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Evaluating performance of national oil and gas production facilities: A fuzzy network approach to manage undesirable outputs

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Abstract Exploitation centers are pivotal in multiple industries, especially in the oil and gas sector, contributing significantly to national revenue through exports. The oil and gas extracted are vital to many industrial sectors and end consumers. However, heavy crude oil exploitation and refining operations have undergone substantial changes to meet market demands and comply with environmental regulations. This paper presents a fuzzy network model designed to assess the efficiency of the country's oil and gas exploitation centers, considering undesirable outputs and weak disposability, focusing specifically on the oil exploitation centers of Khuzestan province. Network data envelopment analysis was employed to evaluate the efficiency of these centers, with toxic gases such as CO2 and SO2 identified as undesirable outputs at each stage. The analysis of nine centers revealed that none achieved an efficiency score of one. The primary reasons for this inefficiency were due to the use of outdated equipment resulting from sanctions and the failure to use liquefied and natural gases instead of diesel and gasoline in the machinery used for exploiting and refining crude oil. The model was then extended to the oil exploitation centers of Khuzestan province as a case study, validating its functionality. The results demonstrated the model's ability to effectively evaluate the efficiency of current units. Based on these findings, the adoption of renewable energy and the installation of appropriate filters in the equipment were suggested.

Keyword: Efficiency evaluation, network data envelopment analysis, undesirable outputs, weak disposability, oil and gas exploitation centers.

1 Introduction

The oil and gas sector stand as the cornerstone of global energy production, supplying vital resources to economies and societies worldwide [1]. Alongside its undeniable importance, this industry also faces numerous environmental and social challenges resulting from its activities, including greenhouse gas emissions, habitat disruption, and community displacement. In response to growing concerns about sustainability and social impacts,

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environmental management concepts aimed at reducing pollutants and corporate social responsibility (CSR) have gained increasing importance in this sector [2].

Today, enhancing efficiency in industries has gained paramount significance, and effectiveness and ultimately productivity across all industries is a reliable path to achieving higher economic growth with the same resources. The oil and gas industry, as an essential sector in the country's economic development process and infrastructure creation, plays a crucial role in providing the foundations for dynamic growth across various economic, industrial, cultural, and social domains. Therefore, the continuous progress of the country in the path of economic development and the enhancement of social welfare levels require continuous efforts to increase the extraction capacity of oil from exploitation centers and to enhance efficiency, effectiveness, and ultimately productivity in every sector [3].

To enhance industrial efficiency, it is essential to evaluate their performance through efficiency measurement. One of the challenges in performance evaluation is the production of undesirable outputs alongside desirable outputs, which in traditional literature, only the quantities of desirable outputs are considered. Ignoring undesirable outputs in the final evaluation can lead to incorrect results; therefore, recent evaluations also consider undesirable outputs and propose a new type of efficiency called eco-efficiency.

Data Envelopment Analysis (DEA) is a widely-used method in operations research for measuring the performance efficiency of organizations or production units. In 1957, Farrell pioneered the idea of measuring the efficiency of a production unit with multiple inputs (resources) and a single output (product), drawing inspiration from the concept of productive efficiency in engineering sciences. He introduced the efficiency concept using the ratio of the weighted average of inputs to the output of each production unit. Building on Farrell's work, Charnes and colleagues introduced the first DEA model in 1978, known as the CCR model. This model calculates the relative efficiency of Decision-Making Units (DMUs) by maximizing the ratio of the weighted sum of outputs to the weighted sum of inputs, under specific constraints on the weights. Since then, numerous DEA models have been developed as extensions of the CCR model. One of DEA's main advantages is its ability to identify inefficiencies within production units by highlighting levels of inefficiency. By addressing these inefficiencies, organizations can take corrective actions to eliminate the root causes. Additionally, DEA allows for the analysis of technical inefficiencies, showing how a product can improve its efficiency without the need for new inputs or technologies, thereby providing low-cost improvement opportunities [4].

In practice, many systems consist of complex structures with multiple stages, where the performance of individual components affects the overall efficiency. To address this complexity, Fare and Grosskopf (2000) introduced network data envelopment analysis models. These models assess the efficiency of intricate systems by defining relationships and intermediate variables, using series and parallel subsections. Network models offer a more accurate representation of system performance by considering the internal relationships within the system [5].

In network models, the overall system performance is calculated considering internal process constraints, establishing a link between the overall system efficiency and process efficiency. In classical data envelopment analysis models, if a decision-making unit has internal processes, the efficiency of each internal process and the overall process are calculated independently, with no relationship between the overall system efficiency and process efficiency [6]

Kao [7] divided network models into three categories: series, parallel, and composite models. Kao stated that when activities within a system occur sequentially, the system has a

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series structure, and when activities occur in parallel, the system has a parallel structure. Additionally, a combination of series and parallel forms a composite structure. To calculate the overall network efficiency in series or parallel modes, typically, the product of the stage efficiencies or the weighted average of the stage efficiencies is used, respectively. In a series or parallel structure, a decision-making unit is efficient only when all its subprocesses are efficient. Following the introduction of network data envelopment analysis models, numerous studies have been conducted in this area.

In recent years, there has been a particular focus on the role of undesirable factors in data envelopment analysis models. Lio and Leo [8] classified working with undesirable outputs as follows: the first method is to ignore undesirable outputs, the second method is to limit the spread of undesirable outputs or consider undesirable outputs as a nonlinear DEA model, and the third method is to consider undesirable outputs as inputs, with negative signs in outputs, or by applying a monotonic decreasing transformation.

In recent years, researchers have considered the role of undesirable factors in production processes using network DEA models to measure efficiency. The recent evolutionary trend of undesirable factors is moving towards utilizing undesirable factors to produce desirable factors. For example, in a new approach, Wu et al. [9] considered an interactive network composed of two stages, where the first stage introduces undesirable outputs to the second stage, and ultimately, the second stage produces desirable outputs, effectively utilizing undesirable outputs for production.

The oil and gas sector encompass a wide range of activities, including exploration, extraction, refining, and distribution of fossil fuels [10]. From offshore drilling platforms to onshore refineries, this industry operates in diverse geographical areas, often in environmentally sensitive regions. Its operations are aimed at meeting global energy needs, yet they frequently intersect with ecological habitats, indigenous lands, and communities, leading to complex social, environmental, and ethical considerations. In light of increasing concerns about climate change, pollution, and social equity, the necessity for the oil and gas sector to adopt environmental monitoring and social responsibility is undeniable [11].

These principles emphasize the industry's responsibility to minimize its ecological footprint, support ethical business practices, and contribute positively to the communities in which it operates. By integrating environmental monitoring and social responsibility into their strategies and operations, oil and gas companies can reduce adverse impacts, enhance their reputation, and promote long-term sustainability [12].

The exploration stage involves identifying and evaluating potential oil and gas reserves through geological surveys, seismic testing, and exploratory drilling [13,14]. Sustainability concerns at this stage include habitat disruption, water usage, and the risk of environmental contamination from drilling activities. During the drilling stage, wells are drilled to extract oil and gas from underground reservoirs. Challenges at this stage include optimizing drilling efficiency, reducing drilling waste, and minimizing the risk of accidents and spills that could harm the environment [15].

In the production stage, oil and gas are extracted from wells and processed for transportation and distribution. Sustainability concerns at this stage include greenhouse gas emissions, energy consumption, and water usage in refining and processing operations [6]. The distribution phase involves transporting oil and gas from production facilities to end consumers through pipelines, tankers, and other transportation methods. Sustainability challenges at this stage include the risk of leaks and spills during transportation, as well as the energy consumption associated with transportation infrastructure [16].

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Oil and gas exploitation centers prevent the import of petroleum products and the wastage of national revenue by supplying domestic energy. However, the refining industry remains an industrial activity with high fossil fuel consumption, leading to high emissions of NO2, SO2, and CO2. Therefore, in evaluating the performance of refineries, it is not sufficient to only measure efficiency; instead, pollution must be considered as an undesirable output in efficiency measurement, i.e., eco-efficiency must be measured.

In Iran, studies on eco-efficiency are limited, and to date, the eco-efficiency of oil and gas exploitation centers has not been specifically measured across three main stages from extraction to oil transfer to refineries using a three-stage DEA method under uncertainty conditions. Section 2 reviews the research background; Section 3 presents the research method and model to calculate the efficiency of decision-making units. Section 4 provides data analysis, and finally, Section 5 concludes with summary findings and recommendations. In the literature review, previous studies highlight the application of the Fuzzy Delphi Method for extracting efficiency measurement criteria, demonstrating its effectiveness in achieving consensus among experts. Building on this foundation, we present a novel three-stage fuzzy model for efficiency measurement, designed to incorporate the fuzzy logic principles that address uncertainties in the evaluation process. The model is evaluated through a case study, utilizing determined inputs and outputs to assess its performance. The results are interpreted to provide insights into the efficiency of the units studied, revealing areas of improvement and validating the robustness of the proposed model. This comprehensive approach underscores the importance of integrating fuzzy logic into efficiency measurement frameworks to enhance accuracy and reliability. The stages of this research are briefly illustrated in the following figure:

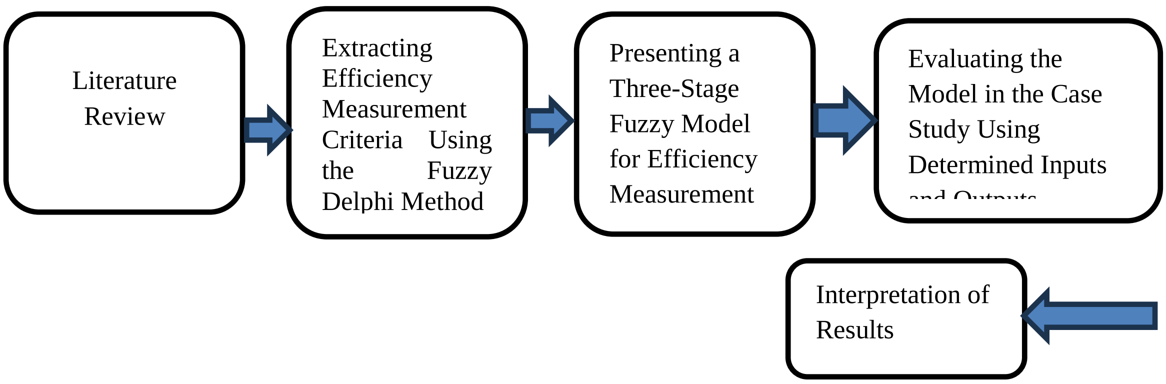

Fig. 1 Stages of the Research Process

2 Literature Review

Mohammadzadeh et al. [17] evaluated the energy, economic, and environmental performance using an integrated approach of DEA and game theory. The study aimed to assess the performance of selected energy-exporting countries using the integrated DEA approach and game theory. The methodology included super-efficiency and cross-efficiency methods for ranking efficient countries before the cooperation stage. In the cooperation stage, each country was assessed using cooperative game theory and the Shapley value. The developed model was implemented, and the rankings of efficient countries using the super-efficiency and cross-efficiency methods (before cooperation) were compared with the Shapley value

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method (after cooperation). The results indicated that Qatar and Yemen had the highest energy efficiency, while Lebanon and Jordan had the lowest. Kuwait, Qatar, and Turkmenistan had the highest economic efficiency, whereas Iran and Turkey had the lowest. The UAE and Qatar exhibited the highest environmental efficiency, while Iran and Jordan had the lowest.

De Oliveira et al. [4] analyzed the efficiency of oil refineries using window DEA, cluster analysis, and the Malmquist productivity index. This study utilized DEA to provide improvement targets for production units based on efficiency indicators. Additionally, window DEA integrated with the Malmquist productivity index and cluster analysis was used to evaluate efficiency and the factors differentiating refineries over various time periods. Numerical analysis using data collected from 12 Brazilian oil refineries between 2012 and 2020 showed a steady increase in production and efficiency over the years.

Sueyoshi et al. [18] evaluated the operational performance of power plants in Japan and South Korea using a non-radial measurement. The researchers introduced a novel DEA approach for measuring performance by utilizing managerial and natural availabilities to better assess the efficiency of power plants. This approach initially controls for "zero" in the dataset and then restricts coefficients without any prior information to enhance empirical reliability.

Dalei et al. [19] assessed the efficiency of twelve Indian oil refineries from 2011 to 2016 using an input-oriented DEA-BCC model and a Tobit model. In this study, no refinery was fully efficient, and only three refineries had efficiency rates above 95%. Potential solutions identified included the feasibility of renewable energy sources and reducing high sulfur content oil production.

Atris [20] examined the operational performance of 696 units in oil and gas refineries from 2008 to 2017, dividing them into four global clusters (USA & Canada, Europe, Asia-Pacific, and Africa & Middle East) using input-oriented DEA and DEA-DA (discriminant analysis). The results showed that the USA and Canada cluster performed better than the other three clusters, attributed to the vertically integrated operations of American oil companies, increased profits, and lower risks.

Wang et al. [21] evaluated the technological innovation efficiency (TIE) of ten Daqing Oil Company refineries from 2012 to 2015 using an input-oriented DEA-BCC model and the Malmquist index. The results indicated that the company had a high level of TIE, but its total factor productivity (TFP) decreased annually. It was also found that technological progress had declined more than overall technological efficiency, suggesting that the TFP decrease was mainly due to insufficient technological advancements.

Azadeh et al. [22] measured the interaction between resilience engineering and managerial and organizational factors in 41 gas refineries using DEA and statistical models.

Khalili-Damghani et al. [23] proposed a DEA model to address scale efficiency problems in combined cycle power plants, modeling the units used for electricity production as inputs and the units consuming fuel as undesirable outputs.

SONG et al. [24] they used a network DEA model to divide efficiency scores into two subsets, providing more precise feedback. In China, changes in production and environmental efficiency in twenty local oil companies were evaluated. Environmental assessment studies by

Sueyoshi et al. [25]: Sueyoshi and colleagues analyzed the environmental efficiency of 50 oil companies in the United States in 2012, separating them into independent and integrated companies. This approach helped verify corporate sustainability, with integrated companies performing better in terms of corporate sustainability compared to independent ones.

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Barros et al. [26] Efficiency and Productivity Analysis in a Sample of Oil Blocks in Angola from 2002 to 2008.The results indicate that the oil blocks in Angola experienced some growth in productivity during the analysis period, and the emergence of technological advancements was positive.

LEE et al. [27] Using DEA and multi-criteria analysis, LEE and colleagues evaluated energy technologies against rising oil prices. The relative efficiency score of energy technology in the face of rising oil prices can provide essential information for decision-makers on how to allocate resources effectively.

Although various studies have been conducted on the performance evaluation of refineries and their downstream supply chain, which includes exploitation centers, it seems that comprehensive research specifically focusing on the performance evaluation of oil and gas exploitation centers aimed at reducing environmental pollutants has not been extensively executed. To evaluate the efficiency of oil and gas exploitation centers in three interdependent subprocesses, the fuzzy non-parametric linear programming DEA model (LPP) has been used. On the other hand, traditional DEA modeling is deterministic and precise.

Fuzzy DEA is employed when variables change annually due to economic conditions or macroeconomic factors. Therefore, to overcome uncertainty, efficiency at each stage is modeled as a triangular fuzzy number. Conversely, the closed fuzzy DEA system is considered to prevent the inclusion of additional variables at each stage as inputs to the next stage, which may alter the target in each subprocess. The proposed method evaluates the performance of each subprocess and specifies the standard DEA results for all three stages of each DMU.

This study is the first of its kind to comprehensively assess the environmental performance efficiency in the oil and gas exploitation sector in Iran using a closed three-stage fuzzy DEA model with the presence of undesirable outputs. Additionally, intermediate data has so far only been considered as desirable data, and undesirable intermediate data has not been discussed, which is addressed in this research.

3 Proposed Method

In this research, we aim to evaluate and compare the relative performance of *n* DMUs. The performance of each unit is assessed based on three groups of factors, including *m* inputs, ss desirable outputs, and *w* undesirable outputs. Considering the undesirable outputs and the principle of weak disposability, the following notations are used to formulate the proposed model:

x_i: The i-th input (i=1, 2..., m)

y_r: The r-th desirable output (r=1, 2…, s)

b_k: The k-th undesirable output (k=1, 2..., w)

λ(lambda) : The intensity variable representing the contribution of each DMU in forming the efficient frontier

Table 1 Indices, Variables, and Parameters

Indices, Variables, and Parameters		
η_n :Weight of the n -th Desirable Output in the Third Stage	w_{rj}^{L} : Lower Bound of the j th Undesirable Output for the DMU in the Second Stage r	J **:**Number of Decision-Making Units (DMUs)

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α_1 :First stage parameter to determine the lower bound of efficiency	w_{rj}^{M} :Middle bound of r-th safe undesirable output of the j safe decision-making unit of the second stage	I :Number of first stage entries
β_1 :First stage parameter for determining the middle bound of efficiency	w_{rj}^{U} : Upper bound of the r trustee Undesirable output of the j trustee Decision-making unit Second stage	B :Number of undesirable outputs of the first stage
δ_1 :First stage parameter to determine the upper bound of efficiency	f_{sj}^{L} : Lower bound of s-the safe middle index of j-the safe decision-making unit of the second to third stage (output of the second stage and input of the third stage)	T :Number of desired outputs of the first stage - inputs of the second stage (intermediate index)
α_2 :Second stage parameter to determine the lower bound of efficiency	f_{sj}^{M} : middle bound of s-th middle index Decision-making unit of j- the second to third stage (output of the second stage and input of the third stage)	R :Number of undesirable outputs of the second stage
β_2 :Second stage parameter for determining the middle bound of efficiency	f_{sj}^{U} : Upper bound of s-th middle index Decision-making unit of j- the second to third stage (output of the second stage and input of the third stage)	S :Number of desired outputs of the second stage - inputs of the third stage (intermediate index)
δ_2 :Second stage parameter to determine the upper bound of efficiency	x_{qj}^{3L} :Lower bound of q-the input of j-the decision-making unit of the third stage	Q :Number of third stage entries
α_3 :Third stage parameter to determine the lower bound of efficiency	x_{qj}^{3M} : Middle bound of q-the input of j-the decision-making unit of the third stage	N :Number of desired outputs of the third stage
β_3 :Third stage parameter for determining the middle bound of efficiency	x_{qj}^{3U} :Upper bound of q-the input of j-the decision-making unit of the third stage	D :Number of undesirable outputs in the third stage
δ_3 :Third stage parameter to determine the upper bound of efficiency	v_{nj}^{L} :Lower bound of n- the safe desired output of j-the safe decision-making unit of the third stage	x_{ij}^{1L} :Lower bound of i -the input of the decision-making unit of j-the first stage.
E_o^{*L} :Fuzzy efficiency lower bound	v_{nj}^{M} :Middle bound of n- the safe desired output of j-the safe decision-making unit of the third stage	x_{ij}^{1M} :Middle bound of i-the safe input of j-the safe decision-making unit of the first stage -
E_o^{*M} :Intermediate bound of fuzzy efficiency	v_{nj}^{U} :Upper bound of n- the safe desired output of j-the safe decision-making unit of the third stag	x_{ij}^{1U} : Upper bound of i-the safe input of the safe decision-making unit of the first stage
E_o^{*U} :Upper bound of fuzzy efficiency	y_{dj}^{L} :Lower bound of d-the undesired output of j-the decision-making unit of the third stage.	u_{bj}^{L} :Lower bound of b-the undesired output of j- the decision-making unit of the first stage.
$E_o^{*Overall}$:efficiency	y_{dj}^{M} : Middle bound of d-the undesired output of j-the decision-making unit of the third stage.	u_{bj}^{M} : Middle bound of b-the safe input of j-the safe decision-making unit of the first stage
y_{dj}^{U} : Upper bound of d-the Undesirable output of j-the Decision-making unit Third stage		u_{bj}^{U} :Upper bound of b-the trustee Undesirable output of j-the trustee Decision-

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	making unit of the first stage
μ_s :The weight of s-the middle index of the second-third stage (output of the second stage and input of the third stage)	z_{tj}^{L} :Lower bound of t-the intermediate index of j- the decision-making unit of the first to the second stage (output of the first stage and input of the second stage)
ζ_q :The weight of q-the third stage input	z_{tj}^{M} : Middle bound :of t-the intermediate index of j- the decision-making unit of the first to the second stage (output of the first stage and input of the second stage)
λ_d :The weight of d-th Undesirable output of the third stage	z_{tj}^{U} :Upper bound :of t-the intermediate index of j- the decision-making unit of the first to the second stage (output of the first stage and input of the second stage)
η_n : The weight of n-the Desired output of the third stage	γ_i :The weight of i-the first stage input
α_1 :First stage parameter to determine the lower bound of efficiency	κ_b : The weight of b-the Undesirable output of the first stage
β_1 :First stage parameter for determining the middle bound of efficiency	φ_t :The weight of t -the Intermediate index of the first-second stage (output of the first stage and input of the second stage)
δ_1 :First stage parameter to determine the upper bound of efficiency	ρ_r :The weight of r-the second stage undesirable output
α_2 : Second stage parameter to determine the lower bound of efficiency	λ_d : The weight of d- the third stage undesirable output

Triangular Fuzzy Number:

In the context of fuzzy logic, a triangular fuzzy number is a simple way to represent uncertainty and imprecision in data. It is defined by three parameters: the lower bound, the middle value, and the upper bound. These parameters form a triangle shape when plotted on a graph, representing the degree of membership for each value within the range.

For a triangular fuzzy number $\tilde{A}$, it is represented as (a_l, a_m, a_u), where:

(a_l) is the lower bound (the minimum possible value).

(a_m) is the middle value (the most likely or average value).

(a_u) is the upper bound (the maximum possible value).

The membership function $\mu_{\tilde{A}}(X)$ for a triangular fuzzy number is defined as:

$$\mu_{\tilde{A}}(X) = \begin{cases} 1, & \text{IF } y \in Y \\ 0, & \text{IF } y \notin Y \\ (0,1) & \text{IF } y \text{ is partly in } Y \end{cases} \tag{1}$$

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Fuzzy results are traditionally converted to deterministic values because fuzzy calculations cannot be applied in many real-world scenarios. Since the efficiency scores of decision-making units (DMUs) are deterministic rather than one or several fuzzy values, defuzzification is carried out using the mean of grades integration. This technique, being one of the most commonly used defuzzification methods in the existing literature, reduces the complexity and tediousness of the massive operations involved in the original fuzzy membership function [28].

$$E_o^{*Overall} = \frac{E_o^{*L} + 4E_o^{*M} + E_o^{*U}}{6} \tag{2}$$

Based on the above discussion, the general form of the model in its non-fuzzy state is as follows:

$$\xi_1 + \xi_2 + \xi_3 = 1 \tag{3}$$

The above model can be converted into three fuzzy models as follows:

$$\begin{aligned}
&E_o^* = Max\,\xi_1.\left(\frac{\sum_{t=1}^{T}\varphi_t z_{to} - \sum_{b=1}^{B}\kappa_b u_{bo}}{\sum_{i=1}^{I}\gamma_i x_{io}^1}\right) + \xi_2.\left(\frac{\sum_{s=1}^{S}\mu_s f_{so} - \sum_{r=1}^{R}\rho_r w_{ro}}{\sum_{t=1}^{T}\varphi_t z_{to}}\right) + \xi_3.\left(\frac{\sum_{n=1}^{N}\eta_n v_{no} - \sum_{d=1}^{D}\lambda_d y_{do}}{\sum_{s=1}^{S}\mu_s f_{so} + \sum_{q=1}^{Q}\zeta_q x_{qo}^3}\right)\\
&S.t.\\
&\frac{\sum_{t=1}^{T}\varphi_t z_{tj} - \sum_{b=1}^{B}\kappa_b u_{bj}}{\sum_{i=1}^{I}\gamma_i x_{ij}^1} \le 1, j = 1,\dots,J,\\
&\frac{\sum_{s=1}^{S}\mu_s f_{sj} - \sum_{r=1}^{R}\rho_r w_{rj}}{\sum_{t=1}^{T}\varphi_t z_{tj}} \le 1, j = 1,\dots,J,\\
&\frac{\sum_{n=1}^{N}\eta_n v_{nj} - \sum_{d=1}^{D}\lambda_d y_{dj}}{\sum_{s=1}^{S}\mu_s f_{sj} + \sum_{q=1}^{Q}\zeta_q x_{qj}^3} \le 1, j = 1,\dots,J,\\
&\sum_{t=1}^{T}\varphi_t z_{tj} - \sum_{b=1}^{B}\kappa_b u_{bj} \ge 0, j = 1,\dots,J,\\
&\sum_{s=1}^{S}\mu_s f_{sj} - \sum_{r=1}^{R}\rho_r w_{rj} \ge 0,\\
&\sum_{n=1}^{N}\eta_n v_{nj} - \sum_{d=1}^{D}\lambda_d y_{dj} \ge 0,\\
&\varphi_t, \gamma_i, \mu_s, \rho_r, \eta_n, \lambda_d, \zeta_q, \kappa_b \ge 0, \forall t, i, s, r, n, d, q, b.
\end{aligned} \tag{4}$$

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$$E_o^{*U} = Max\alpha_1.\left(\frac{\sum_{t=1}^{T}\varphi_t z_{to}^{U} - \sum_{b=1}^{B}\kappa_b u_{bo}^{L}}{\sum_{i=1}^{I}\gamma_i x_{io}^{1L}}\right) + \alpha_2.\left(\frac{\sum_{s=1}^{S}\mu_s f_{so}^{U} - \sum_{r=1}^{R}\rho_r w_{ro}^{L}}{\sum_{t=1}^{T}\varphi_t z_{to}^{L}}\right) + \alpha_3.\left(\frac{\sum_{n=1}^{N}\eta_n v_{no}^{U} - \sum_{d=1}^{D}\lambda_d y_{do}^{L}}{\sum_{s=1}^{S}\mu_s f_{so}^{L} + +\sum_{q=1}^{Q}\zeta_q x_{qo}^{3L}}\right)$$

$$\begin{aligned}
&S.t.\\
&\frac{\sum_{t=1}^{T}\varphi_t z_{tj}^{U} - \sum_{b=1}^{B}\kappa_b u_{bj}^{L}}{\sum_{i=1}^{I}\gamma_i x_{ij}^{1L}} \leq 1, j = 1,\ldots,J,\\
&\frac{\sum_{s=1}^{S}\mu_s f_{sj}^{U} - \sum_{r=1}^{R}\rho_r w_{rj}^{L}}{\sum_{t=1}^{T}\varphi_t z_{tj}^{L}} \leq 1, j = 1,\ldots,J,\\
&\frac{\sum_{n=1}^{N}\eta_n v_{nj}^{U} - \sum_{d=1}^{D}\lambda_d y_{dj}^{L}}{\sum_{s=1}^{S}\mu_s f_{sj}^{L} + \sum_{q=1}^{Q}\zeta_q x_{qj}^{3L}} \leq 1, j = 1,\ldots,J,\\
&\sum_{t=1}^{T}\varphi_t z_{tj}^{L} - \sum_{b=1}^{B}\kappa_b u_{bj}^{U} \geq 0, j = 1,\ldots,J,\\
&\sum_{s=1}^{S}\mu_s f_{sj}^{L} - \sum_{r=1}^{R}\rho_r w_{rj}^{U} \geq 0, j = 1,\ldots,J,\\
&\sum_{n=1}^{N}\eta_n v_{nj}^{L} - \sum_{d=1}^{D}\lambda_d y_{dj}^{U} \geq 0, j = 1,\ldots,J,\\
&\varphi_t, \gamma_i, \mu_s, \rho_r, \eta_n, \lambda_d, \zeta_q, \kappa_b \geq 0, \forall t, i, s, r, n, d, q, b.
\end{aligned} \tag{5}$$

$$E_o^{*M} = Max\alpha_1.\left(\frac{\sum_{t=1}^{T}\varphi_t z_{to}^{M} - \sum_{b=1}^{B}\kappa_b u_{bo}^{M}}{\sum_{i=1}^{I}\gamma_i x_{io}^{1M}}\right) + \alpha_2.\left(\frac{\sum_{s=1}^{S}\mu_s f_{so}^{M} - \sum_{r=1}^{R}\rho_r w_{ro}^{M}}{\sum_{t=1}^{T}\varphi_t z_{to}^{M}}\right) + \alpha_3.\left(\frac{\sum_{n=1}^{N}\eta_n v_{no}^{M} - \sum_{d=1}^{D}\lambda_d y_{do}^{M}}{\sum_{s=1}^{S}\mu_s f_{so}^{M} + +\sum_{q=1}^{Q}\zeta_q x_{qo}^{3M}}\right)$$

$$\begin{aligned}
&S.t.\\
&\frac{\sum_{t=1}^{T}\varphi_t z_{tj}^{U} - \sum_{b=1}^{B}\kappa_b u_{bj}^{L}}{\sum_{i=1}^{I}\gamma_i x_{ij}^{1L}} \leq 1, j = 1,\ldots,J,\\
&\frac{\sum_{s=1}^{S}\mu_s f_{sj}^{U} - \sum_{r=1}^{R}\rho_r w_{rj}^{L}}{\sum_{t=1}^{T}\varphi_t z_{tj}^{L}} \leq 1, j = 1,\ldots,J,\\
&\frac{\sum_{n=1}^{N}\eta_n v_{nj}^{U} - \sum_{d=1}^{D}\lambda_d y_{dj}^{L}}{\sum_{s=1}^{S}\mu_s f_{sj}^{L} + \sum_{q=1}^{Q}\zeta_q x_{qj}^{3L}} \leq 1, j = 1,\ldots,J,\\
&\sum_{t=1}^{T}\varphi_t z_{tj}^{L} - \sum_{b=1}^{B}\kappa_b u_{bj}^{U} \geq 0, j = 1,\ldots,J,\\
&\sum_{s=1}^{S}\mu_s f_{sj}^{L} - \sum_{r=1}^{R}\rho_r w_{rj}^{U} \geq 0, j = 1,\ldots,J,\\
&\sum_{n=1}^{N}\eta_n v_{nj}^{L} - \sum_{d=1}^{D}\lambda_d y_{dj}^{U} \geq 0, j = 1,\ldots,J,\\
&\varphi_t, \gamma_i, \mu_s, \rho_r, \eta_n, \lambda_d, \zeta_q, \kappa_b \geq 0, \forall t, i, s, r, n, d, q, b.
\end{aligned} \tag{6}$$

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$$
\begin{aligned}
E_o^{*L} = Max\delta_1.\left(\frac{\sum_{t=1}^{T}\varphi_t z_{to}^L - \sum_{b=1}^{B}\kappa_b u_{bo}^L}{\sum_{i=1}^{I}\gamma_i x_{io}^{1U}}\right) + \delta_2.\left(\frac{\sum_{s=1}^{S}\mu_s f_{so}^L - \sum_{r=1}^{R}\rho_r w_{ro}^U}{\sum_{t=1}^{T}\varphi_t z_{to}^U}\right) + \\
\delta_3.\left(\frac{\sum_{n=1}^{N}\eta_n v_{no}^L - \sum_{d=1}^{D}\lambda_d y_{do}^U}{\sum_{s=1}^{S}\mu_s f_{so}^U + \sum_{q=1}^{Q}\zeta_q x_{qo}^{3U}}\right) \\
S.t. \\
\frac{\sum_{t=1}^{T}\varphi_t z_{tj}^U - \sum_{b=1}^{B}\kappa_b u_{bj}^L}{\sum_{i=1}^{I}\gamma_i x_{ij}^{1L}} \le 1, j = 1,\ldots,J, \\
\frac{\sum_{s=1}^{S}\mu_s f_{sj}^U - \sum_{r=1}^{R}\rho_r w_{rj}^L}{\sum_{t=1}^{T}\varphi_t z_{tj}^L} \le 1, j = 1,\ldots,J, \\
\frac{\sum_{n=1}^{N}\eta_n v_{nj}^U - \sum_{d=1}^{D}\lambda_d y_{dj}^L}{\sum_{s=1}^{S}\mu_s f_{sj}^L + \sum_{q=1}^{Q}\zeta_q x_{qj}^{3L}} \le 1, j = 1,\ldots,J, \\
\sum_{t=1}^{T}\varphi_t z_{tj}^L - \sum_{b=1}^{B}\kappa_b u_{bj}^U \ge 0, j = 1,\ldots,J, \\
\sum_{s=1}^{S}\mu_s f_{sj}^L - \sum_{r=1}^{R}\rho_r w_{rj}^U \ge 0, j = 1,\ldots,J, \\
\sum_{n=1}^{N}\eta_n v_{nj}^L - \sum_{d=1}^{D}\lambda_d y_{dj}^U \ge 0, j = 1,\ldots,J, \\
\varphi_t, \gamma_i, \mu_s, \rho_r, \eta_n, \lambda_d, \zeta_q, \kappa_b \ge 0, \forall t, i, s, r, n, d, q, b.
\end{aligned}
\tag{7}
$$

We assume that this is the problem for writing:

$$\delta_1 + \delta_2 + \delta_3 = 1, \beta_1 + \beta_2 + \beta_3 = 1, \alpha_1 + \alpha_2 + \alpha_3 = 1$$

$$\alpha_1 = \frac{\sum_{t=1}^{T}\varphi_t z_{to}^L}{\sum_{i=1}^{I}\gamma_i x_{io}^L + \sum_{t=1}^{T}\varphi_t z_{to}^L + \sum_{s=1}^{S}\mu_s f_{so}^L + \sum_{q=1}^{Q}\zeta_q x_{qo}^{3L}}$$

$$\alpha_2 = \frac{\sum_{t=1}^{T}\varphi_t z_{to}^L}{\sum_{i=1}^{I}\gamma_i x_{io}^L + \sum_{t=1}^{T}\varphi_t z_{to}^L + \sum_{s=1}^{S}\mu_s f_{so}^L + \sum_{q=1}^{Q}\zeta_q x_{qo}^{3L}}$$

$$\alpha_3 = \frac{\sum_{s=1}^{S}\mu_s f_{so}^L + \sum_{q=1}^{Q}\zeta_q x_{qo}^{3L}}{\sum_{i=1}^{I}\gamma_i x_{io}^L + \sum_{t=1}^{T}\varphi_t z_{to}^L + \sum_{s=1}^{S}\mu_s f_{so}^L + + \sum_{q=1}^{Q}\zeta_q x_{qo}^{3L}}$$

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$$\beta_1=\frac{\sum_{t=1}^{T}\varphi_t z_{to}^{M}}{\sum_{i=1}^{I}\gamma_i x_{io}^{M}+\sum_{t=1}^{T}\varphi_t z_{to}^{M}+\sum_{s=1}^{S}\mu_s f_{so}^{M}+\sum_{q=1}^{Q}\zeta_q x_{qo}^{3M}}$$

$$\beta_2=\frac{\sum_{t=1}^{T}\varphi_t z_{to}^{M}}{\sum_{i=1}^{I}\gamma_i x_{io}^{M}+\sum_{t=1}^{T}\varphi_t z_{to}^{M}+\sum_{s=1}^{S}\mu_s f_{so}^{M}+\sum_{q=1}^{Q}\zeta_q x_{qo}^{3M}}$$

$$\beta_3=\frac{\sum_{s=1}^{S}\mu_s f_{so}^{M}+\sum_{q=1}^{Q}\zeta_q x_{qo}^{3M}}{\sum_{i=1}^{I}\gamma_i x_{io}^{M}+\sum_{t=1}^{T}\varphi_t z_{to}^{M}+\sum_{s=1}^{S}\mu_s f_{so}^{M}+\sum_{q=1}^{Q}\zeta_q x_{qo}^{3M}}$$

$$\delta_1=\frac{\sum_{t=1}^{T}\varphi_t z_{to}^{U}}{\sum_{i=1}^{I}\gamma_i x_{io}^{U}+\sum_{t=1}^{T}\varphi_t z_{to}^{U}+\sum_{s=1}^{S}\mu_s f_{so}^{U}+\sum_{q=1}^{Q}\zeta_q x_{qo}^{3U}}$$

$$\delta_2=\frac{\sum_{t=1}^{T}\varphi_t z_{to}^{U}}{\sum_{i=1}^{I}\gamma_i x_{io}^{U}+\sum_{t=1}^{T}\varphi_t z_{to}^{U}+\sum_{s=1}^{S}\mu_s f_{so}^{U}+\sum_{q=1}^{Q}\zeta_q x_{qo}^{3U}}$$

$$\delta_3=\frac{\sum_{s=1}^{S}\mu_s f_{so}^{U}+\sum_{q=1}^{Q}\zeta_q x_{qo}^{3U}}{\sum_{i=1}^{I}\gamma_i x_{io}^{U}+\sum_{t=1}^{T}\varphi_t z_{to}^{U}+\sum_{s=1}^{S}\mu_s f_{so}^{U}+\sum_{q=1}^{Q}\zeta_q x_{qo}^{3U}}$$

The linear form of models (4), (5), and (6) can be expressed as follows:

$$\begin{aligned}
&E_o^{*U}=Max\sum_{t=1}^{T}\varphi_t z_{to}^{U}-\sum_{b=1}^{B}\kappa_b u_{bo}^{U}+\sum_{s=1}^{S}\mu_s f_{so}^{U}-\sum_{r=1}^{R}\rho_r w_{ro}^{L}+\sum_{n=1}^{N}\eta_n v_{no}^{U}-\sum_{d=1}^{D}\lambda_d y_{do}^{L}\\
&S.t.\\
&\sum_{i=1}^{I}\gamma_i x_{io}^{L}+\sum_{t=1}^{T}\varphi_t z_{to}^{L}+\sum_{s=1}^{S}\mu_s f_{so}^{L}+\sum_{q=1}^{Q}\zeta_q x_{qo}^{3L}=1,\\
&\sum_{t=1}^{T}\varphi_t z_{tj}^{U}-\sum_{i=1}^{I}\gamma_i x_{ij}^{L}-\sum_{b=1}^{B}\kappa_b u_{bj}^{L}\le 0, j=1,\dots,J,\\
&\sum_{s=1}^{S}\mu_s f_{sj}^{U}-\sum_{r=1}^{R}\rho_r w_{rj}^{L}-\sum_{t=1}^{T}\varphi_t z_{tj}^{L}\le 0, j=1,\dots,J,\\
&\sum_{n=1}^{N}\eta_n v_{nj}^{U}-\sum_{d=1}^{D}\lambda_d y_{dj}^{L}-\sum_{s=1}^{S}\mu_s f_{sj}^{L}-\sum_{q=1}^{Q}\zeta_q x_{qj}^{3L}\le 0, j=1,\dots,J,\\
&\sum_{t=1}^{T}\varphi_t z_{tj}^{L}-\sum_{b=1}^{B}\kappa_b u_{bj}^{U}\ge 0, j=1,\dots,J,\\
&\sum_{s=1}^{S}\mu_s f_{sj}^{L}-\sum_{r=1}^{R}\rho_r w_{rj}^{U}\ge 0, j=1,\dots,J,\\
&\sum_{n=1}^{N}\eta_n v_{nj}^{L}-\sum_{d=1}^{D}\lambda_d y_{dj}^{U}\ge 0, j=1,\dots,J,\\
&\varphi_t,\gamma_i,\mu_s,\rho_r,\eta_n,\lambda_d,\zeta_q,\kappa_b\ge 0,\forall t,i,s,r,n,d,q,b.
\end{aligned}\tag{8}$$

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$$
\begin{aligned}
&E_o^{*M} = Max \sum_{t=1}^{T} \varphi_t z_{to}^M - \sum_{b=1}^{B} \kappa_b u_{bo}^M + \sum_{s=1}^{S} \mu_s f_{so}^M - \sum_{r=1}^{R} \rho_r w_{ro}^M + \sum_{n=1}^{N} \eta_n v_{no}^M - \sum_{d=1}^{D} \lambda_d y_{do}^M \\
&S.t. \\
&\sum_{i=1}^{I} \gamma_i x_{io}^M + \sum_{t=1}^{T} \varphi_t z_{to}^M + \sum_{s=1}^{S} \mu_s f_{so}^M + \sum_{q=1}^{Q} \zeta_q x_{qo}^{3M} = 1, \\
&\sum_{t=1}^{T} \varphi_t z_{tj}^U - \sum_{i=1}^{I} \gamma_i x_{ij}^L - \sum_{b=1}^{B} \kappa_b u_{bj}^L \le 0, j = 1, \ldots, J, \\
&\sum_{s=1}^{S} \mu_s f_{sj}^U - \sum_{r=1}^{R} \rho_r w_{rj}^L - \sum_{t=1}^{T} \varphi_t z_{tj}^L \le 0, j = 1, \ldots, J, \\
&\sum_{n=1}^{N} \eta_n v_{nj}^U - \sum_{d=1}^{D} \lambda_d y_{dj}^L - \sum_{s=1}^{S} \mu_s f_{sj}^L - \sum_{q=1}^{Q} \zeta_q x_{qj}^{3L} \le 0, j = 1, \ldots, J, \\
&\sum_{t=1}^{T} \varphi_t z_{tj}^L - \sum_{b=1}^{B} \kappa_b u_{bj}^U \ge 0, j = 1, \ldots, J, \\
&\sum_{s=1}^{S} \mu_s f_{sj}^L - \sum_{r=1}^{R} \rho_r w_{rj}^U \ge 0, j = 1, \ldots, J, \\
&\sum_{n=1}^{N} \eta_n v_{nj}^L - \sum_{d=1}^{D} \lambda_d y_{dj}^U \ge 0, j = 1, \ldots, J, \\
&\varphi_t, \gamma_i, \mu_s, \rho_r, \eta_n, \lambda_d, \zeta_q, \kappa_b \ge 0, \forall t, i, s, r, n, d, q, b.
\end{aligned}
\tag{9}
$$

$$
\begin{aligned}
&E_o^{*L} = Max \sum_{t=1}^{T} \varphi_t z_{to}^L - \sum_{b=1}^{B} \kappa_b u_{bo}^U + \sum_{s=1}^{S} \mu_s f_{so}^L - \sum_{r=1}^{R} \rho_r w_{ro}^U + \sum_{n=1}^{N} \eta_n v_{no}^L - \sum_{d=1}^{D} \lambda_d y_{do}^U \\
&S.t. \\
&\sum_{i=1}^{I} \gamma_i x_{io}^U + \sum_{t=1}^{T} \varphi_t z_{to}^U + \sum_{s=1}^{S} \mu_s f_{so}^U + \sum_{q=1}^{Q} \zeta_q x_{qo}^{3U} = 1, \\
&\sum_{t=1}^{T} \varphi_t z_{tj}^U - \sum_{i=1}^{I} \gamma_i x_{ij}^L - \sum_{b=1}^{B} \kappa_b u_{bj}^L \le 0, j = 1, \ldots, J, \\
&\sum_{s=1}^{S} \mu_s f_{sj}^U - \sum_{r=1}^{R} \rho_r w_{rj}^L - \sum_{t=1}^{T} \varphi_t z_{tj}^L \le 0, j = 1, \ldots, J, \\
&\sum_{n=1}^{N} \eta_n v_{nj}^U - \sum_{d=1}^{D} \lambda_d y_{dj}^L - \sum_{s=1}^{S} \mu_s f_{sj}^L - \sum_{q=1}^{Q} \zeta_q x_{qj}^{3L} \le 0, j = 1, \ldots, J, \\
&\sum_{t=1}^{T} \varphi_t z_{tj}^L - \sum_{b=1}^{B} \kappa_b u_{bj}^U \ge 0, j = 1, \ldots, J, \\
&\sum_{s=1}^{S} \mu_s f_{sj}^L - \sum_{r=1}^{R} \rho_r w_{rj}^U \ge 0, j = 1, \ldots, J, \\
&\sum_{n=1}^{N} \eta_n v_{nj}^L - \sum_{d=1}^{D} \lambda_d y_{dj}^U \ge 0, j = 1, \ldots, J, \\
&\varphi_t, \gamma_i, \mu_s, \rho_r, \eta_n, \lambda_d, \zeta_q, \kappa_b \ge 0, \forall t, i, s, r, n, d, q, b.
\end{aligned}
\tag{10}
$$

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To defuzzify the overall efficiency score of the system, we use the following method:

$$E_o^{*Overall} = \frac{E_o^{*L} + 4E_o^{*M} + E_o^{*U}}{6} \tag{11}$$

4 Research Methodology

The research was conducted using a library and documentary method, and the non-parametric approach was employed with the help of GAMS software. The required information and statistics for this research were collected from the Planning Management Unit of the oil and gas exploitation centers in the country. The data used in this research were selected using the Fuzzy Delphi Method (FDM), which was introduced by Ishikawa and colleagues in 1993. FDM is a structured communication approach that combines fuzzy set theory and the Delphi method to assess experts' linguistic preferences during decision-making. This method addresses the high execution costs and the risk of filtering unique expert opinions by organizers, which is less frequently achieved with the conventional Delphi approach.

To resolve some uncertainties, the Delphi Consensus Panel, FDM, which integrates the Delphi Consensus Panel and Fuzzy Set Theory (FST), and membership degree to determine the membership function for each participant, is used. Therefore, FDM can be used to assess the importance of parameters and screen key criteria [29].

In the first step, to determine the key evaluation criteria of exploitation centers' performance, 35 criteria were extracted as inputs and 33 criteria as outputs using the research literature. The Fuzzy Delphi Method was used to select the most important input and output criteria. The first stage of this process is selecting experts. Given the research domain, 20 experts in the oil and refining industry and university professors were selected. Next, questionnaires were sent to the experts, and after completion, the collected results of the first round were sent back to them in the form of a questionnaire. After reviewing the initial results and receiving feedback, they were asked to provide their opinions again. After collecting and analyzing the experts' opinions in the second round, the mean difference is examined. If this difference is less than 0.2, consensus is reached, and the Fuzzy Delphi stages are completed. Otherwise, the results of this round are re-analyzed and sent to the experts again. This back-and-forth process continues until the experts reach a consensus on all criteria. If the experts decide to add a criterion in these rounds, it is added to the next questionnaire, and opinions on this criterion are collected.

Finally, to validate and screen the criteria, the acquired value of each criterion is compared with the threshold value. The threshold value is calculated in several ways, but generally, a value of 0.7 is considered the threshold [30] . For this purpose, the triangular fuzzy numbers of the experts' opinions are calculated first, and then the fuzzy average of the n respondents' opinions is estimated to calculate the mean of opinions. In this study, Table 3 below was used to convert linguistic terms into triangular fuzzy numbers:

Table 3 Linguistic Terms and Their Fuzzy Values Based on the 5-Point Likert Scale

Linguistic Term	Fuzzy Value
Very important	(0.75, 0.75,1)
important	(0.50,0.75,1)

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Relatively important	(0.25, 0.50, 0.75)
unimportant	(0.00,0.25,0.50)
Very unimportant	(0.00,0.00,0.25)

In the next phase, the efficiency of the units within the oil and gas exploitation centers will be assessed using the Fuzzy Data Envelopment Analysis (DEA) network model, with the principle of weak disposability. This approach will provide a comprehensive evaluation of the performance of each unit, considering both desirable and undesirable outputs and addressing the inherent uncertainties in the data through fuzzy logic. This method allows for a more accurate and realistic analysis, ensuring that the operational efficiency of each unit is effectively measured and compared.

5 Findings

In the first round of the Fuzzy Delphi Method, we began with a thorough review of existing literature and the outcomes of previous research. We carefully examined the input and output concepts relevant to evaluating the efficiency of oil and gas exploitation units, considering inputs, desirable outputs, and undesirable outputs from various perspectives. Among 35 inputs and 33 outputs, priorities or importance levels of different indices were determined using a questionnaire to collect expert opinions.

The questionnaire was designed using a five-option Likert scale to determine the relative importance of each index. In each perspective, indices with the highest average importance were selected. The results indicated that among the 35 inputs and 33 outputs, the first-stage inputs include the number of personnel, research and development costs, total unit costs, environmental protection costs, and production capacity.

The first-stage outputs, which are actually inputs for the second stage, include oil and gas. The second-stage outputs, which are somewhat inputs for the third stage, include oil, gas, electricity or diesel consumed by turbines, and energy payment costs. In some cases, second-stage outputs may also include pollutant gases. Finally, the third-stage outputs, which are of higher importance compared to other indices, include environmental pollutants (CO_2, SO_2), and pure oil and gas.

In the second round, to calculate the importance of the criteria for evaluating the performance of oil exploitation centers from experts' perspectives, a questionnaire was sent again to 20 university experts, asking them to provide their opinions. Given that the average difference in expert opinions in this round is less than 0.2, consensus was achieved, and the above criteria were identified as essential for evaluating the performance of oil and gas exploitation centers. Figure 2 shows the inputs and outputs obtained through the Fuzzy Delphi Method in the three-stage model, while Figure 3 displays the efficiency of the units in the three stages and the overall efficiency.

This methodology ensures that the most important criteria are accurately identified and used for the comprehensive evaluation of the performance of oil and gas exploitation centers.

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Table 4 Results of the Second Round of the Fuzzy Delphi Method for Selecting Performance Evaluation Criteria for Oil Exploitation Centers

linguistic Term	**Very Low**	**Low**	**Medium**	**High**	**Very High**	**Average Expert Opinions**	**Difference in Average Expert Opinions**	**Approval/ Rejection**	
Criterion Code	**Criterion - Fuzzy Value**	**(0.0, 0.0, 0.25)**	**(0.0, 0.25, 0.50)**	**(0.25, 0.50, 0.75)**	**(0.50, 0.75, 1.0)**	**(0.75, 0.75, 1.0)**	**-**	--	--
1	Number of Personnel	4	7	5	4	0	0.5	0.8	Approved
2	Assets	3	5	5	5	2	0.6	0.1	Rejected
3	Total Cash and Short-term Investments	0	1	4	8	7	0.6	0.1	Rejected
4	Total Liabilities	1	1	4	6	8	0.5	0.1	Rejected
5	Asset-to-Debt Ratio	3	1	4	3	1	0.4	0.9	Rejected
6	Comprehensive Energy Consumption per Output Unit	4	5	5	6	1	0.6	0.1	Rejected
7 . . .	Total Cost per Unit	1	0	2	7	10	0.8	0.12	Approved
66	Overall Organizational Value	7	4	5	4	0	0.5	0.1	Rejected
67	Production Volume	1	1	6	7	5	0.9	0.1	Approved
68	Toxic Emissions (CO2, SO2)	1	2	2	7	8	0.8	0.1	Approved

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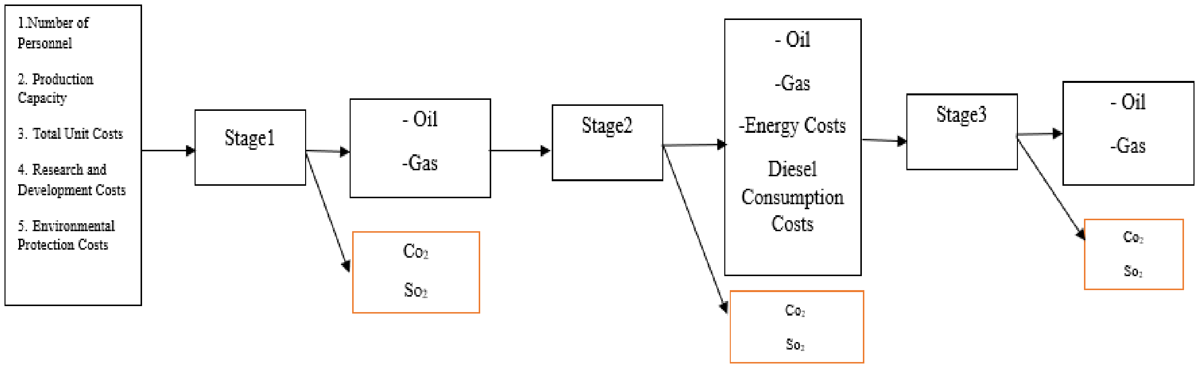

Fig. 2 Inputs and Outputs of the Three-Stage Model

Table 5 Variables Considered by Experts for Evaluating the Efficiency of Oil Exploitation Centers

Variable	Unit of Measurement	Average	Max	Min	S. D
- Number of Personnel	(Person)	7859	9892	5208	1699
Research and Development Costs	(Billion Tomans)	4082.22	4689.72	3685.4	332.3468
Total Unit Costs	(Billion Tomans)	133258.889	163328.41	106134.9	17914.3227
Environmental Protection Costs	(Billion Tomans)	32.888	37.95	27.43	3.1071
Production Capacity	(Barrels)	636703472.6	69392011	59208047	3630440.94
Second Stage Oil	(Liters)	615355227.1	678920275	440591598	65451048.92
Second Stage Gas	(Liters)	426498.44	479921	363104	35333.741
Diesel Consumption of Turbines	(BTU)	45425531.44	68994051	32969082	10705923.36
Energy Payment Costs	(Million Tomans)	4867.89	7733.531	2557.853	1868.735
CO_2 Emissions	(Kilograms)	1429560.24	2471218.788	122379.1989	854440.306
SO_2 Emissions	(Kilograms)	6548825.57	10054452.22	239763.1862	3116328.29
Pure Oil	(Barrels)	415355227.1	49920275	280591598	42451048.92
Pure Gas	(Liters)	42539	47595	37242	4041.804

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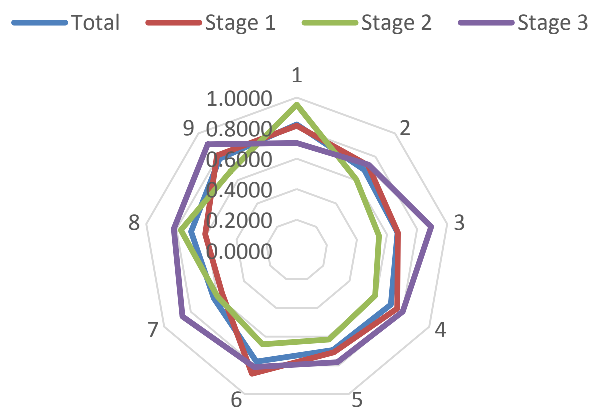

Fig. 3 Efficiency of Units

Table 6 Efficiency of Units in Fuzzy Conditions

	Total			EOL			EOM			EOU		
	EOL	EOM	EOU	Stage1	Stage2	Stage3	Stage1	Stage2	Stage3	Stage1	Stage2	Stage3
1	0.7441	0.811	0.9583	0.7177	0.9134	0.6094	0.7947	0.9511	0.6854	1	1	0.8676
2	0.6355	0.684	0.7494	0.6842	0.5561	0.6502	0.7258	0.6091	0.7128	0.7719	0.6383	0.8939
3	0.6126	0.6698	0.7286	0.594	0.5221	0.8322	0.6737	0.5485	0.8806	0.7414	0.5656	1
4	0.6664	0.7058	0.7678	0.7245	0.5477	0.731	0.7496	0.5976	0.7892	0.8281	0.6137	0.9138
5	0.6308	0.689	0.7732	0.6443	0.5754	0.6853	0.6995	0.6197	0.7767	0.8109	0.6636	0.8772
6	0.7047	0.7746	0.8408	0.7218	0.6396	0.769	0.8561	0.654	0.8133	1	0.6715	0.8492
7	0.5665	0.6256	0.6903	0.5107	0.5535	0.753	0.5642	0.5954	0.8592	0.6069	0.6578	0.995
8	0.653	0.7008	0.7541	0.5639	0.7385	0.7395	0.6077	0.7666	0.8146	0.6505	0.8085	0.8981
9	0.7164	0.7752	0.8848	0.7093	0.6495	0.828	0.7867	0.6743	0.9032	1	0.6936	1

Table 7 Efficiency of Units in DE fuzzified Conditions Across Different Stages and Final Efficiency

Unit	Total	Stage 1	Stage 2	Stage 3
1	0.8244	0.8161	0.9530	0.7031
2	0.6868	0.7266	0.6051	0.7326
3	0.6701	0.6717	0.5470	0.8924
4	0.7096	0.7585	0.5920	0.8003
5	0.6933	0.7089	0.6196	0.7782
6	0.7740	0.8577	0.6545	0.8119
7	0.6265	0.5624	0.5988	0.8641
8	0.7017	0.6075	0.7689	0.8160
9	0.7837	0.8094	0.6734	0.9068

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In Table 7, the efficiency calculation results for the oil and gas exploitation centers are presented. As observed, none of the exploitation centers have achieved an efficiency score of 1. The highest efficiency is related to Unit 1, with a value of 0.8244. Although the overall efficiency is derived from the efficiency of each stage, the efficiency in the first stage was 0.8161, and in the second stage, it was 0.9530. However, the decrease in efficiency in the third stage, which was 0.7031 led to a reduction in the unit's overall efficiency. Therefore, it is necessary for Unit 1 to take necessary actions in the third stage of oil exploitation and refining to increase efficiency.

Furthermore, the lowest efficiencies are related to Units 7, 3, and 2, where the efficiency of individual stages has led to an overall decrease in efficiency. Therefore, considering the decrease in the efficiency of units in each stage, it is necessary to implement appropriate measures related to each stage in each unit. One of the most important reasons for the inefficiency of units is the sanctions preventing the purchase and equipping of machinery and equipment related to oil exploitation and the production of pure oil and gas from the extracted materials from underground.

This explanation highlights the importance of addressing specific stages in the process to improve overall efficiency and tackles the external challenges faced by these units.

6 Conclusion and Suggestions

This analysis offers several contributions to current research, combining different techniques for analyzing productivity and efficiency and aiding managers in their decision-making process. It also opens up opportunities for new advancements, such as integrating multi-criteria analyses with environmental, social, and economic aspects into the efficiency analysis developed in this work Understanding the performance of exploitation centers over specific time periods is the first step towards implementing sustainable actions. A refinery with less than minimum efficiency in operations cannot be considered environmentally responsible.

In this study, the efficiency of oil and gas exploitation centers in Khuzestan Province was measured using the Fuzzy Network Data Envelopment Analysis method, considering undesirable outputs with the principle of weak disposability. The research calculations revealed that none of the oil and gas exploitation centers are efficient and they contribute significantly to environmental pollution. However, the efficiency of Unit 1 is higher than that of the other units. The overall efficiency is derived from the efficiency of three stages, which significantly impacts the total efficiency. The higher efficiency value can be attributed to the equipment, costs, and production capacity of the center.

Currently, most exploitation centers process heavy oil, resulting from excessive extraction from oil wells. For better performance, it is recommended to upgrade the equipment for extracting and refining heavy crude oil or initially refine heavy oil to light oil. One of the main factors reducing the efficiency of exploitation centers is the use of diesel in machinery for heavy oil refining, which is a major cause of environmental pollution. Replacing diesel with natural gas or liquefied gas can reduce the pollution percentage. Additionally, the amount of crude oil extracted for domestic consumption exceeds the need, somewhat reducing the efficiency of the centers. Therefore, to increase efficiency and reduce environmental pollution, it is recommended to establish more exploitation centers and use modern, environmentally-friendly equipment to minimize pollution.

Advanced instrumentation and control systems have emerged as key tools in achieving these dual goals. They enable operators to optimize production processes, enhance safety, and

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ensure compliance with regulations. These systems play a critical role at every stage of oil and gas production, from exploration and drilling to refining and distribution. They provide real-time monitoring and control of key parameters such as temperature, pressure, flow rates, and chemical composition, allowing operators to make informed decisions that optimize production and minimize downtime. Moreover, advanced systems can detect potential equipment anomalies and failures early, enabling preventive maintenance and reducing the risk of costly shutdowns.

One of the primary advantages of advanced instrumentation and control systems is their ability to improve process optimization. By continuously monitoring and analyzing production data, these systems can identify inefficiencies and areas for improvement, leading to increased production rates and reduced operational costs. Regarding labor costs and research and development, it can be argued that due to sanctions, reduced export capacity, and the inability of the country to refine heavy oil into light oil and petroleum derivatives, the revenues are not sufficient to cover the costs associated with labor and maintenance of old machinery, resulting in reduced efficiency over various stages.

In conclusion, it is necessary to note that oil exploitation for export and domestic use is inevitable. Therefore, the process cannot be reduced or stopped merely due to the creation of pollutants. Instead, the process of oil exploitation and extraction should be directed towards minimizing the production of toxic pollutants by using appropriate and up-to-date equipment. Filters can be used to minimize the emission of harmful pollutants and reduce noise pollution caused by machinery and equipment.

This research, like other studies, faced challenges and limitations, with the most important ones being access to information on greenhouse gases and the costs of each unit. Furthermore, the information was examined at a specific point in time, so it is recommended to use panel data methods over a 10-year period to evaluate unit efficiency. Environmental and social aspects were not considered in this analysis because they require subjective evaluations from decision-makers and experts and defining relevant criteria to make their development more reliable.

It is suggested to analyze social and sustainable factors in the oil and gas industry, particularly the exploitation centers and supply chain, using other DEA approaches such as Malmquist. Awareness of the performance of exploitation centers based on time periods is the first step towards considering sustainable actions. In most analyzed periods, there will be significant differences between technical efficiency data and the profits and losses between periods in each refinery, with technological advancements providing more discrete changes in values.

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