutions such as clear communication and risk management frameworks. It also highlights future trends like digital transformation, smart contracts, and sustainability initiatives. This demonstrates how these innovations can enhance efficiency, reduce costs, and maintain competitiveness in drilling operations. Arifin and Hidayat [21] conducted an empirical study within Indonesia's upstream oil and gas sector, assessing how cost recovery mechanisms under Production Sharing Contracts (PSCs) influence government revenue generation. The research highlights the importance of accurately categorizing cost posts in cost recovery to reduce production costs for cooperation contract operators, based on data from SKK MIGAS over a 35-year period. Patidar et al. [3] presented a comprehensive review of the oil and gas sector, examining the upstream, midstream, and downstream stages involved in the extraction, processing, and distribution of hydrocarbons. It delves into geological exploration, petroleum reservoir identification, and basic engineering methods for exploration and production, while also discussing the evolution of the industry and the distinction between conventional and unconventional reservoirs.

Ghoddusi et al. [22] studied the motivations for countries exporting oil and gas, particularly OPEC members, to include downstream industries, such as refining and petrochemicals, as a strategy to hedge against price fluctuations and foster economic development. It explores various factors, including price differentiation, efficiency, industrial organization, and political economy, and emphasizes that these strategies are only effective when political considerations, such as monopolies and subsidies, are minimized. This paper addresses the optimization of petroleum supply chains (PSCs) in the transition to clean energy, introducing a nonlinear mixed-integer programming framework designed for strategic planning of infrastructure capacity, which integrates technological factors, such as hydraulic and pump system efficiency. In addition, it demonstrates that traditional minimum-cost approaches can lead to inefficient energy use, offering a more sustainable alternative for the petroleum sector's future projects.

Korauš et al. [23] proposed a managerial approach aimed at enhancing the efficiency and utilization of secondary energy resources, specifically focusing on the VAT tax gap related to petrol and diesel in Slovakia. The tax gap represents the variation between the VAT the government could collect according to the law and what is actually collected, primarily due to unpaid or undeclared taxes. The study, a joint effort by the IMF and the Institute for Financial Policy, estimates the corporate tax gap in Slovakia from 2010 to 2017. The data shows a decreasing trend in the tax gap, especially from 2014, due to the improving economic conditions in Slovakia. This trend reflects a reduction in tax losses and an increase in taxable profits. In the literature on cost of capital, previous studies have focused on analyzing the impact of factors such as market risks, regulatory changes, and capital structure on WACC across different industries [24]. Special attention has been given to the energy sector, with many studies highlighting the specificities influencing capital cost estimation, including taxation policies, the type of energy company, and regulatory conditions unique to the market.

3. Problem Description

The oil and gas industry's business activities are conventionally divided into three primary segments (Figure 1) [25]:

- Upstream – Exploration and production: includes drilling operations, locating crude oil and natural gas reserves, as well as raw resources extraction.
- Midstream – Transportation and storage: encompasses the movement of extracted hydrocarbons via pipelines, tankers, and other means, as well as their temporary storage.
- Downstream – Refining and marketing: involves the processing of crude oil into finished products and their subsequent distribution and sale to end consumers.

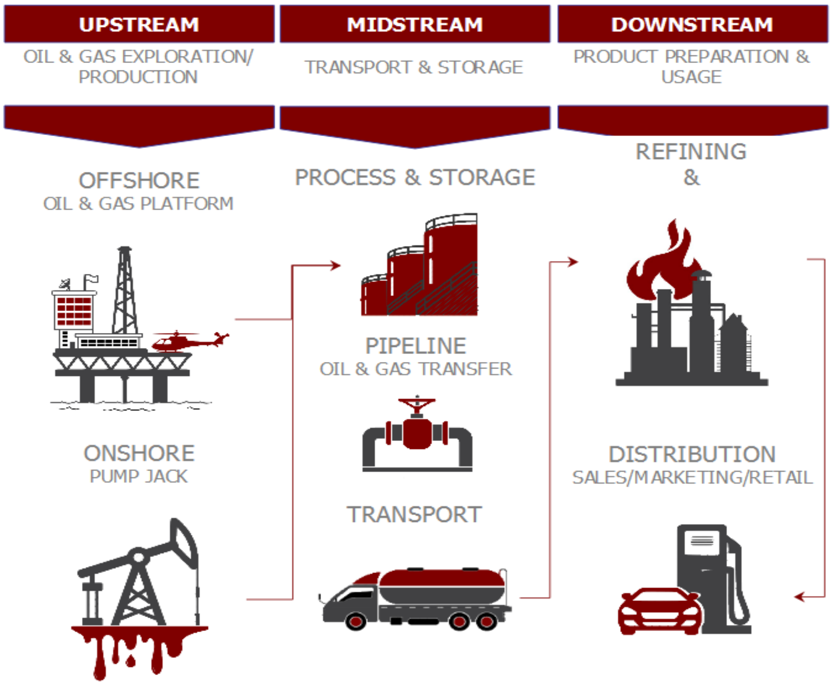


Fig. 1. Three main sectors in oil industry [26]

The upstream sector specifically covers:

- geological surveys and studies,
- site analysis and evaluation,
- drilling and well construction,
- recovery of crude oil or natural gas from subsurface reservoirs.

The upstream segment is particularly capital-intensive due to several factors:

- It requires substantial upfront investments in activities such as seismic surveys, exploratory drilling, equipment procurement, and the development of production infrastructure.
- It carries a high level of risk, as exploration activities may not always result in commercially viable discoveries.
- The sector typically experiences a long payback period, as significant time often elapses between the initial investment and the realization of revenue from production activities.

Given these characteristics, cost control in upstream operations is critical for oil companies' financial health and competitiveness. Effective cost management strategies are essential to mitigate financial risks and guarantee the long-term viability and economic efficiency of exploration and extraction operations, especially in fluctuating commodity prices and increasing operational complexities.

The exploration and production segment of the oil and gas sector is characterized by substantial capital investment requirements, significant operational risks, and a prolonged return on investment period. As for IOCs engaged in upstream activities, they must allocate substantial financial resources to exploration, drilling, and production processes, which are often characterized by conditions of extreme technical complexity and uncertain geological outcomes. Consequently, the implementation of effective cost control strategies is critical, which can sustain profitability, maintain competitive advantage, and ensure long-term operational viability.

Cost control in upstream operations involves systematically planning, monitoring, and managing expenditures across throughout all exploration and production stages. IOCs must adopt dynamic and flexible approaches tailored to internal operational requirements and external market conditions, due to the inherent uncertainties and the potential for substantial cost overruns.

Some key cost control strategies in upstream business are as follows:

- **Standardization of Equipment and Processes**
  Standardization of equipment, technologies, and operational procedures across projects not only reduces engineering complexity and procurement costs but also simplifies maintenance operations. By using standardized components and best practices, economies of scale can be achieved and technical risks can also be minimized.
- **Implementation of Digital Technologies and Automation**
  Implementation of real-time monitoring technologies, Internet of Things (IoT) devices, predictive data analysis, and digital twin frameworks enhances operational visibility and decision-making. Automation is important for human error minimization, production efficiency enhancement, and downtime reduction, leading to significant cost savings over the life cycle of upstream projects.
- **Outsourcing Specialized Services**
  Engagement of third-party contractors for activities (e.g., drilling, maintenance, and logistics) allows companies to convert fixed costs into variable costs. Outsourcing reduces the need for internal resources, lowers overhead, and transfers certain operational risks to external service providers.
- **Lean Management of Projects and Operations**
  Utilizing lean methodologies, including waste elimination, workflow optimization, and continuous improvement, helps streamline exploration and production processes. Lean management focuses on maximizing value-added activities while minimizing non-productive time and resources.
- **Integrated Planning of Drilling and Production Activities**
  Coordinating drilling, completion, and production operations into integrated workflows (e.g., batch drilling techniques) reduces idle time, improves resource utilization, and lowers logistics and mobilization costs.
- **Capital Cost Reduction through Phased Development**
  Instead of making large upfront investments, companies can develop oil and gas fields in phases based on evolving geological data and market conditions. Phased development reduces financial exposure, aligns investment with project maturity, and provides greater flexibility in capital allocation.
- **Optimization of Supply Chain and Procurement Operations**

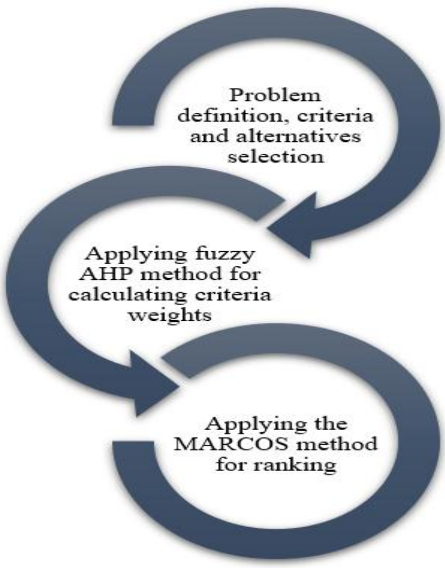
Streamlining procurement processes by engaging in bulk purchasing, long-term contracts, supplier partnerships, and local sourcing helps reduce procurement costs, shorten lead times, and improve supply chain resilience.

- **Effective Risk Management and Contingency Planning**
  Development of comprehensive risk management frameworks allows companies to identify, assess, and mitigate key geological, operational, and financial risks early. By planning for contingencies, companies can avoid costly disruptions and better control project budgets.
- **Utilization of Modular and Mobile Facilities**
  Deploying modular, pre-fabricated, or mobile production units enables faster deployment, easier relocation, and lower construction costs compared to building permanent infrastructure. This approach enhances project flexibility and reduces upfront capital expenditures.
- **Collaboration through Joint Ventures and Farmout Agreements**
  Forming strategic partnerships with other companies to share the costs and risks of exploration and development activities allows for resource pooling, risk diversification, and improved project viability, especially in high-risk or frontier regions.

Given the volatility of oil prices and the increasing pressure from stakeholders to maintain both financial discipline and environmental responsibility, IOCs must integrate cost control strategies not merely as a reactionary measure, but as a fundamental component of their strategic and operational planning. The ability to effectively manage costs in the upstream sector enhances short-term financial performance and supports long-term resilience in an increasingly complex and dynamic global energy landscape.

4. Methodology

As noted in the introduction, in the first phase problem was defined, as well as criteria and alternatives used in this paper. The framework constructed in this research relies on the application of FAHP in the second phase to establish the weighting of evaluation criteria (the process unfolds in five steps, which are elaborated in the subsequent sections – corresponding to the second iteration illustrated in Figure 2), and the MARCOS method in the third phase (the process is carried out through seven steps and is further elaborated upon in the subsequent sections of this study – corresponding to the third iteration illustrated in Figure 2) for ranking the cost strategies in the second phase. Figure 2 shows the methodological steps of the model's implementation.



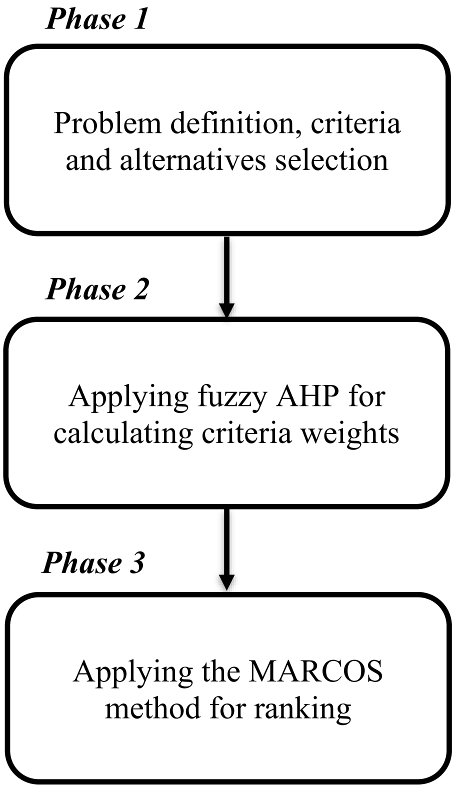


Fig. 2. Implementation steps of the model

4.1 FAHP method

FAHP is implemented below [27, 28].

Step 1 - Decision Problem Structuring

To begin, the problem must be organized into a hierarchical framework, as required by both the AHP and FAHP methodologies. This hierarchy structure ought to encompass the overall objective at the highest level, followed by the pertinent criteria, associated sub-criteria, and the set of potential alternatives.

Step 2 - Conducting Pairwise Comparisons

Pairwise comparisons are carried out using Saaty's 1 to 9 scale in AHP. Fuzzy sets in FAHP are defined along this same scale. All criteria and sub-criteria must be compared relative to the next higher hierarchy level. Table 1 shows the linguistic terms used for assessment alongside their associated triangular fuzzy number equivalents.

Table 1. Linguistic scale used for assessment

Linguistic term	Triangular fuzzy number
Absolutely preferable (AP)	(8,9,10)
Very preferable (VP)	(7,8,9)
Strongly preferable (SP)	(6,7,8)
Pretty preferable (PP)	(5,6,7)
Quite preferable (QP)	(4,5,6)
Moderately preferable (MP)	(3,4,5)
Remotely preferable (RP)	(2,3,4)
Barely preferable (BP)	(1,2,3)
Equally important (EI)	(1,1,2)

Step 3 - Constructing the Fuzzy Comparison Matrix

This stage involves the development of a fuzzy pairwise comparison matrix for each set of criteria or sub-criteria. This matrix, denoted as $\widetilde{\in}$, contains triangular fuzzy numbers in each element and is expressed as:

$$\widetilde{\in}= \begin{bmatrix} \tilde{a}_{11} & \cdots & \tilde{a}_{in} \\ \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \cdots & \tilde{a}_{nn} \end{bmatrix}, \tag{1}$$

Step 4 – Determining the Relative Importance of Criteria

$W = (w_1, \dots, w_n)$, a priority vector, where all weights are positive and their sum equals 1, is computed. The methodology known as Logarithmic Fuzzy Preference Programming (LFPP), introduced by Wang and Chin [29] is used for this purpose. Each fuzzy element in the matrix is denoted by a triangular fuzzy number $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$. The LFPP method approximates the logarithmic transformation of each fuzzy number:

$$\ln \tilde{a}_{ij} \approx (\ln l_{ij}, \ln m_{ij}, \ln u_{ij})\,; i,j = 1, \dots, n, \tag{2}$$

$$Min\, J = (1-\lambda)^2 + M \times \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} (\delta_{ij}^2 + \eta_{ij}^2), \tag{3}$$

$$s.t. \begin{cases} x_i - x_j - \lambda \ln(m_{ij}/l_{ij}) + \delta_{ij} \geq \ln l_{ij}, i = 1, \dots, n-1; j = i+1, \dots, n \\ -x_i + x_j - \lambda \ln(u_{ij}/m_{ij}) + \eta_{ij} \geq -\ln u_{ij}, i = 1, \dots, n-1; j = i+1, \dots, n \\ \lambda, x_i \geq 0, i = 1, \dots, n \\ \delta_{ij}, \eta_{ij} \geq 0, i = 1, \dots, n-1; j = i+1, \dots, n \end{cases} \tag{4}$$

where, x_i^* represents the optimal solution for criterion *i*, and a large constant $M = 10^3$ is used to ensure feasibility. λ represents the lowest level of membership indicating how well the crisp priority vector aligns with all the fuzzy pairwise comparisons. The variables δ_{ij} and η_{ij} are included to maintain non-negativity and to satisfy the following logarithmic inequalities:

$$\ln w_i - \ln w_j - \lambda \ln\left(\frac{m_{ij}}{l_{ij}}\right) + \delta_{ij} \geq \ln l_{ij}, i = 1, \dots, n-1; j = i+1, \dots, n, \tag{5}$$

$$-\ln w_i + \ln w_j - \lambda \ln(m_{ij}/l_{ij}) + \eta_{ij} \geq -\ln u_{ij}, i = 1, \dots, n-1; j = i+1, \dots, n, \tag{6}$$

Each criterion's normalized weight (crisp value) is then calculated:

$$w_j = \frac{w_j^l + 4w_j^m + w_j^u}{6}, j = 1, 2, \dots, n \tag{7}$$

Step 5 – Checking Consistency

To ensure consistency in judgments, each comparison matrix's Consistency Ratio (CR) is calculated using:

$$CR = \frac{CI}{RI}, \tag{8}$$

The Consistency Index (CI) is derived from Wind and Saaty [30]:

$$CI = \frac{Z_{max} - 0}{0 - 1}, \tag{9}$$

where, Z_{max} represents the fuzzy matrix's principal eigenvalue, and *RI* is the random index depending on matrix size, which is available in Saaty's reference tables. The CR value must be less than 0.10 to be considered acceptable.

4.2 MARCOS method

The procedure for applying MARCOS, following Stević et al. [13, 31], involves several steps:

Step 1 – Construct the preliminary decision matrix by employing *m* options evaluated against *n* assessment criteria.

Step 2 – Augment the matrix by incorporating both the ideal (AI) and the anti-ideal (AAI) reference solutions, according to Equation (10).

$$\begin{array}{c} \\ AAI \\ A_1 \\ A_2 \\ \dots \\ A_m \\ AI \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{aa1} & x_{aa2} & \dots & x_{aan} \\ x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \\ x_{ai1} & x_{ai2} & \dots & x_{ain} \end{bmatrix} \end{array} \tag{10}$$

The structure of the extended matrix includes all original alternatives along with the AI and AAI rows, where AI represents the best performance, while AAI represents the worst, which are computed by Equations (11) and (12):

$$AAI = \min_i x_{ij} \ if\ j \in B\ and\ \max_i x_{ij}\ if\ j \in C \tag{11}$$
$$AI = \max_i x_{ij}\ \ if\ j \in B\ and\ \min_i x_{ij}\ \ if\ j \in C \tag{12}$$

where beneficial criteria are marked as *B*, while cost criteria as *C*.

Step 3 – Use the following rules in Equations (13) and (14) to normalize the extended matrix:

$$n_{ij} = \frac{x_{ai}}{x_{ij}}\ if\ j \in C \tag{13}$$
$$n_{ij} = \frac{x_{ij}}{x_{ai}}\ if\ j \in B \tag{14}$$

Step 4 – Each element in the normalized matrix is multiplied by its associated criterion weight to generate the weighted normalized decision matrix.

$$v_{ij} = n_{ij} \times w_j \tag{15}$$

Step 5 – Determine the following utility degrees for each alternative by applying Equations (16) and (17).

$$K_i^- = \frac{S_i}{S_{aai}} \tag{16}$$
$$K_i^+ = \frac{S_i}{S_{ai}} \tag{17}$$

where, S_i represents each alternative's sum of weighted normalized values.

Decision Making: Applications in Management and Engineering
Volume 7, Issue 1 (2024) 719-734

$$S_i = \sum_{i=1}^{n} V_{ij} \tag{18}$$

Step 6 – Calculate each alternative's utility function, which balances the influence of *AI* and *AAI* using Equation (19).

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f(K_i^+)}{f(K_i^+)} + \frac{1-f(K_i^-)}{f(K_i^-)}} \tag{19}$$

The following individual component utility functions are determined below.

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{20}$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{21}$$

Step 7 – Finally, according to the utility function values *f(Ki)*, arrange the available alternatives from highest to lowest based on their evaluated performance scores.

5. Numerical Example

In order to test the developed model, a case study of an oil company aiming to implement a cost control strategy to enhance its business performance was conducted. Accordingly, the following 10 alternatives (cost control strategies) were defined, assessed, and ranked:

1. Standardization of Equipment and Processes (A1),
2. Implementation of Digital Technologies and Automation (A2),
3. Outsourcing Specialized Services (A3),
4. Lean Management of Projects and Operations (A4),
5. Integrated Planning of Drilling and Production Activities (A5),
6. Phased Development (A6),
7. Optimization of Supply Chain and Procurement (A7),
8. Effective Risk Management and Contingency Planning (A8),
9. Modular and Mobile Facilities (A9),
10. Collaboration through Joint Ventures and Farmout (A10).

The ranking was performed based on five criteria, namely [1,12,14-16]:

1. Potential for cost reduction (C1) – describes to what extent can the strategy contribute to overall cost reduction,
2. Risk reduction (C2) – describes to what extent does the strategy reduce operational and financial risks,
3. Ease of implementation (C3) – describes how easy is it to implement the strategy under current conditions,
4. Required investment (C4) – describes what is the level of initial investment needed for implementation,
5. Time to realize benefits (C5) – describes how quickly can the company observe tangible benefits from implementation.

The initial decision matrix was constructed after defining the alternatives and criteria. Given that all criteria are qualitative in nature, a 1–5 scale was used to evaluate each criterion (Table 2).

The process began with a pairwise comparison in accordance with FAHP, using a linguistic scale to perform the comparisons (Table 3). The values of the linguistic scale used for the comparisons were obtained from Table 1.

The following step involved the conversion of these linguistic assessments into triangular fuzzy numbers in accordance with FAHP (Table 4). Based on this, the criteria weights were determined.

Table 2. Input data

Alternative (Cost Control Strategy)	C1	C2	C3	C4	C5
A1	4	3	4	2	3
A2	4	4	3	4	3
A3	3	4	4	2	4
A4	3	3	3	2	3
A5	3	2	3	3	4
A6	4	4	3	3	2
A7	4	3	4	2	4
A8	3	4	3	3	3
A9	3	3	2	4	3
A10	3	4	3	3	2

Table 3. Linguistic pairwise comparison

	C1	C2	C3	C4	C5
C1	1	EI	MP	QP	PP
C2	-	1	QP	RP	QP
C3	-	-	1	EI	BP
C4	-	-	-	1	QP
C5	-	-	-	-	1

The results presented in Table 4 were used to derive the fuzzy weights of all criteria (Table 5). In the final step of the FAHP method, defuzzification was performed using Equation (7).

Table 4. Triangular fuzzy numbers assessment

	C1	C2	C3	C4	C5
C1	1	1 1 2	3 4 5	4 5 6	5 6 7
C2	1/2 1 1	1	4 5 6	2 3 4	4 5 6
C3	1/5 1/4 1/3	1/6 1/5 1/4	1	1 1 2	1 2 3
C4	1/6 1/5 1/4	1/4 1/3 1/2	1/2 1 1	1	4 5 6
C5	1/7 1/6 1/5	1/6 1/5 1/4	1/3 1/2 1	1/6 1/5 1/4	1

The highest weight, and therefore the greatest importance, was assigned to criterion C1, followed by C2, C4, C3, and finally C5, which had the lowest weight, as shown in Table 5.

Table 5. Criteria weights

Criteria	w_j^l	w_j^m	w_j^u	w_j *(crisp)*
C1	0.387	0.387	0.436	0.395
C2	0.297	0.352	0.352	0.343
C3	0.086	0.094	0.114	0.096
C4	0.104	0.119	0.123	0.117
C5	0.045	0.047	0.054	0.049

Then MARCOS was employed for available alternative ranking. Accordingly, for each evaluation criterion, both the ideal and anti-ideal reference solutions were incorporated into the original decision matrix, along with the weights determined in the preceding stage of the model's application (Table 6).

Table 6. Extended initial matrix

Alternatives/Criteria	C1	C2	C3	C4	C5
Weight	0.395	0.343	0.096	0.117	0.049
AAI	3	2	2	4	2
A1	4	3	4	2	3
A2	4	4	3	4	3
A3	3	4	4	2	4
A4	3	3	3	2	3
A5	3	2	3	3	4
A6	4	4	3	3	2
A7	4	3	4	2	4
A8	3	4	3	3	3
A9	3	3	2	4	3
A10	3	4	3	3	2
AI	4	4	4	2	4

Thereafter, normalization was performed in accordance with the type of each criterion (Table 7). In this study, all criteria except for C4 are of the maximization type, while C4 is the only one of the minimization type.

Table 7. Normalized matrix

Alternatives/Criteria	C1	C2	C3	C4	C5
AAI	0.7500	0.5000	0.5000	0.5000	0.5000
A1	1.0000	0.7500	1.0000	1.0000	0.7500
A2	1.0000	1.0000	0.7500	0.5000	0.7500
A3	0.7500	1.0000	1.0000	1.0000	1.0000
A4	0.7500	0.7500	0.7500	1.0000	0.7500
A5	0.7500	0.5000	0.7500	0.6667	1.0000
A6	1.0000	1.0000	0.7500	0.6667	0.5000
A7	1.0000	0.7500	1.0000	1.0000	1.0000
A8	0.7500	1.0000	0.7500	0.6667	0.7500
A9	0.7500	0.7500	0.5000	0.5000	0.7500
A10	0.7500	1.0000	0.7500	0.6667	0.5000
AI	1.0000	1.0000	1.0000	1.0000	1.0000

As shown in Table 8, the weighted decision matrix was derived through the element-wise multiplication of the normalized values within the decision matrix and their respective assigned weights.

Table 8. Weighted decision matrix

Alternatives/Criteria	C1	C2	C3	C4	C5
AAI	0.2963	0.1715	0.0480	0.0585	0.0245
A1	0.3950	0.2573	0.0960	0.1170	0.0368
A2	0.3950	0.3430	0.0720	0.0585	0.0368
A3	0.2963	0.3430	0.0960	0.1170	0.0490
A4	0.2963	0.2573	0.0720	0.1170	0.0368
A5	0.2963	0.1715	0.0720	0.0780	0.0490
A6	0.3950	0.3430	0.0720	0.0780	0.0245
A7	0.3950	0.2573	0.0960	0.1170	0.0490
A8	0.2963	0.3430	0.0720	0.0780	0.0368
A9	0.2963	0.2573	0.0480	0.0585	0.0368
A10	0.2963	0.3430	0.0720	0.0780	0.0245
AI	0.3950	0.3430	0.0960	0.1170	0.0490

In the following step, the S_i values for each alternative were determined using Equation (18), which are essential for ensuring the ongoing implementation of the MARCOS methodology, as shown in Table 9.

Table 9. S_i values

Alternatives	S_i
Saai	0.5988
A1	0.9020
A2	0.9053
A3	0.9013
A4	0.7793
A5	0.6667
A6	0.9125
A7	0.9143
A8	0.8260
A9	0.6968
A10	0.8138
Sai	1.0000

In the penultimate step, the values of K_i^- and K_i^+ i.e., the utility degrees of the alternatives, were calculated (Table 10).

Finally, the utility function values corresponding to each option were computed, after which the options were ordered based on their resulting scores (Table 11).

Table 10. Utility degree of alternatives

Alternatives	K_i^-	K_i^+
A1	1.5065	0.9020
A2	1.5119	0.9053
A3	1.5052	0.9013
A4	1.3015	0.7793
A5	1.1136	0.6667
A6	1.5240	0.9125
A7	1.5269	0.9143
A8	1.3795	0.8260
A9	1.1637	0.6968
A10	1.3591	0.8138

Table 11. Alternatives ranking

Alternatives	$f(K_i^-)$	$f(K_i^+)$	$f(K_i)$	Ranking
A1	0.3745	0.6255	0.7368	4
A2	0.3745	0.6255	0.7394	3
A3	0.3745	0.6255	0.7362	5
A4	0.3745	0.6255	0.6365	8
A5	0.3745	0.6255	0.5446	10
A6	0.3745	0.6255	0.7454	2
A7	0.3745	0.6255	0.7468	1
A8	0.3745	0.6255	0.6747	6
A9	0.3745	0.6255	0.5691	9
A10	0.3745	0.6255	0.6647	7

Based on the results obtained by utilizing the proposed model, the highest-ranked alternative is A7 (Optimization of Supply Chain and Procurement), whereas the lowest-ranked alternative is A5 (Integrated Planning of Drilling and Production Activities). The reason why A7 is the best-ranked strategy lies in the fact that it involves optimization at the highest level, while also incorporating all other mentioned strategies and applicable tools. Accordingly, it is essential for companies to engage in continuous optimization, as it is an ongoing process rather than a one-time improvement. In this regard, managers can employ various optimization tools, including the model developed in this study.

6. Conclusion

Controlling expenditures in the upstream sector of the oil industry holds significant strategic importance due to the sector's high operational complexity, capital intensity, and exposure to volatile market conditions. Therefore, the ability to select and implement effective cost management strategies directly influences a company's competitiveness and long-term sustainability. By developing structured decision-making models tailored to this context, companies can respond more efficiently to uncertainty and make informed strategic choices. Thus, creating reliable and adaptable models for cost control strategy evaluation contributes theoretically and practically in energy sector management.

This research highlights the relevance of applying an integrated model based on FAHP and MARCOS for cost control decision-making in upstream IOCs. The model allows to systematically and objectively evaluate alternative strategies under uncertainty, combining expert judgment with quantitative analysis. The application results indicate that Alternative A7 (Optimization of Supply Chain and Procurement) is the most suitable strategy. However, A5 (Integrated Planning of Drilling and Production Activities) ranks the lowest. Criteria C1 and C5 emerged as the most and least influential, respectively. These findings validate the criteria selected and the methodological framework. The model has proven to be a robust tool, which is applicable to similar decision-making scenarios across different sectors. It is a valuable resource for managers aiming to enhance cost efficiency because it can flexibly and precisely identify optimal strategies.

Integration of the presented model with other multi-criteria decision-making approaches or optimization techniques should be considered in future research, aiming to enhance its robustness and adaptability. To validate its generalizability, it is also recommended to test the model on various case studies across different oil companies and geographic markets. Dynamic criteria weight exploration over time could provide additional insights into evolving industry priorities. Finally, the model's applicability in fast-changing operational environments may be further improved by incorporating real-time data and digital tools.

Data Availability Statement

The simulated data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Arora, S. (2012). Investment decision making in the upstream oil industry: An analysis, 1-13. Available at SSRN: http://doi.org/10.2139/ssrn.1983123

[2] Shafiee, M., Animah, I., Alkali, B., & Baglee, D. (2019). Decision support methods and applications in the upstream oil and gas sector. Journal of Petroleum Science and Engineering, 173, 1173-1186. https://doi.org/10.1016/j.petrol.2018.10.050

[3] Patidar, A. K., Agarwal, U., Das, U., & Choudhury, T. (2023). Understanding the oil and gas sector and its processes: Upstream, downstream. In Understanding Data Analytics and Predictive Modelling in the Oil and Gas Industry, 1-20. https://doi.org/10.1201/9781003357872

[4] Kim, S. T., & Choi, B. (2019). Price risk management and capital structure of oil and gas project companies: Difference between upstream and downstream industries. Energy economics, 83, 361-374. https://doi.org/10.1016/j.eneco.2019.07.008

[5] Abdulwahhab, R., Naimi, S., & Abdullah, R. (2022). Managing cost and schedule evaluation of a construction project via BIM technology and experts' points of view. Mathematical Modelling of Engineering Problems, 9, 1515-1522. https://doi.org/10.18280/mmep.090611

[6] Paradzal, L., Wadesango, N., & Sitsha, L. (2023). Impact of Activity Based Costing System on Financial Performance of SMEs: A Case of Lester Trading Private Limited. Journal of Accounting, Finance and Auditing Studies, 9, 108-126. https://doi.org/10.32602/jafas.2023.026

[7] Nugroho, W., Ambarwati, R., Prapanca, D., & Wahyuni, A. (2025). Developing cost frameworks for sustainable water supply utility: A bibliometric analysis and systematic literature review. International Journal of Sustainable Development and Planning, 20, 227-244. https://doi.org/10.18280/ijsdp.200122

[8] Mohammedi, I., Belimane, W., & Bouchetara, M. (2024). Enhancing the Golden Triangle (Cost, Time, Quality) in Infrastructure Projects through Risk Management: A Case Study of the Algiers Metro Project. Journal of Corporate Governance, Insurance, and Risk Management, 11, 227-245. https://doi.org/ 10.56578/jcgirm110403

[9] Sehgal, K., Kaur, H., Kaur, S., Singh, S., Channi, H. K., & Stević, Ž. (2025). Cost-Effective Optimization of Hybrid Renewable Energy System for Micro, Small, and Medium Enterprises: A Decision-Making Framework Integrating MEREC and MARCOS. *Opportunities and Challenges in* Sustainability, 4, 17-32. https://doi.org/10.56578/ocs040102

[10] Andrejić M. & Pajić V. (2025). Integrated BWM–QFD–MARCOS Framework for Strategic Decision-Making in Cold Chain Logistics. Journal of Operational and Strategic Analytics, 3, 23-33. https://doi.org/10.56578/josa030103

[11] Marino, S. (2022). Developing a Sustainable Development Goals Research Hub among MERCOSUR's Universities: A Case Study. Opportunities and Challenges in Sustainability, 1, 2-12. https://doi.org/10.56578/ocs010102

[12] Peng, G., Han, L., Liu, Z., Guo, Y., Yan, J., & Jia, X. (2021). An application of fuzzy analytic hierarchy process in risk evaluation model. Frontiers in Psychology, 12, 715003. https://doi.org/10.3389/fpsyg.2021.715003

[13] Stević, Ž., Pamučar, D., Puška, A., & Chatterjee, P. (2020). Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to Compromise solution (MARCOS). Computers & Industrial Engineering, 140, 106231. https://doi.org/10.1016/j.cie.2019.106231

[14] Akenbor, C. O., & Agwor, T. C. (2015). Standard costing and cost control in Nigerian oil and gas industry. Journal of Modern Accounting and Auditing, 11(4), 185-193. http://doi.org/10.17265/1548-6583/2015.04.001

[15] Akpe, A. T., Nuan, S. I., Solanke, B., & Iriogbe, H. O. (2024). Development and implementation of cost control strategies in oil and gas engineering projects. Global Journal of Advanced Research and Reviews, 2(1), 001-022. https://doi.org/10.58175/gjarr.2024.2.1.0028

[16] Sylvester, J. I., Nwosi-Anele, A. S., & Ehirim, E. O. (2022). Cost control in offshore oil and gas operations. In SPE Nigeria Annual International Conference and Exhibition, Lagos, Nigeria, p. SPE-211950-MS. https://doi.org/10.2118/211950-MS

[17] Gu, Y. (2017). Study on the life-Cycle engineering cost management of large chemical projects. Chemical Engineering Transactions, 62, 1465-1470. https://doi.org/10.3303/CET1762245

[18] Guo, D., & Zhang, C. (2015). Evaluation of cost management controlling system in petroleum enterprise. Open Petroleum Engineering Journal, 8(1), 358-362. https://doi.org/ 10.2174/1874834101508010358

[19] Egbumokei, P. I., Dienagha, I. N., Digitemie, W. N., Onukwulu, E. C., & Oladipo, O. T. (2024). Strategic supplier management for optimized global project delivery in energy and oil & gas. *International Journal of Multidisciplinary Research and Growth Evaluation*, 5, 984-1002. http://doi.org/10.54660/.IJMRGE.2024.5.5.984-1002

[20] Egbumokei, P. I., Dienagha, I. N., Digitemie, W. N., Onukwulu, E. C., & Oladipo, O. T. (2024). Strategic contract management for drilling efficiency and cost reduction: Insights and perspectives. International Journal of Multidisciplinary Research and Growth Evaluation, 5, 1042-1050. https://doi.org/10.54660/.IJMRGE.2024.5.5.1042-1050.

[21] Arifin, K., & Hidayat, D. (2021). Cost recovery analysis in production sharing contract in upstream oil and gas industry (Study on gas upstream industries Indonesia). Dinasti International Journal of Economics, Finance & Accounting, 1, 1023-1047. https://doi.org/10.38035/DIJEFA

[22] Ghoddusi, H., Moghaddam, H., & Wirl, F. (2022). Going downstream–an economical option for oil and gas exporting countries? Energy Policy, 161, 112487. https://doi.org/10.1016/j.enpol.2021.112487

[23] Korauš, A., Gombár, M., Vagaská, A., Šišulák, S., & Černák, F. (2021). Secondary energy sources and their optimization in the context of the tax gap on petrol and diesel. Energies, 14, 4121. https://doi.org/10.3390/en14144121

[24] Franc-Dąbrowska, J., Mądra-Sawicka, M., & Milewska, A. (2021). Energy sector risk and cost of capital assessment—companies and investors perspective. Energies, 14(6), 1613. https://doi.org/10.3390/en14061613
[25] Mcclay, R. (2024). How the Oil and Gas Industry Works. Available online: shorturl.at/3GDcb
[26] ScheduleReader (2019). Oil and Gas Industry Overview. Available online: https://www.schedulereader.com/oil-and-gas-industry-overview.
[27] Tadić, S., Krstić, M., Dabić-Miletić, S., & Božić, M. (2023). Smart material handling solutions for city logistics systems. Sustainability, 15, 6693. https://doi.org/10.3390/su15086693
[28] Holecek, P., & Talašová, J. (2016). A free software tool implementing the fuzzy AHP method. In Proceedings of the 34th International Conference on Mathematical Methods in Economics, 6, 266-271. https://doi.org/10.1007/s10700-016-9241-0.
[29] Wang, Y. M., & Chin, K. S. (2011). Fuzzy analytic hierarchy process: A logarithmic fuzzy preference programming methodology. International Journal of Approximate Reasoning, 52, 541-553. https://doi.org/10.1016/j.ijar.2010.12.004
[30] Wind, Y., & Saaty, T. L. (1980). Marketing applications of the analytic hierarchy process. Management Science, 26, 641-658. https://doi.org/10.1287/mnsc.26.7.641
[31] Stevic, Z., Mujakovic, N., Goli, A., & Moslem, S. (2023). Selection of logistics distribution channels for final product delivery: FUCOM-MARCOS model. Journal of Intelligent Management Decision, 2, 172-178. https://doi.org/10.56578/jimd020402