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Green Efficiency of an Energy Supply Chain: A Multi-Stage Network DEA Application to Iranian Petrochemicals

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ABSTRACT

Objective: This study aims to evaluate the greenness and efficiency of the Iranian petrochemical supply chain, a sector that plays a vital role in both economic performance and environmental sustainability. Despite its importance, limited studies have comprehensively analyzed this industry's efficiency using multi-dimensional and uncertainty-sensitive approaches.

Methods: To address this issue, an integrated Network Data Envelopment Analysis (NDEA) framework combined with the Fuzzy Delphi Method was developed to assess the performance of ten leading petrochemical companies in Iran. Seventeen evaluation criteria were identified and validated, and the companies were analyzed under optimistic and pessimistic scenarios to capture a balanced and realistic view of their efficiency.

Results: The findings revealed that only a few companies were efficient under both scenarios, while others exhibited inefficiencies due to high environmental costs, excessive employment, and poor-quality management systems. Sensitivity analysis showed that reducing undesirable outputs and optimizing dual-role variables significantly improves performance. Efficient companies should also focus on sustaining competitiveness by optimizing their pessimistic efficiency scores.

Conclusion: The results suggest that the proposed NDEA–Delphi approach provides a comprehensive and realistic tool for assessing the green efficiency of industrial supply chains. This framework can support decision-makers in identifying improvement areas, reducing resource waste, and developing environmentally responsible operational strategies in the petrochemical sector.

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Introduction

In the global economy, the petrochemical industry plays a significant role in supplying the world's chemical product demand. This industry operates in a variety of countries within competitive business environments. The petrochemical industries are typically large corporations with diverse stakeholders actively managing their supply chains. This sector focuses on the manufacturing of chemicals from petroleum as well as chemicals extracted from petroleum refinery byproducts. In addition to supporting many other industries, including agriculture, automobiles, construction, and pharmaceuticals, the petrochemical industry contributes significantly to the economy of both developed and developing countries. It is estimated that 96 percent of all manufactured goods have traces of chemical manufacturing, according to the American Chemistry (Council, 2019). For an industry with a high product mix, multiple raw material suppliers, and multiple markets, it is vital to maintain the efficiency of operations throughout the supply chain to remain competitive. This realization has led to increasing recognition of the importance of good supply chain management practices within the petrochemical industry (Yakideh & Moradi, 2023). This is particularly true with the increasing importance of logistics in the chemical manufacturing industry, becoming ever more apparent as the cost of logistics in chemicals is rapidly outstripping the cost of other operating expenses (Z. Wang & Fan, 2024).

Compared to other industries, supply chain management in the petrochemical sector poses distinct challenges that require technically complex supply chain solutions (Abbood, 2025; Sayardoost Tabrizi et al., 2024). Petrochemical facilities run on a continuous production line, creating a stream of goods such as plastics, soaps, fertilizers, and paints that are produced from crude oil (Z. Wang & Fan, 2025). The raw materials for these products are continually supplied, and their delivery is scheduled to ensure that manufacturing is not interrupted. Petrochemical goods are packed in various configurations to accommodate multiple means of transportation, and they are often flammable or toxic, necessitating careful handling. Similar logistical complexities are also observed in other large-scale supply chains, where optimization models such as multi-cross-docking rescheduling can play a vital role in enhancing efficiency (Sahebi et al., 2024). The enduring necessity to maintain uninterrupted operation of the plants and continuous delivery of finished goods is the culprit of much of the complexity that prevails within the management of the supply chain for petrochemicals (Sayardoost Tabrizi et al., 2025). Because of the dynamic nature of the sector, it is challenging to establish reliable forecasting and schedule the logistics of sourcing, delivery, and transportation.

To achieve continuous production in the petrochemical industry, selecting the chemical process route is a key design decision in the early phases of chemical plant development and design. Economic considerations used to be the primary factor in selecting the chemical process method. However, environmental risk and industrial safety in the development of petrochemical supply chains have recently become two of the most critical planning objectives for the petrochemical industry. This is attributed to recent overarching concerns of global warming and increasing awareness of the size of environmental pollution generated by petrochemical industries. As a result of the potential for harmful environmental impacts caused by the petrochemical sector, environmental concerns, particularly the green supply chain efficiency of this sector, have risen to the forefront of national and international strategic policy-making (Yakideh et al., 2024). This is similar to the trend in governmental regulation of environmental standards and the growing demand of consumers for green products in the supply chain, which includes the product flow from raw materials to the delivery of goods to end-consumers along with information flow across the supply chain, have led to the emergence of the "green supply chain management" concept (Ghasemian Sahebi et al., 2024; Z. Wang & Fan, 2025).

There has been a scarcity of research on petrochemical supply chain management (Abbood, 2023; Wang & Fan, 2024). Notably, research on understanding the environmental ramifications of the petrochemical industry is limited (Sayardoost Tabrizi et al., 2025; Yakideh et al., 2024). For example, (Sayardoost Tabrizi et al., 2025) focused on ranking the petrochemical industry suppliers in a circular supply chain. (Z. Wang & Fan, 2025) researched the petrochemical industry's adoption of green technologies and DEA-based evaluations to facilitate more environmentally friendly processes. Similar multi-criteria decision-making approaches, such as Fuzzy ISM–DEMATEL, have been effectively applied to identify and prioritize sustainability barriers in renewable energy supply chains (Ghasemian Sahebi et al., 2024), offering methodological insights for petrochemical sector studies. Due to the scarcity and uncertainty of data on many chemical production processes, (Yakideh & Moradi, 2023) estimated crucial production parameters to shed light on the environmental performance of a chemical manufacturing process by employing mass and energy flow data.

While existing studies provided insights into issues related to the sustainability of the petrochemical industry, they are limited in scope and number. Due to the complexity of the petrochemical supply chain, analyzing performance and decision-making is very challenging. Similar methodological approaches have also been successfully applied in Iranian industries, such as service productivity evaluation with DEA-based methods (Etezadi et al., 2023) and efficiency assessment using the Malmquist productivity index (Habibpoor et al., 2022), which further highlights the potential of DEA-based frameworks for assessing environmental efficiency. There is a need for holistic decision-support tools to assist decision-making in the context of the green efficiency of the petrochemical supply chain. Thus, the novelty of this study lies not in proposing a new methodological framework but in its innovative application of an integrated Fuzzy Delphi–NDEA approach to the Iranian petrochemical supply chain, providing a comprehensive and context-specific assessment of green efficiency. Thus, this study seeks to answer the following questions:

RQ (1): How can a relevant set of key performance evaluation criteria for the petrochemical supply chain be determined?

RQ (2): How can the efficiency of the petrochemical supply chain be evaluated under qualitative and imprecise criteria?

The rest of this manuscript is organized as follows: Section 2 reviews previous studies on the efficiency assessment of petrochemical supply chains. Section 3 presents the NDEA model. Section 4 discusses the results. Section 5 elaborates on the results and highlights managerial implications. Section 6 concludes this paper and highlights future research directions.

Literature Background

This section: a) reviews key prior studies pertinent to the petrochemical supply chain management and places these research contributions in context, b) provides theoretical backgrounds of DEA and NDEA models, and c) reviews previous studies utilizing the DEA technique and highlights its application to petrochemical supply chains. In this section, we outline the research gap in prior studies and briefly highlight DEA and its extension, NDEA, as an appropriate method for assessing the efficiency of petrochemical supply chains.

Petrochemical companies and supply chains rely on the steady flow of materials, whereas manufacturing companies are primarily engaged in discrete production processes (Louw & Pienaar, 2011). Petrochemical supply chains add value to materials by mixing, separating, forming, or purifying them through chemical reactions (Lima et al., 2016). Because of its steady modes of production, size, and complexity, as well as its economic and social relevance, the petroleum sector involves a highly complex supply chain (Lababidi et al., 2004). Due to its complexity, recently, there has been growing attention among scholars and policymakers to focus on efficient supply chain operations and green technologies in petrochemical supply chains (see also studies on carbon emission costs in supply chain contracts: (Zegordi & Shahidi, 2023); and green routing networks in food logistics: (Pashang et al., 2025) to maximize environmental efficiency and reduce costs (Sayardoost Tabrizi et al., 2024; Z. Wang & Fan, 2025).

The supply chain of the petroleum industry is very complex compared to other industries. It is divided into two different, yet closely related, major segments: the upstream and downstream supply chains. The upstream supply chain involves the acquisition of crude oil, which is the specialty of the oil companies. The upstream process includes the exploration, forecasting, production, and logistics management of delivering crude oil from remotely located oil wells to refineries. The downstream supply chain starts at the refinery, where the crude oil is manufactured into the consumable products that are the specialty of refineries and petrochemical companies. The downstream supply chain involves the process of forecasting, production, and logistics management of delivering crude oil derivatives to customers around the globe. Challenges and opportunities exist now in upstream and downstream supply chains (Abbood, 2025; Hussain et al., 2006).

While there have been several studies on performance evaluation and efficiency assessment of the petrochemical industry, these studies are limited in scope and number. This research focuses on the efficiency assessment of petrochemical supply chains using data envelopment analysis. Recent advancements also highlight the integration of machine learning and multi-stage network DEA better to address uncertainties and dynamic conditions in petrochemical operations (Yakideh & Moradi, 2023). In addition, recent contributions have explored the role of blockchain adoption in supporting green supply chains (Sadeghi et al., 2023), providing insights into how technological innovation can complement DEA-based evaluations. The following sections summarize data envelopment analysis before delving into its application to the petrochemical supply chain. Table 1 summarizes previous studies utilizing the DEA technique in petrochemical supply chains.

Table 1. A summary of DEA models applied to the petrochemical industry

No.	Title	Reference	Type Of DEA	undesirable output	Case Study
1	Sustainability-oriented modelling of petrochemical logistics processes	(Abbood, 2025)	NDEA	✓	Petrochemical logistics
2	Green DEA-based sustainability evaluation for international petrochemical supply chains	(Z. Wang & Fan, 2025)	Green DEA	✓	International petrochemical supply chain
3	Clustering with machine learning and using NDEA in development planning: A case study in the petrochemical two-stage sustainable supply chain	(Sayardoost Tabrizi et al., 2024)	NDEA	✓	Petrochemical supply chain
4	Assessing the sustainability of supply chain performance using machine learning and network DEA	(Yakideh & Moradi, 2023)	NDEA-ML	✓	Petrochemical supply chain
5	A new Fuzzy DEA model for green supplier evaluation considering undesirable outputs	(H. Wang et al., 2020)	FDEA	✓	Simulated data
6	Developing a Double Frontier Version of the Dynamic Network DEA Model: Assessing Sustainability of Supply Chains	(Samavati et al., 2020)	DNDEA	×	Bumpers supply chain
7	A novel network DEA-R model for evaluating hospital services supply chain performance	(Gerami et al., 2020)	NDEA	×	Hospitals supply chain

8	A supplier performance evaluation framework using single and bi-objective DEA efficiency modeling approach: individual and cross-efficiency perspective	(Goswami & Ghadge, 2020)	DEA	✓	Steel supply chain
9	Measuring and improving adaptive capacity in resilient systems using an integrated DEA-Machine learning approach	(Salehi et al., 2020)	DEA-MLP	×	Simulated data
10	An integrated weighting and ranking model based on entropy, DEA, and PCA, considering two aggregation approaches for the resilient supplier selection problem	(Davoudabadi et al., 2020)	DEA	×	Simulated data
11	Green Supplier Selection Based on DEA Model in Interval-Valued Pythagorean Fuzzy Environment	(Wu et al., 2019)	DEA in IVPFE	×	Simulated data
12	Evaluating green suppliers: Improving supplier performance with DEA in incomplete data.	(Dobos & Vörösmarty, 2019)	DEA	×	Simulated data
13	Performance Management of Supply Chain Sustainability in Small and Medium-Sized Enterprises Using a Combined Structural Equation Modelling and Data Envelopment Analysis	(Dey et al., 2019)	DEA	×	Simulated data
14	A new DEA model for evaluation of supply chains: A case of selection and assessment of environmental efficiency of suppliers	(Krmac & Djordjević, 2019)	Non-radial DEA	✓	Simulated data
15	Assessing the sustainability of supply chains by a chance-constrained two-stage DEA model in the presence of undesirable factors	(Izadikhah & Saen, 2018)	NDEA	✓	Pasta supply chain
16	Supply chains' performance with undesirable factors and reverse flows: A DEA-based approach.	(Jahani Sayyad Noveiri et al., 2018)	Radial DEA	×	Textile supply chains
17	Green Efficiency Analysis of Longan Supply Chains: A Two-Stage DEA Approach	(Panmanee et al., 2018)	NDEA	×	Steel supply chain
18	Performance Evaluation in Green Supply Chain using BSC, DEA, and Data Mining	(Khalili & Alinezhad, 2018)	DEA-based MPI	×	Simulated data
19	Supplier selection study under the respect of the low-carbon supply chain: A hybrid evaluation model based on FA-DEA-AHP	(He & Zhang, 2018)	DEA	×	Steel supply chain
20	Sustainability evaluation of the supply chain with undesired outputs and dual-role factors based on double frontier network DEA	(Su & Sun, 2018)	NDEA	✓	Tea supply chain

Note: Type of DEA Column: FDEA: Fuzzy DEA, DNDEA: Dynamic Network DEA, NDEA: Network DEA, MPI: Malmquist Productivity Index, MLP: Multilayer perceptron, IVPFE: Interval-Valued Pythagorean Fuzzy Environment.

The main weaknesses of the studies listed in Table 1 are summarized as follows:

- First: Table 1 shows that all the papers assume the inputs and outputs are deterministic. However, in the real world, there might be incomplete data.
- Second: All the DEA models are radial (i.e., CCR and BCC). The radial DEA models assume the proportional changes of inputs, outputs, and intermediate measures.
- Third: literature treats a DMU as a closed system in which all the outputs enter the next stage as inputs. However, in many cases, outputs might leave the system at one of the stages without entering the next stage. On the other hand, external inputs might enter the network in one of the stages.

Most of the earlier works exploited complete data, and incomplete data (Incompleteness in data can refer to noise in either the input (Shrestha et al., 2019; Tiwari & Naskar, 2017) or in the labels(Nigam et al., 2000; Tsuboi et al., 2008). Also, previous studies mainly employed quantitative criteria, and qualitative criteria have been used less frequently. Therefore, the present study represents one of the first comprehensive applications of NDEA to the performance evaluation of the petrochemical supply chain.

Materials and Methods

The present study is applied research in terms of objectives and descriptive-analytical in terms of data collection. It is mathematical in nature and cross-sectional. This work seeks to evaluate the performance of the petrochemical green supply chain. The statistical population consisted of Iranian petrochemical companies in green production. The study population was Iranian petrochemical companies active in green output, from which 10 leading companies active in green products were selected based on the researcher's familiarity, the availability of information, and admission to the Tehran Stock Exchange. Due to the companies' data confidentiality, their names have not been mentioned. A total of 10 famous green production companies were selected based on the author’s knowledge. Also, nine experts were invited to participate in the study. Table 4 describes the expert panel.

Table 4. Profile of research experts

No.	Position	Level of Education	Experience (year)	Age (year)
1	Managing Director	BSc	15	37
2	Managing Director	BSc	20	43
3	Managing Director	Ph.D.	12	48
4	Managing Director	BSc	25	52
5	Managing Director	MSc	17	46
6	Managing Director	MSc	30	65
7	Managing Director	MSc	19	52
8	Managing Director	MSc	20	56
9	Production manager	Ph.D.	7	30

Energy resources in Iran are the third largest oil reserves and the second largest natural gas reserves in the world (Kazemi et al., 2013). Figure 2 depicts the geographical distribution of the selected companies.

Fig. 2. Geographical distribution of the DMUs

According to the above, this study was conducted in the following steps:

- Performance measurement criteria (input and output variables) were extracted from the literature.
- The extracted criteria were screened using the FDM based on expert opinion to identify measurable criteria in the petrochemical industry.
- Data were collected, and the performance of the green supply chain was evaluated and quantified through the efficiency score.

Data Collection Protocol

Data were collected from ten leading petrochemical companies in Iran through a structured protocol. The firms were selected from the list of petrochemical companies admitted to the Tehran Stock Exchange, with the inclusion criteria being: (i) availability of annual financial and sustainability reports for 2018–2022, (ii) sufficient disclosure of environmental and operational data, and (iii) engagement in green production practices. Companies not meeting these criteria were excluded. Due to confidentiality agreements, the actual company names cannot be disclosed; instead, each company was anonymized and randomly labeled DMU1–DMU10. Quantitative indicators such as energy consumption, environmental costs, and production volumes were obtained from company annual reports, Tehran Stock Exchange disclosures, and sustainability reports covering 2018–2022. Qualitative indicators such as “Supplier Flexibility” and “Customer Satisfaction” were assessed using structured questionnaires rated on a 1–5 Likert scale and validated by the expert panel. Expert judgments were transformed into fuzzy numbers to capture uncertainty. Including objective company data and subjective expert evaluations ensured that all 17 input/output variables were measured transparently and consistently, enhancing the study's replicability.

Fuzzy Delphi Procedure

The Fuzzy Delphi Method (FDM) was employed to validate and finalize the 17 input/output variables used in the study. Nine experts with backgrounds in supply chain management, petrochemical operations, and environmental management participated in a two-round Delphi process. Each expert evaluated the candidate variables using triangular fuzzy numbers (L, M, and U). The fuzzy responses were aggregated and defuzzified using the formula (L + M + U)/3. A threshold of 0.66 was applied, meaning that variables with defuzzified scores above this value were retained. To measure inter-expert agreement, Kendall’s W coefficient was computed and yielded a value of 0.81, indicating strong consensus among experts. After the second round, the procedure converged, selecting 17 final variables (see Appendix B).

NDEA Model Specification

The proposed multi-stage network DEA model was implemented in three configurations: optimistic, pessimistic, and overall evaluation. The models were solved using Lingo 19.0 optimization software, which supports linear and non-linear programming.

The analysis was conducted under a variable return to scale (VRS) assumption to account for scale heterogeneity across the firms. An input-oriented approach was adopted, as the primary managerial interest was identifying potential input reductions while maintaining the same output levels.

Undesired outputs (e.g., CO_2 emissions, environmental waste, and dissatisfied customers) were incorporated into the model by treating them as inputs (i.e., to be minimized). This ensures that higher values of undesirable factors reduce efficiency, consistent with the logic of DEA. Dual-role variables, such as energy consumption efficiency, were modeled according to their functional role in each stage—serving as an output in one stage and an input to the next.

A non-Archimedean infinitesimal constant ($\varepsilon = 10^{-6}$) was used to ensure the feasibility of the linear programming models without affecting efficiency scores. Sensitivity tests with alternative ε values (10^{-4} to 10^{-8}) confirmed that results were stable.

The implementation steps involved:

1. Defining the three sub-stages (suppliers, manufacturers, distributors) and their respective inputs, desirable outputs, and undesirable outputs.
2. Running separate DEA models under optimistic and pessimistic assumptions.
3. Aggregating stage efficiencies to obtain overall network efficiency scores.

This specification ensured consistency across DMUs and robustness of results.

In Table 5, the mathematical description of parameters, variables, and indices of the NDEA-designed model is provided.

Table 5. Designed three-stage NDEA symbols

Description of symptoms	Symptoms
The rth components of the desired output vector for DMU_j flowing from stage *p*, and would not be passed to stage *p*+1	$z_{pr}^{j1^D}$, $r = 1, \dots, R_p$
The rth components of the undesired output vector for DMUj flowing from stage *p*, and would not be passed to stage *p*+1	$z_{pr}^{j1^{UD}}$, $r = 1, \dots, R_p$
The kth components of the output vector for DMUj flowing from stage *p*, and would be passed to stage *p*+1	z_{pk}^{j2} , $k = 1, \dots, K_p$
The ith components of the input vector for DMUj flowing at the stage *p*	z_{pi}^{j3} , $i = 1, \dots, I_p$
The tth components of the dual-role factor vector for DMUj flowing at the stage *p*	y_{pt}^{j4} , $t = 1, \dots, T_p$
The weight for the desired output component $z_{pr}^{j1^D}$ at the stage *p*	u_{pr}
The weight for the undesired output component $z_{pr}^{j1^{UD}}$ at the stage *p*	μ_{pr}
The weight for the output component z_{pk}^{j2} at the stage *p*	η_{pk}
The weight for the input component z_{pi}^{j3} entering the process at the beginning of the stage *p*	υ_{pi}
The weight for the dual-role factor y_{pt}^{j4} when it is treated on the output side	γ_{pt}
The weight for the dual-role factor when it is treated on the y_{pt}^{j4} input side	β_{pt}

Therefore, for $p \geq 2$, the efficiency ratio is calculated as:

$$\theta_p = \frac{\sum_{r=1}^{R_p} u_{pr} z_{pr}^{j1^{UD}} + \sum_{k=1}^{K_p} \eta_{pk}\, z_{pk}^{j2} + \sum_{t=1}^{T_p} \gamma_{pt} y_{pt}^{j4} - \sum_{t=1}^{T_p} \beta_{pt} y_{pt}^{j4}}{\sum_{k=1}^{K_{p-1}} \eta_{p-1,k}\, z_{p-1,k}^{j2} + \sum_{r=1}^{R_p} \mu_{pr} z_{pr}^{j1^{UD}} + \sum_{i=1}^{I_p} \upsilon_{pi} z_{pi}^{j3}} \tag{1}$$

Where $\sum_{r=1}^{R_p} u_{pr} z_{pr}^{j1^{UD}}$ denotes the sum of the desired outputs of DMU_j in stage p, $\sum_{k=1}^{K_p} \eta_{pk}\, z_{pk}^{j2}$ is the sum of the outputs of DMU_j from stage p to stage p+1, $\sum_{t=1}^{T_p} \gamma_{pt} y_{pt}^{j4} - \sum_{t=1}^{T_p} \beta_{pt} y_{pt}^{j4}$ are the outputs of the dual-role factors of DMU_j in stage p, and $\sum_{k=1}^{K_{p-1}} \eta_{p-1,k}\, z_{p-1,k}^{j2} + \sum_{r=1}^{R_p} \mu_{pr} z_{pr}^{j1^{UD}} + \sum_{i=1}^{I_p} \upsilon_{pi} z_{pi}^{j3}$ is the sum of the undesired inputs and outputs of DMU_j In stage p. For p=1, the efficiency ratio is obtained as:

$$\theta_1 = \frac{\sum_{r=1}^{R_1} u_{1r} z_{1r}^{j1^{UD}} + \sum_{k=1}^{K_1} \eta_{1k}\, z_{1k}^{j2} + \sum_{t=1}^{T_1} \gamma_{1t} y_{1t}^{j4} - \sum_{t=1}^{T_1} \beta_{1t} y_{1t}^{j4}}{\sum_{r=1}^{R_1} \mu_{1r} z_{1r}^{j1^{UD}} + \sum_{i=1}^{I_1} \upsilon_{1i} z_{1i}^{j3}} \tag{2}$$

Where $\sum_{r=1}^{R_1} u_{1r} z_{1r}^{j1^{UD}}$ denotes the sum of the desired inputs of DMU_j, $\sum_{k=1}^{K_1} \eta_{1k}\, z_{1k}^{j2}$ is the sum of the outputs of DMU_j from stage 1 to stage p, $\sum_{t=1}^{T_1} \gamma_{1t} y_{1t}^{j4} - \sum_{t=1}^{T_1} \beta_{1t} y_{1t}^{j4}$ is the sum of the outputs of the dual-role factors of DMU_j, and $\sum_{r=1}^{R_1} \mu_{1r} z_{1r}^{j1^{UD}} + \sum_{i=1}^{I_1} \upsilon_{1i} z_{1i}^{j3}$ is the sum of the undesired inputs and outputs of DMU_j in stage p.

Then, the overall performance can be represented by a linear combination of the above-mentioned efficiency scores as:

$$\sum_{p=1}^{P} \omega_p\, \theta_p \;\; where \; \sum_{p=1}^{P} \omega_p = 1 \tag{3}$$

Where ω_p is the consumption rate in stage p for the entire inputs and can be described as follows:

$$\omega_p = \frac{1}{TC}\left(\sum_{k=1}^{K_{p-1}} \eta_{p-1,k}\, z_{p-1,k}^{j2} + \sum_{r=1}^{R_p} \mu_{pr} z_{pr}^{j1^{UD}} + \sum_{i=1}^{I_p} \upsilon_{pi} z_{pi}^{j3}\right), p = 1, \dots, P \tag{4}$$

$$\omega_1 = \frac{1}{TC}\left(\sum_{r=1}^{R_p} \mu_{pr} z_{pr}^{j1^{UD}} + \sum_{i=1}^{I_p} \upsilon_{pi} z_{pi}^{j3}\right) \tag{5}$$

Where TC refers to the total consumption of the process and is given by:

$$TC = \sum_{p=2}^{P} \sum_{k=1}^{K_{p-1}} \eta_{p-1,k}\, z_{p-1,k}^{j2} + \sum_{p=1}^{P} (\sum_{r=1}^{R_p} \mu_{pr} z_{pr}^{j1^{UD}} + \sum_{i=1}^{I_p} \upsilon_{pi} z_{pi}^{j3}) \tag{6}$$

Therefore, the overall performance is rewritten as:

$$\theta = \frac{\sum_{p=1}^{P} (\sum_{r=1}^{R_p} u_{pr} z_{pr}^{j1^{UD}} + \sum_{k=1}^{K_p} \eta_{pk}\, z_{pk}^{j2} + \sum_{t=1}^{T_p} \gamma_{pt} y_{pt}^{j4} - \sum_{t=1}^{T_p} \beta_{pt} y_{pt}^{j4})}{\sum_{p=2}^{P} \sum_{k=1}^{K_{p-1}} \eta_{p-1,k}\, z_{p-1,k}^{j2} + \sum_{p=1}^{P} (\sum_{r=1}^{R_p} \mu_{pr} z_{pr}^{j1^{UD}} + \sum_{i=1}^{I_p} \upsilon_{pi} z_{pi}^{j3})} \tag{7}$$

The Optimistic Efficiency (OE) score should be calculated in the next step. According to (Cook et al., 2010), the OE score of DMU_o in an NDEA model can never exceed 1 by optimizing overall performance θ and constraining individual measures θ_p. Then, by altering the Charnes-Cooper model, the OE score of DMU_o can be written as:

$$\begin{aligned}
&Max\ \varphi_o = \sum_{p=1}^{P} (\sum_{r=1}^{R_p} u_{pr} z_{pr}^{o1^{UD}} + \sum_{k=1}^{K_p} \eta_{pk}\, z_{pk}^{o2} + \sum_{t=1}^{T_p} (\gamma_{pt} - \beta_{pt}) y_{pt}^{o4})\\
&\quad s.t.\\
&\sum_{p=2}^{P} \sum_{k=1}^{K_{p-1}} \eta_{p-1,k}\, z_{p-1,k}^{o2} + \sum_{p=1}^{P} \left(\sum_{r=1}^{R_p} \mu_{pr} z_{pr}^{o1^{UD}} + \sum_{i=1}^{I_p} \upsilon_{pi} z_{pi}^{o3} \right) = 1\\
&(\sum_{r=1}^{R_1} u_{1r} z_{1r}^{j1^{D}} + \sum_{k=1}^{K_1} \eta_{1k}\, z_{1k}^{o2}\\
&\qquad + \sum_{t=1}^{T_1} (\gamma_{1t} - \beta_{1t}) y_{1t}^{o4}) - (\sum_{r=1}^{D_1} \mu_{1r} z_{1r}^{o1^{UD}} + \sum_{i=1}^{I_1} \upsilon_{1i} z_{1i}^{o3}) \le 0\\
&(\sum_{r=1}^{R_p} u_{pr} z_{pr}^{o1^{UD}} + \sum_{k=1}^{K_p} \eta_{pk}\, z_{pk}^{o2} + \sum_{t=1}^{T_p} (\gamma_{pt} - \beta_{pt}) y_{pt}^{o4}) - (\sum_{k=1}^{K_{p-1}} \eta_{p-1,k}\, z_{p-1,k}^{o2}\\
&\qquad + \sum_{r=1}^{D_p} \mu_{pr} z_{pr}^{o1^{UD}} + \sum_{i=1}^{I_p} \upsilon_{pi} z_{pi}^{o3}) \le 0\\
&u_{pr}, \mu_{pr}, \eta_{pk}, \upsilon_{pi}, \gamma_{pt}, \beta_{pt} \ge \varepsilon, p = 1, \dots, P
\end{aligned} \tag{8}$$

The DMU is efficient if its efficiency score is 1; otherwise, it is inefficient ($efficiency\ score < 1$). (Y.-M. Wang et al., 2007) developed the double-frontier DEA model and calculated two efficiency scores (Y.-M. Wang & Chin, 2009; Xu et al., 2017), including (1) an OE score, which is known as the efficiency frontier, and (2) a PE score, which is referred to as the inefficiency frontier. According to (Y.-M. Wang et al., 2007), the PE score of DMU_o can be calculated to be below one by minimizing overall performance θ and constraining individual measures θ_p. By altering the Charnes-Cooper model, the PE score of DMU_o can be derived as:

$$
\begin{aligned}
&Min\ \phi_o = \sum_{p=1}^{P}(\sum_{r=1}^{R_p} u_{pr} z_{pr}^{o1^{UD}} + \sum_{k=1}^{K_p} \eta_{pk}\, z_{pk}^{o2} + \sum_{t=1}^{T_p}(\gamma_{pt} - \beta_{pt}) y_{pt}^{o4}) \\
&s.t. \\
&\sum_{p=2}^{P}\sum_{k=1}^{K_{p-1}} \eta_{p-1,k}\, z_{p-1,k}^{o2} + \sum_{p=1}^{P}\left(\sum_{r=1}^{R_p} \mu_{pr} z_{pr}^{o1^{UD}} + \sum_{i=1}^{I_p} \upsilon_{pi} z_{pi}^{o3}\right) = 1 \\
&(\sum_{r=1}^{R_1} u_{1r} z_{1r}^{j1^{D}} + \sum_{k=1}^{K_1} \eta_{1k}\, z_{1k}^{o2} \\
&\qquad + \sum_{t=1}^{T_1}(\gamma_{1t} - \beta_{1t}) y_{1t}^{o4}) - (\sum_{r=1}^{D_1} \mu_{1r} z_{1r}^{o1^{UD}} + \sum_{i=1}^{I_1} \upsilon_{1i} z_{1i}^{o3}) \geq 0 \\
&\sum_{r=1}^{R_p} u_{pr} z_{pr}^{o1^{UD}} + \sum_{k=1}^{K_p} \eta_{pk}\, z_{pk}^{o2} + \sum_{t=1}^{T_p}(\gamma_{pt} - \beta_{pt}) y_{pt}^{o4}) - (\sum_{k=1}^{K_{p-1}} \eta_{p-1,k}\, z_{p-1,k}^{o2} \\
&\qquad + \sum_{r=1}^{D_p} \mu_{pr} z_{pr}^{o1^{UD}} + \sum_{i=1}^{I_p} \upsilon_{pi} z_{pi}^{o3}) \geq 0 \\
&u_{pr}, \mu_{pr}, \eta_{pk}, \upsilon_{pi}, \gamma_{pt}, \beta_{pt} \geq \varepsilon, p = 1, \dots, P
\end{aligned}
\tag{9}
$$

The DMU is pessimistically inefficient if the efficiency score is 1. Also, if the efficiency score of the DMU is greater than 1, the DMU is non-pessimistically inefficient.

Finally, the Overall performance can be calculated. Optimistic and pessimistic efficiencies are used to rank DMUs from different perspectives. To assign an overall rank to a DMU, it is required to use an overall performance criterion. According to (Y.-M. Wang et al., 2007), an overall performance criterion could be obtained by the geometric mean of optimistic and pessimistic efficiencies. That is, drawing on optimistic and PE scores, an overall DMU performance criterion can be calculated as:

$$
\rho_j = \frac{\varphi_j^*}{\sqrt{\sum_{i=1}^{J} \varphi_i^{*^2}}} + \frac{\phi_j^*}{\sqrt{\sum_{i=1}^{J} \phi_i^{*^2}}} \qquad (j = 1, \dots, J) \tag{10}
$$

Where φ_j^* is the OE score of DMU$_j$ (Eq. (8)), while ϕ_j^* is the PE score of DMU$_j$ (Eq. (9)). Here, j refers to the total number of DMUs.

Limitations

Despite the robustness of the proposed methodology, some limitations must be acknowledged. First, the selection of 10 companies was based on convenience and data availability, which may introduce selection bias and limit generalizability. The relatively small sample size (N=10) further restricts the generalization of the findings. However, given the confidentiality of company-level data and limited disclosure of environmental reports, expanding the sample was not feasible within the scope of this study. Second, the study relies partly on self-reported company data, which may be subject to reporting bias. Third, while the Fuzzy Delphi Method reduced subjectivity in expert judgments, the perspectives of only nine experts were incorporated, which may not fully capture the diversity of stakeholder opinions. Lastly, the NDEA framework used in this study is static and does not account for temporal dynamics in efficiency performance. Future studies should expand the sample size, include longitudinal data, and apply dynamic or hybrid DEA models to provide broader insights.

Results

The performance evaluation of petrochemical supply chains involves many complex qualitative and quantitative criteria. Table 3 lists several performance criteria commonly used in the literature to evaluate the performance of petrochemical supply chains. The input and output criteria before Fuzzy Delphi and expert screening are reported in Table 3.

Table 3. Petrochemical supply chain performance evaluation criteria extracted from the literature

Number	Criteria	Criterion Type		References
		Input	Output	
1	Advertising cost	✓		(Su & Sun, 2018)
2	Operational cost	✓		(Izadikhah & Saen, 2018; Khalili & Alinezhad, 2018; Nguyen, 2020)
3	Number of employees	✓		(Bajec & Tuljak-Suban, 2019; Dey et al., 2019; Goswami & Ghadge, 2020; Jahani Sayyad Noveiri et al., 2018; Krmac & Djordjević, 2019; S. Li, 2018; Y. Li et al., 2019; Ming & Feng, 2019; Mozaffari et al., 2020; Pouralizadeh et al., 2020; Tavassoli, Ketabi, et al., 2020; H. Wang et al., 2020)
4	Environmental cost	✓		(Ang et al., 2019; Bafrooei et al., 2014; Izadikhah & Saen, 2018; Samavati et al., 2020; Wu et al., 2019)
5	Cost of work safety and labor health	✓		(Dey et al., 2019; Samavati et al., 2020; Wu et al., 2019; Zarbakhshnia & Jaghdani, 2018)
6	Offered price from suppliers	✓		(Y. Li et al., 2019; Tavassoli, Saen, et al., 2020)
7	Transportation cost	✓		(Su & Sun, 2018; Tavassoli, Saen, et al., 2020)
8	Annual turnover	✓		(Ang et al., 2019)
9	Cost of participation in green production programs	✓		(Ang et al., 2019)
10	CSR practices	✓		(Dey et al., 2019)
11	Material purchase cost	✓		(Izadikhah & Saen, 2018; Kalantary et al., 2018; S. Li, 2018; Samavati et al., 2020; Su & Sun, 2018)
12	Cost of quality	✓		(Pitchipoo et al., 2018; Su & Sun, 2018)

13	Quality management system	✓		(He & Zhang, 2018)
14	Staff welfare cost	✓		(Su & Sun, 2018)
15	Greenmarket share	✓		(Davoudabadi et al., 2020)
16	Cost of products	✓		(Diouf & Kwak, 2018; Dobos & Vörösmarty, 2019; Karami et al., 2020; C. Wang et al., 2018)
17	Environmental standard certification	✓		(Davoudabadi et al., 2020)
18	CO_2 emission		✓	(Bajec & Tuljak-Suban, 2019; Chen et al., 2017; Dobos & Vörösmarty, 2019; Goswami & Ghadge, 2020; He & Zhang, 2018; Krmac & Djordjević, 2019; Lin et al., 2019; Pouralizadeh et al., 2020; Samavati et al., 2020; Su & Sun, 2018; H. Wang et al., 2020; Zarbakhshnia & Jaghdani, 2018)
19	Export rate		✓	(Tavassoli, Ketabi, et al., 2020)
20	Number of customers		✓	(Pouralizadeh et al., 2020)
21	Wastewater system efficiency		✓	(Dey et al., 2019)
22	Number of green products		✓	(Ang et al., 2019; Khalili & Alinezhad, 2018; Samavati et al., 2020; Su & Sun, 2018)
23	Customer satisfaction		✓	(Ming & Feng, 2019)
24	Profit to sales ratio		✓	(Hossein Ranjbar et al., 2013; Ming & Feng, 2019)
25	Effectiveness of the environmental system		✓	(Dey et al., 2019)
26	Energy efficiency		✓	(Tavassoli, Saen, et al., 2020)
27	Net profit		✓	(S. Li, 2018)
28	Number of dissatisfied customers		✓	(Jahani Sayyad Noveiri et al., 2018)
29	Revenue from green products		✓	(Khalili & Alinezhad, 2018)
30	Internal audit scores		✓	(Khalili & Alinezhad, 2018)
31	Use of renewable resources		✓	(Khalili & Alinezhad, 2018)
32	Total asset return rate		✓	(He & Zhang, 2018)
33	Cost of environmental waste		✓	(Dey et al., 2019)
34	Supplier flexibility		✓	(Su & Sun, 2018)

The initial criteria were screened and localized using the FDM. A total of 34 criteria were employed to measure green supply chain performance. As mentioned, these criteria had been extracted through a literature review (Table 2). Then, these criteria were measured using the FDM to be localized to the petrochemical industry, as shown in Table 5.

Table 5. FDM results

No.	Criteria	Fuzzy value			Defuzzied value	Decision
		L	M	U		
C1	Number of Employees	0.25	0.84	1	0.697	✓
C2	Environmental cost	0.25	0.75	1	0.668	✓
C3	Cost of work safety and labor health	0.25	0.81	1	0.688	✓
C4	Cost of products	0	0.67	1	0.559	×
C5	Operating costs	0.25	0.72	1	0.657	×
C6	Material purchase cost	0.25	0.75	1	0.668	✓
C7	Cost of quality	0.25	0.70	1	0.653	×
C8	Offered price from suppliers	0.25	0.72	1	0.657	×
C9	Transportation cost	0.5	0.93	1	0.813	✓
C10	Supplier flexibility	0.25	0.74	1	0.665	✓
C11	Advertising cost	0.25	0.81	1	0.688	✓
C12	Staff welfare cost	0.25	0.80	1	0.685	✓
C13	Effluent system efficiency	0.5	0.90	1	0.803	✓
C14	Cost of participation in green production programs	0.25	0.81	1	0.688	✓
C15	Number of customers	0	0.69	1	0.566	×
C16	CSR practices	0.25	0.66	1	0.639	×
C17	Quality management system	0.25	0.81	1	0.688	✓
C18	Green market share	0	0.70	1	0.569	×
C19	CO_2 emission	0.25	0.78	1	0.680	✓
C20	Net profit	0.25	0.69	1	0.649	×
C21	Number of green products	0.25	0.84	1	0.697	✓
C22	Profit to sales ratio	0.25	0.67	1	0.642	×
C23	Energy efficiency	0.25	0.84	1	0.697	✓
C24	Environmental standard certification	0.25	0.81	1	0.688	✓
C25	Annual turnover	0.25	0.73	1	0.660	×
C26	Customer satisfaction	0.5	0.79	1	0.767	✓
C27	Effectiveness of the environmental system	0.25	0.68	1	0.645	×
C28	Internal audit status	0	0.57	1	0.527	×
C29	Export rate	0.25	0.69	1	0.649	×
C30	Number of dissatisfied customers	0.25	0.70	1	0.653	×
C31	Revenue from green products	0.25	0.72	1	0.657	×
C32	Cost of environmental waste	0.25	0.75	1	0.668	✓
C33	Use of renewable resources	0.25	0.62	1	0.625	×
C34	Total asset return rate	0.25	0.64	1	0.549	×

As shown in Table 5, the experts verified 17 of the 34 supply chain performance criteria used as input and output of the green supply chain research. There is a supplier–manufacturer–distributor green supply chain for each petrochemical company, which is shown in Figure 3.

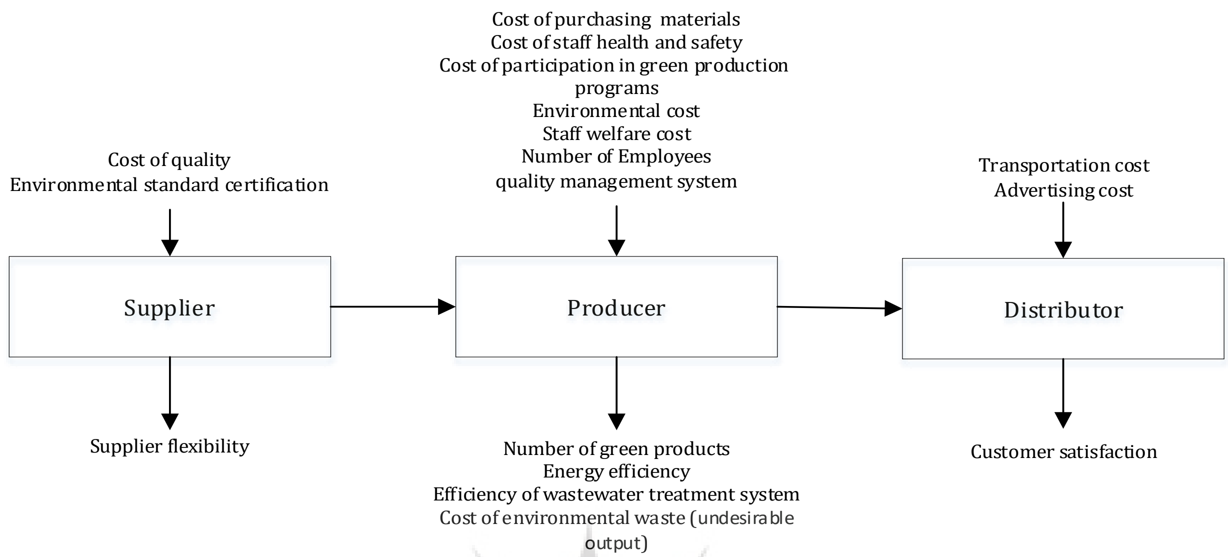


Fig. 3. NDEA structure based on supplier–manufacturer–distributor of DMUs

This section describes the NDEA results. Table 6 represents summarized definitions of the criteria. Tables 7-9 report the efficiency measurement data of the ten petrochemical companies.

Table 6. Summarized definitions of the criteria

Stage	Indices	Definitions	Unit
Supplier	z_{11}^{j3}	Environmental standard certification	Number
	z_{12}^{j3}	CO_2 emission	Million rials
	$z_{11}^{j1^D}$	Supplier flexibility	1-5 (qualitative)
Producer	z_{21}^{j3}	Cost of purchasing raw materials	Million rials
	z_{22}^{j3}	Cost of staff health and safety	Million rials
	z_{23}^{j3}	Cost of participation in green production programs	Million rials
	z_{24}^{j3}	Environmental cost	Million rials
	z_{25}^{j3}	Staff welfare cost	Million rials
	z_{26}^{j3}	Number of Employees	People
	z_{27}^{j3}	quality management system	Number
	$z_{21}^{j1^D}$	Number of green products	Number
	$z_{22}^{j1^D}$	Energy efficiency	Percentage
	$z_{23}^{j1^D}$	Efficiency of the wastewater treatment system	Percentage
	$z_{24}^{j1^{UD}}$	Cost of environmental waste (undesirable output)	Million rials
Distributor	z_{31}^{j3}	Transportation cost	Million rials
	z_{32}^{j3}	Advertising cost	Million rials
	$z_{31}^{j1^D}$	Customer satisfaction	Percentage

Table 7. Input and output data of the suppliers

DMU	Supplier		
	Inputs		Outputs
	z_{11}^{j3}	z_{12}^{j3}	$z_{11}^{j1^{UD}}$
DMU_1	1	3024	3
DMU_2	2	1534567	4
DMU_3	1	358522	5
DMU_4	2	10153	5
DMU_5	2	280934	5
DMU_6	1	230579	3
DMU_7	2	512135	3
DMU_8	1	15240	4
DMU_9	2	14240	3
DMU_{10}	1	23259	4

Table 8. Input and output data of the distributors

DMU	Distributor		
	Inputs		Outputs
	z_{31}^{j3}	z_{32}^{j3}	$z_{31}^{j1^{UD}}$
DMU_1	66282	32756	0.79
DMU_2	9898969	51500	0.83
DMU_3	1159898	5947	0.77
DMU_4	6802422	227157	0.87
DMU_5	6707144	153718	0.95
DMU_6	4487285	4664	0.89
DMU_7	12999264	144594	0.88
DMU_8	415256	55431	0.92
DMU_9	304006	68287	0.82
DMU_{10}	8042261	7641	0.89

Table 9. Input and output data of the manufacturers

DMU	Producer										
	Inputs							Outputs			
	z_{21}^{j3}	z_{22}^{j3}	z_{23}^{j3}	z_{24}^{j3}	z_{25}^{j3}	z_{26}^{j3}	z_{27}^{j3}	$z_{21}^{j1^{UD}}$	$z_{22}^{j1^{UD}}$	$z_{23}^{j1^{UD}}$	$z_{24}^{j1^{UD}}$
DMU_1	6992162	9106	1540	259132	33213	615	3	1	0.74	0.88	1297
DMU_2	113665000	901794	697	2229000	5130939	6799	4	2	0.86	0.84	1274533
DMU_3	20157331	13805	322	743016	14617	1942	3	2	0.656	0.83	28538
DMU_4	20198892	244695	1234	353577	248793	709	3	2	0.86	0.9	3814
DMU_5	90544253	10719	23205	155085	3485157	2460	2	0	0.91	0.92	1211602
DMU_6	93269056	14539	1162	136735	602259	2459	2	1	0.82	0.87	357044
DMU_7	85240055	13441	6761	483036	500970	781	1	0	0.86	0.76	152574
DMU_8	59367664	3519	2457	617571	747264	3229	2	1	0.91	0.86	106754
DMU_9	4152852	41919	58	221615	270927	1191	1	1	0.83	0.92	712109
DMU_{10}	13672872	23259	1697	83233	189023	1160	2	1	0.74	0.74	415604

As mentioned, the present study sought to evaluate the efficiency of ten petrochemical companies through an NDEA model to identify and rank efficient companies and make improvement suggestions. The optimistic efficiencies of the petrochemical companies were calculated using Eq. (8), as reported in Table 10, where the last column represents the arithmetic mean of the efficiency for each DMU.

Table 10. OE Scores of DMUs

DMU	OE			Overall OE
	Supplier	Producer	Distributor	
DMU_1	1	1	1	1
DMU_2	0.4	0.61	0.125	0.378
DMU_3	1	1	1	1
DMU_4	0.78	1	0.097	0.625
DMU_5	0.57	1	0.13	0.566
DMU_6	0.64	1	1	0.88
DMU_7	0.31	1	0.08	0.463
DMU_8	1	1	0.61	0.87
DMU_9	0.44	1	0.47	0.636
DMU_{10}	0.99	1	0.61	0.866

A DMU is assumed to be efficient if its efficiency is 1; efficiency scores below 1 represent inefficient DMUs. According to Table 10, DMU3 and DMU1 were efficient in the optimistic scenario, while the remaining companies were concluded to be inefficient. The efficiency of DMU3 and DMU1 is mainly explained by their investments in cleaner technologies, adoption of robust quality management systems, and better utilization of human resources. In contrast, the inefficiency of other DMUs can be attributed to high environmental costs, excessive staff welfare expenses, and unbalanced workforce structures. Figure 4 illustrates the OE scores of the DMUs for suppliers, manufacturers, and distributors.

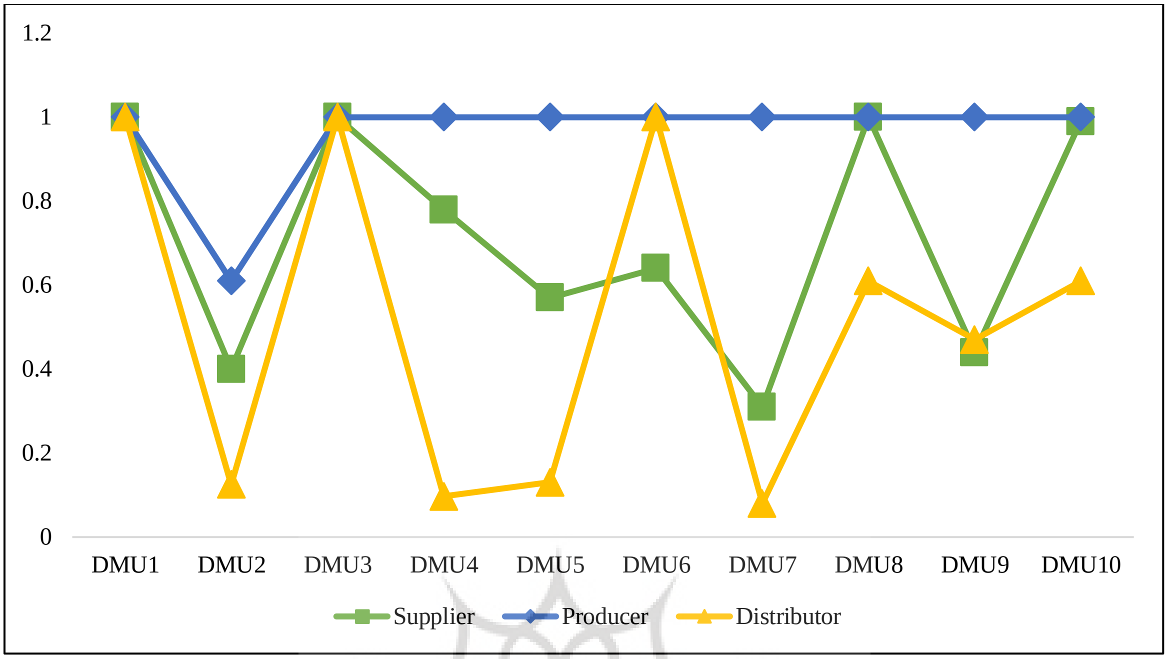


Fig. 4. OE scores of suppliers, manufacturers, and distributors

The PE of the petrochemical companies was calculated by Eq. (9). Table 11 provides the PE results of the ten petrochemical companies' suppliers, manufacturers, and distributors. It should be noted that the last column stands for the arithmetic mean efficiency of the DMUs.

Table 11. PE scores of DMUs

DMU	PE			Overall PE
	Supplier	Producer	Distributor	
DMU_1	2	1	6.29	3.096
DMU_2	1	1	1.23	1.076
DMU_3	3.12	1.017	9.8	4.645
DMU_4	1.66	1.3	1	1.32
DMU_5	1.66	1	1.42	1.36
DMU_6	2	1.02	2.94	1.986
DMU_7	1	1	1	1
DMU_8	2.66	1.41	4.33	2.8
DMU_9	1	1.64	3.13	1.923
DMU_{10}	2.66	1.34	1.63	1.876

A DMU is considered to be inefficient if its PE score is 1. The DMU with a PE score greater than one is assumed to be non-pessimistically inefficient. According to Table 11, DMU7 was found to be pessimistically inefficient, whereas the remaining companies were non-pessimistically inefficient. The inefficiency of DMU7 reflects weaknesses in managing transportation and advertising costs and lower customer satisfaction. Conversely, efficient DMUs such as DMU3 and DMU8 achieved better results by optimizing distribution networks and implementing higher safety and environmental standards. Figure 5 depicts the PE of the companies' suppliers, manufacturers, and distributors.

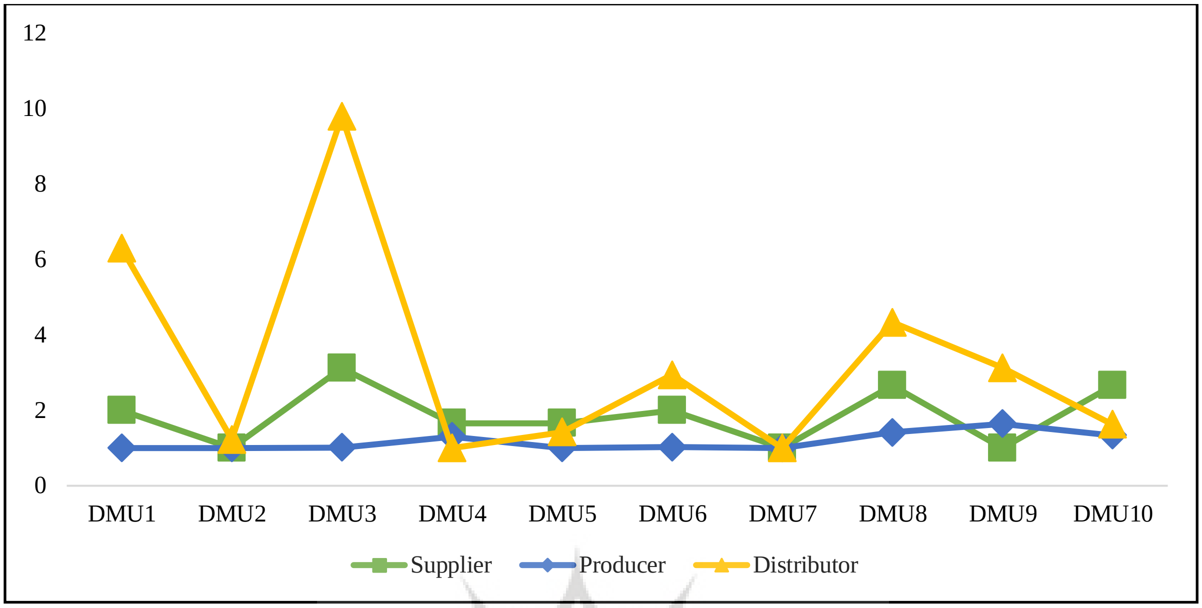


Fig. 5. PE scores of suppliers, manufacturers, and distributors

Overall performance was obtained using Eq. (10). Table 12 reports the companies' manufacturers, suppliers, and distributors' overall performance scores (the arithmetic mean). As can be seen, the distributor of DMU3 had the highest performance, while the distributor of DMU7 had the lowest performance. Also, the manufacturers of DMU9 and DMU2 were found to have the highest and lowest performance scores, respectively. The supplier of DMU3 had the highest performance, whereas DMU7 was found to have the lowest performance. Moreover, DMU3 and DMU2 were calculated to have the highest and lowest overall performances. The superior performance of DMU3 is linked to its more integrated supply chain and compliance with environmental standards, while the poor performance of DMU2 is mainly due to excessive labor-related costs and insufficient investment in green technologies. Figure 6 shows the overall performance results of the companies' suppliers, manufacturers, and distributors.

Table 12. Overall performance scores

DMU	Supplier	Producer	Distributor	Overall efficiency
DMU_1	0.730	0.591	0.966	0.763
DMU_2	0.323	0.464	0.154	0.314
DMU_3	0.907	0.596	1.227	0.910
DMU_4	0.585	0.671	0.122	0.459
DMU_5	0.498	0.591	0.170	0.420
DMU_6	0.581	0.596	0.717	0.631
DMU_7	0.286	0.591	0.114	0.330
DMU_8	0.834	0.700	0.626	0.720
DMU_9	0.340	0.761	0.467	0.523
DMU_{10}	0.830	0.681	0.425	0.645

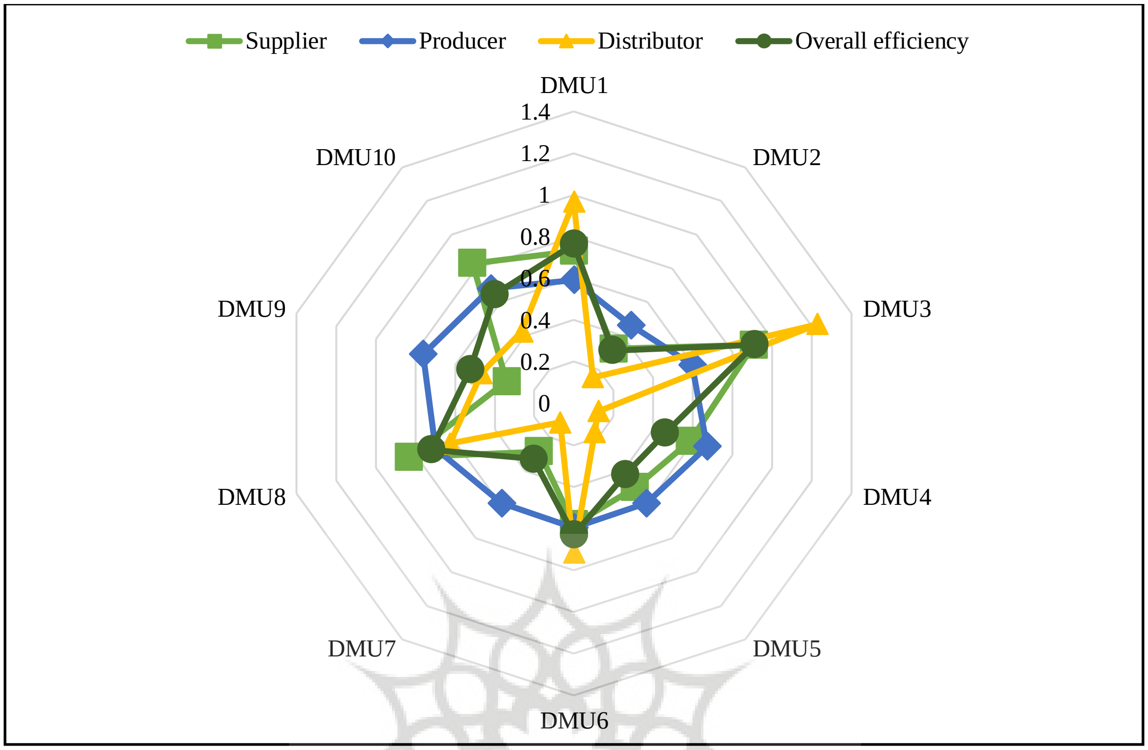


Fig. 6. Overall performance of the suppliers, manufacturers, and distributors

Table 13 and Figure 7 rank the companies based on OE, PE, and overall performance. As can be seen, DMU3 was observed to be the most efficient company, whereas DMU2 was found to be the most inefficient one among the ten DMUs. Slack analysis further indicates that DMU2 should reduce staff welfare costs and advertising expenses to increase efficiency while benchmarking best practices from DMU3. Other inefficient DMUs (e.g., DMU4, DMU5, and DMU7) can enhance their performance by optimizing environmental costs and improving energy efficiency.

Robustness Analysis

To further confirm the robustness of these findings, we conducted additional sensitivity checks (see Appendix C). The results show that efficiency rankings remain generally stable under moderate adjustments of key inputs and outputs, which supports the credibility of the managerial recommendations presented in this study. As further confirmed by the bootstrap analysis (Appendix D), the observed efficiency patterns are statistically robust, with efficient units such as DMU1 and DMU3 maintaining stability across replications and inefficient units like DMU2 consistently underperforming.

Table 13. Ranks of the petrochemical companies

DMU	OE	PE	Overall efficiency	Rank
DMU_1	1	3.096	0.763	2
DMU_2	0.378	1.076	0.314	10
DMU_3	1	4.645	0.910	1
DMU_4	0.625	1.32	0.459	7
DMU_5	0.566	1.36	0.420	8
DMU_6	0.88	1.986	0.631	5
DMU_7	0.463	1	0.330	9
DMU_8	0.87	2.8	0.720	3
DMU_9	0.636	1.923	0.523	6
DMU_{10}	0.866	1.876	0.645	4

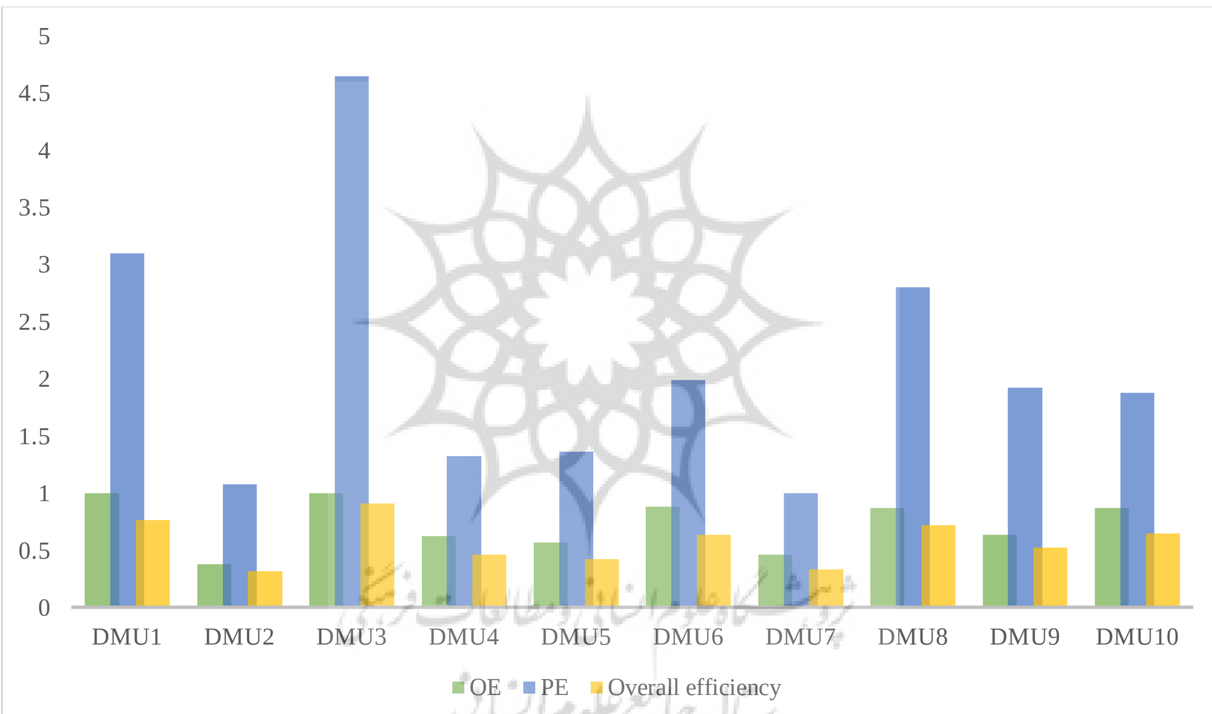


Fig. 7. NDEA results of DMUs

As defined in DEA models, a DMU is considered DEA-efficient or "optimistic efficient" if its best relative efficiency equals one; otherwise, it is categorized as DEA-non-efficient or optimistic non-efficient. Performance can also be evaluated from a pessimistic perspective. In this case, the efficiency assessed is referred to as the worst relative efficiency (pessimistic efficiency), and its value is restricted to quantities greater than or equal to one. A DMU is considered DEA-inefficient or pessimistically inefficient if the value of its worst relative efficiency equals one; otherwise, it is classified as DEA-non-inefficient or pessimistically non-inefficient. Optimistic and pessimistic efficiencies must be assessed concurrently to evaluate each DMU's performance comprehensively.

Accordingly, our NDEA model simultaneously measures the efficiency of the petrochemical supply chain in terms of OE, PE, and overall efficiency.

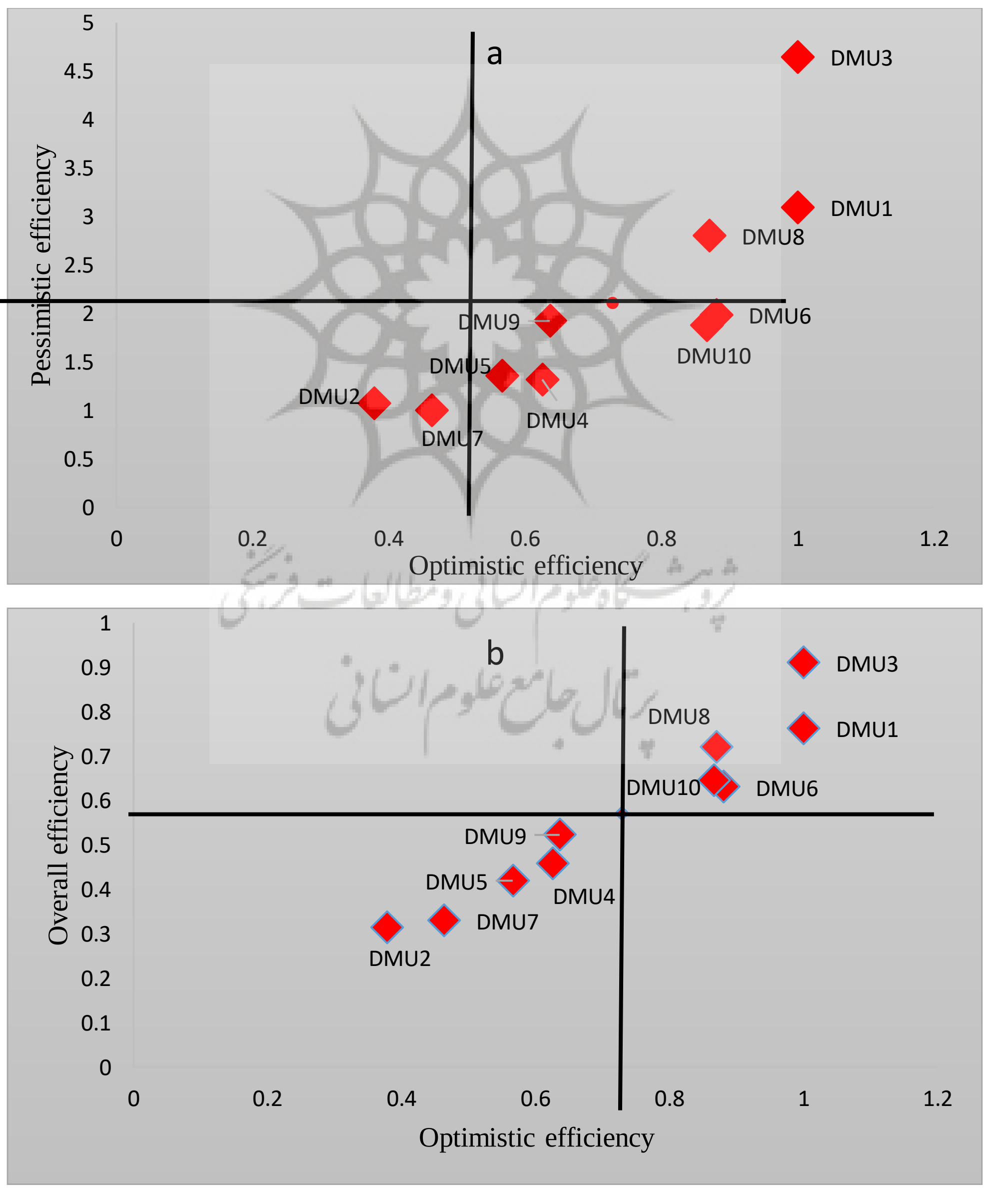
Before introducing Figure 8, it is important to explain how the axes and quadrants should be interpreted. In each matrix, the horizontal axis represents the efficiency score of the first dimension being compared (e.g., OE). In contrast, the vertical axis corresponds to the second dimension (e.g., PE or overall efficiency). The upper-right quadrant identifies “star performers” with above-average scores in both dimensions. The lower-left quadrant includes underperforming DMUs with below-average results on both axes. The upper-left and lower-right quadrants reflect asymmetric performance, where DMUs may perform excellently in one dimension but poorly in the other. This explanatory framing provides readers with a clear mental map for interpreting the relative positioning of DMUs before examining the charts.

Figure 8 compares Optimistic Efficiency (OE), Pessimistic Efficiency (PE), and overall efficiency. The DMUs are grouped into four categories in each figure based on their average efficiency scores. These comparisons distinguish efficient and inefficient DMUs and provide practical insights for improvement. Specifically, DMUs with low scores across all dimensions (such as DMU2 and DMU7) must focus simultaneously on reducing environmental and welfare costs and enhancing quality management systems. Conversely, efficient DMUs (such as DMU3 and DMU1) should continue investing in technological innovation and customer satisfaction initiatives to maintain their competitive advantage. The main findings are illustrated as follows:

- Figure 8a compares the average OE and the average PE. The horizontal axis is OE with an average efficiency score of 0.7284. The vertical axis is PE with an average efficiency score of 2.1082. The lower-right quadrant has two DMUs with high OE and low PE. DMU6 and DMU10 should focus on the PE to achieve better performance. This can be achieved by providing increasing safety standards and increasing customer satisfaction. The DMUs with low OE and PE are placed in the lower-left quadrant (DMU2, DMU4, DMU5, DMU7, and DMU9). These DMUs should focus on increasing OE and PE concurrently. The DMUs with high OE and PE are placed in the upper-right quadrant (DMU1, DMU3, and DMU8).

- Figure 8b compares the average OE and overall efficiency of DMUs. The horizontal axis displays OE with an average efficiency score of 0.7284. The vertical axis displays overall efficiency with an average efficiency score of 0.5715. As is seen in Fig. 8b, the DMUs’ positions are similar to those in Fig. 8a, as there is a high correlation between PE and overall efficiency. The DMUs with low OE (DMU_2, DMU_4, DMU_5, DMU_7, and DMU_9) can improve their OE by improving the cost of environmental waste, CO_2 emission, fuel, and the cost of purchasing raw materials.

❖ Figure 8c compares the average PE and the average overall efficiency. The horizontal axis displays PE with an average efficiency score of 2.1082. The vertical axis displays overall efficiency with an average efficiency score of 0.5715. As is seen, there is no DMU in the lower-right quadrants. The lower-left quadrant has five DMUs (DMU_2, DMU_4, DMU_5, DMU_7, and DMU_9). These DMUs should increase their PE and overall efficiency. This can be achieved by the optimal use of resources, reducing the cost of participation in green production programs, environmental costs, and staff welfare costs. The best DMUs are placed in the upper-right quadrant (DMU_3, DMU_1, and DMU_8). The DMUs with low PE (DMU_6, DMU_{10}) can improve their efficiency by reducing environmental costs, staff welfare costs, employee numbers, and quality management systems.



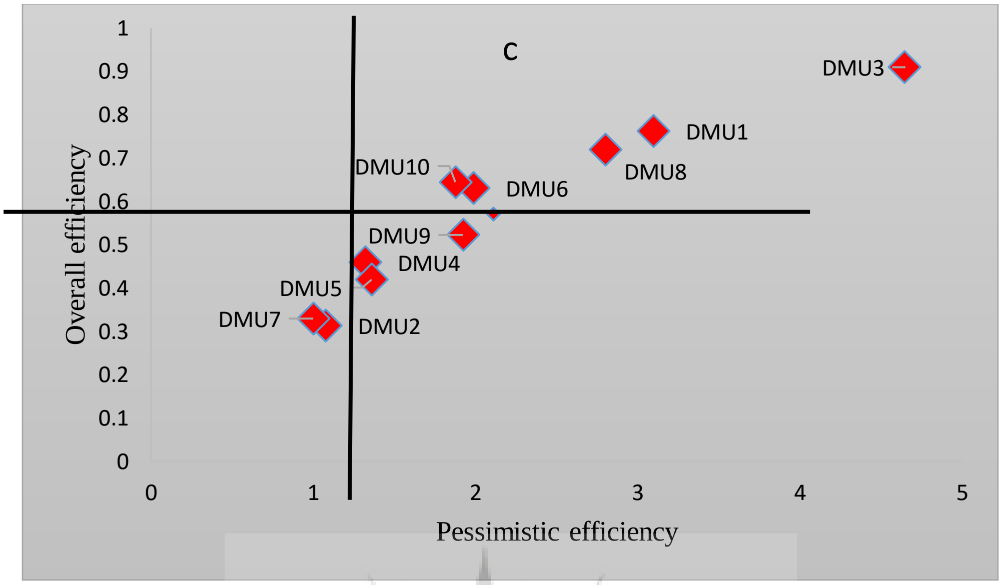


Fig. 8. a) OE vs. PE. b) OE vs. overall efficiency. c) PE vs. overall efficiency

Discussion

Our results suggest that DMU3 and DMU1 were efficient in the optimistic scenario, while the remaining companies were inefficient. This finding is directly supported by Table 10, where both DMUs reached an OE score of 1, showing their ability to optimize resources across suppliers, manufacturers, and distributors. In contrast, DMU2 obtained the lowest OE score (0.378), highlighting its structural inefficiencies. The efficiency of DMU3 and DMU1 can be attributed to their balanced allocation of resources across suppliers, manufacturers, and distributors, combined with lower environmental costs and higher customer satisfaction compared to other DMUs. The DMU7 was determined to be inefficient under the pessimistic scenario, and the remaining companies were inefficient non-pessimistically.

According to Table 11, DMU7's PE score of 1 indicates pessimistic inefficiency, which is linked to disproportionately high transportation and welfare costs (see Table 8) and weak performance in quality management. The inefficiency of DMU7 can be attributed to its disproportionately high transportation and welfare costs, combined with underperformance in quality management and energy efficiency, which resulted in resource waste without yielding proportional outputs. Regarding overall performance, the distributors of DMU3 and DMU7 had the highest and lowest efficiencies, respectively. Specifically, DMU3's distributor achieved an overall efficiency score above 1.2 (Table 12), reflecting effective logistics and customer engagement, while DMU7's distributor recorded only 0.114, confirming its weak cost structure and poor customer satisfaction. The superior distributor efficiency of DMU3 reflects effective logistics management and strong customer engagement, whereas the weak performance of

DMU7's distributor highlights excessive cost structures and limited customer satisfaction. DMU9 and DMU2 were found to have the most and least efficient manufacturers. For instance, DMU9's producer scored 0.761, the highest among all, while DMU2's producer scored 0.464, demonstrating how excessive labor costs and health/safety expenditures weakened DMU2's performance. In the Iranian petrochemical sector, staff welfare and labor-related expenditures are often shaped by structural and institutional conditions such as semi-state ownership models, legally mandated benefit schemes, and centralized labor regulations.

These sector-specific constraints can lead to inflated welfare costs that do not necessarily translate into proportional productivity gains, which helps explain why such expenditures emerged as key inefficiency drivers among some DMUs in this study. DMU9's manufacturer achieved efficiency through maintaining high safety standards and moderate costs, while DMU2's manufacturer struggled with excessive labor force size and high health and safety expenses. The supplier of DMU3 had the highest efficiency, while DMU7's was found to have the lowest efficiency. DMU3 and DMU2 were found to have the highest and lowest overall performances, respectively. The companies were ranked in OE, PE, and overall performance. DMU3 was observed to be the most efficient one among the ten petrochemical companies, while DMU2 was found to be the most inefficient company. It was observed that the supplier of DMU1 was the most efficient one. Also, DMU1 had the most efficient manufacturer. Eventually, DMU1 was found to have the most efficient distributor.

According to the results obtained from inefficient suppliers, it can be concluded that the inefficient unit of DMU2, in order to be efficient, must model its reference unit, the DMU3 unit, and after obtaining the virtual composite unit, reduce or increase its inputs and outputs. However, these adjustments should be interpreted as scenario-based guidance instead of prescribing exact reductions (e.g., cutting 491 employees). For example, Table 12 shows that if DMU2 reduces labor-related costs by even 10%, its overall efficiency could move closer to 0.40, narrowing the gap with more efficient peers. The supplier of DMU2 must reduce the cost of its quality. This suggests that DMU2 needs to enhance supplier flexibility and adopt quality control mechanisms similar to DMU3 to eliminate wasteful costs. It is analyzed in the same way for other inefficient units. Also, according to the results obtained from inefficient manufacturers, the inefficient unit of DMU2, in order to be efficient, should model its reference units, i.e., DMU3, DMU4, and DMU9 units, and after obtaining a virtual composite unit, reduce or increase its inputs and outputs. Benchmarking against these efficient peers shows that reallocating expenditures from staff welfare to environmental initiatives can increase resilience.

This is consistent with Wang & Fan (2025), who emphasized that reducing environmental costs while maintaining production efficiency enhances long-term competitiveness. The manufacturer of DMU2 must reduce 491 of its employees and 794663 of its health and safety costs, while the number of its green products remains unchanged. It is analyzed similarly for the rest of its inputs and outputs. In other words, reducing redundant labor and optimizing safety expenditure are key corrective measures for DMU2's manufacturer. Also, according to the results obtained from inefficient distributors of companies, the inefficient unit of DMU2, in order to be efficient, should model its reference units, namely DMU1 and DMU3 units, and after obtaining a virtual composite unit, reduce or increase its inputs and outputs. For example, DMU2's advertising costs (Table 8) are nearly triple those of DMU1 for comparable output levels. A sensitivity scenario suggests that reducing promotional expenses by 15% while improving logistics quality would increase DMU2's distributor efficiency above 0.20. Therefore, DMU2's distributor can improve efficiency by benchmarking against DMU1 and DMU3, especially by rationalizing promotional spending and adopting more sustainable logistics practices.

These conclusions are consistent with the robustness checks reported in Appendices C and D, which further confirm the stability of the results.

Most of the earlier works exploited complete data, and incomplete data (Incompleteness in data can refer to noise in either the input (Shrestha et al., 2019; Tiwari & Naskar, 2017) or in the labels (Nigam et al., 2000; Tsuboi et al., 2008). Also, previous studies mainly employed quantitative criteria, and qualitative criteria have been used less frequently. Therefore, this study provides a context-specific application of NDEA for evaluating the performance of petrochemical supply chains, offering practical insights for managers and policymakers. Our findings partially align with Abbood (2025), who identified logistics costs as a driver of inefficiency. However, unlike that study, our results also reveal that staff welfare costs are a critical inefficiency factor in the Iranian petrochemical context. This difference may arise from country-specific labor regulations and cultural expectations.

Finally, given the limited sample size (N=10), the results should be interpreted cautiously. DEA rankings in small samples may be sensitive to outliers or extreme values. As in Chen et al. (2017), where small datasets also constrained petrochemical DEA evaluation, our analysis emphasizes patterns and managerial implications rather than universal generalizations.

By explicitly incorporating qualitative measures (e.g., customer satisfaction, supplier flexibility) and quantitative measures (e.g., environmental cost, CO_2 emissions), this research provides a more comprehensive view of efficiency that better reflects real-world conditions in the petrochemical industry. Our findings align with recent studies that applied DEA-based models for efficiency analysis in Iranian industries, such as electricity distribution (Etezadi et al., 2023) and banking (Habibpoor et al., 2022), confirming that DEA and its extensions provide robust tools for addressing inefficiency in complex service and industrial systems. The model developed is an appropriate decision support tool for meeting management's needs for analyzing the efficiency of petrochemical firms in order to make efficient strategic and operational decisions. The proposed models allow petrochemical companies to conduct a multiple-criteria performance efficiency assessment.

Comparative Insights with Prior Research

Our findings align with and extend existing research on DEA-based environmental performance. For example, Dobos & Vörösmarty (2019) showed that European chemical suppliers achieved efficiency mainly through strict environmental regulations and advanced auditing systems, whereas in our case study, staff welfare costs and customer satisfaction emerged as decisive inefficiency factors. Similarly, Liu et al. (2021) found that CO_2 emissions are the primary undesirable output in Chinese manufacturing. However, transportation cost and energy consumption efficiency played a stronger role in the Iranian petrochemical sector, reflecting infrastructure and energy dependency differences. Furthermore, while Cook et al. (2010) emphasized methodological innovation in multi-stage DEA, our study's novelty lies not in the model itself but in its application to a high-impact industry with scarce sustainability data. Thus, the present study contributes by contextualizing well-established DEA frameworks within the unique challenges of an emerging economy's petrochemical supply chain. These comparative insights are summarized in Table 14, which positions our study in relation to prior DEA-based research.

Table 14. Comparative positioning of this study in relation to prior literature

Contribution relative to prior work	Key findings	Methodological focus	Context	Study
We apply this framework empirically to petrochemicals rather than proposing a new model.	Introduced optimistic/pessimistic frontiers	Multi-stage NDEA framework	DEA theory	Cook et al. (2010)
Our study shows inefficiency driven by welfare and logistics factors in Iran.	Efficiency driven by regulations and auditing	DEA with environmental criteria	European chemical suppliers	Dobos & Vörösmarty (2019)
We highlight transport cost and energy use as stronger determinants in petrochemicals.	CO_2 emissions are the dominant inefficiency factor	DEA with undesirable outputs	Chinese manufacturing	Liu et al. (2021)
We integrate fuzzy Delphi + NDEA to select and validate 17 petrochemical indicators.	Identified trade-offs between cost and environmental metrics	DEA + sustainability indicators	Green supply chain benchmarking	Abbood et al. (2025)
Provides the first comprehensive green efficiency assessment in Iran's petrochemical sector using an integrated FDM–NDEA framework	7 out of 10 DMUs are inefficient; inefficiency is mainly due to staff welfare, transport cost, and low energy productivity	Fuzzy Delphi + three-stage NDEA	Iranian petrochemical supply chain	This study

Managerial Implications

The results of this study provide several actionable implications for managers in the petrochemical industry:

- **Balancing efficiency perspectives:** Managers should not rely solely on optimistic efficiency scores but must also consider pessimistic outcomes to ensure robust performance under varying conditions. For instance, some firms exhibited strong efficiency under favorable assumptions but showed vulnerabilities when evaluated under more conservative scenarios. This highlights the need for a **balanced interpretation of efficiency results combined with risk management practices**.
- **Targeting stage-specific weaknesses:** Since suppliers and distributors showed more variability in efficiency than manufacturers, firms should prioritize collaboration and capability-building in these two stages. In particular, **distribution network optimization, supplier development programs, and long-term partnerships** are likely to reduce variability and strengthen overall supply chain performance.
- **Strategic investment in sustainability:** Improvement in CO_2 emission control, waste reduction, and renewable resource utilization directly contributes to higher overall efficiency. **Investments in cleaner technologies, energy-saving systems, and eco-friendly practices** can deliver environmental and economic benefits. This finding echoes prior studies showing that reducing environmental costs enhances sustainable competitiveness.
- **Enhancing customer-related outcomes:** Low customer satisfaction and increasing dissatisfaction were recurring inefficiency factors. To enhance satisfaction and loyalty, managers should adopt quality management systems, responsive after-sales services, and customer engagement initiatives. Strengthening customer relationships not only improves efficiency scores but also ensures long-term competitiveness.
- **Resilience-oriented strategies:** Firms with efficiency gaps between optimistic and pessimistic evaluations demonstrate the risks of overreliance on short-term optimal outcomes. To mitigate this, managers should invest in **supply chain flexibility, safety standards, and contingency planning** to ensure resilience in adverse conditions. Building resilience is critical for navigating volatility in energy markets and logistics systems.

By addressing these managerial implications, petrochemical companies can improve their measured efficiency scores while strengthening long-term sustainability, resilience, and competitiveness. Moreover, the stage-specific patterns observed in our analysis provide managers with a roadmap for benchmarking, where inefficient firms can adopt the best practices of efficient peers, thereby turning quantitative insights into actionable strategic programs.

Conclusion

Although the petroleum industry contributes significantly to global pollution, little research has been conducted on evaluating the green efficiency of petroleum supply chains. Considering Iran's abundant oil reserves and growing industry expansion, it is imperative to address the environmental performance of petrochemical corporations. We formulated 17 criteria to address the green efficiency of petrochemical supply chains in Iran. We then developed a three-stage network data envelopment analysis model, addressing the green efficiency of petrochemical supply chains in Iran. Iranian petrochemical companies were examined to demonstrate the developed model's applicability. We presented an in-depth efficiency analysis of each company concerning optimistic and pessimistic efficiency, and recommended policies to improve their performance.

This study's contributions extend the applications of DEA-based evaluations previously used in other industries, such as service productivity in electricity distribution (Etezadi et al., 2023), supplier selection in green supply chains (AmirSalami & Alaei, 2023), and carbon emission cost analysis in agri-food supply chains (Zegordi & Shahidi, 2023). Applying a three-stage NDEA to the petrochemical sector demonstrates that environmental efficiency analysis can be generalized to large-scale industrial supply chains with complex stakeholder structures. Furthermore, including quantitative (e.g., costs, emissions) and qualitative (e.g., customer satisfaction, supplier flexibility) criteria represents a methodological advancement, ensuring the model reflects the multidimensional nature of green supply chain performance.

Given that environmental costs and staff welfare expenditures were identified as major sources of inefficiency, future research could investigate how macro-level policies-such as labor regulations, subsidy reforms, and environmental taxation-shape these drivers across different petrochemical firms and time periods. This study assessed the efficiency of DMUs assuming a static context. An NDEA model can be developed to rank DMUs better using the cross-efficiency technique to assess the efficiency of DMUs in multiple periods. Future research should also integrate dynamic efficiency analysis to capture changes over time and explore the resilience of supply chains under uncertainty. The defined input and output criteria can be considered along with intermediate options to deploy new and complex models of the NDEA and explore efficiency in a more enhanced way. Moreover, hybrid approaches combining NDEA with artificial intelligence techniques, such as artificial neural networks, can further increase the accuracy of performance measurement and prediction. Using stochastic boundary functions to measure performance and compare the results with the findings of this study. Another worthwhile future direction could be developing a two-stage fuzzy data envelopment analysis to overcome the ambiguity and uncertainty in some input data, such as customer satisfaction, and compare the results with the findings of this study. Additionally, future research may incorporate dynamic NDEA models to capture time-dependent changes in performance, particularly in light of technological advancements and evolving environmental regulations.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. Due to confidentiality agreements with participating companies, detailed raw data cannot be publicly shared.

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Ethical considerations

All procedures performed in this study were conducted in accordance with ethical standards. The study did not involve human participants or animals; all data were handled confidentially and used solely for academic purposes.

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Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Appendix A. Descriptive Statistics of Variables

Table A reports descriptive statistics (mean, standard deviation, minimum, maximum) for all 17 input and output variables across the 10 anonymized DMUs to enhance transparency while maintaining confidentiality. This provides an overview of the dataset and allows readers to evaluate the variability and scale of the indicators without disclosing company identities.

Table A. Descriptive statistics of input/output variables (N = 10 DMUs)

Variable	Min	Max	Mean	SD
Environmental standard certification	1	2	1.5	0.53
CO_2 emission	10,153	1,534,567	308,281	491,050
Supplier flexibility (1–5)	3	5	3.9	0.74
Number of employees	615	6,799	2,243	1,913
Quality management system (1–5)	0	4	2.1	0.83
Cost of staff health and safety	3,519	901,794	190,444	289,153
Staff welfare cost	14,617	5,130,939	1,046,412	1,447,501
Cost of purchasing raw materials	1,162	113,665,000	41,368,293	33,594,404
Cost of participation in green production programs	58	23,205	4,233	6,445
Environmental cost	83,233	2,229,000	568,595	676,272
Energy efficiency	0.656	0.91	0.83	0.08
Number of green products	0	2	1.1	0.74
Efficiency of the wastewater treatment system	0.74	0.92	0.87	0.05
Cost of environmental waste (undesirable output)	1,297	1,274,533	367,849	419,540
Advertising cost (rial)	4,664	227,157	76,419	71,572
Transportation cost (million rial)	66,282	12,999,264	5,301,190	4,270,362
Customer satisfaction (1–5)	0.77	0.95	0.87	0.06

Note: Values are aggregated from the 2018–2022 reporting period. Due to confidentiality agreements, raw company-level data cannot be disclosed; anonymized descriptive statistics are provided instead.

Appendix B. Fuzzy Delphi Expert Responses and Consensus

Table B. Fuzzy Delphi results: expert responses and consensus

Criterion	Variable (Translated)	Crisp Value	Decision (Retained/Not)
C1	Number of employees	0.697	Yes
C2	Environmental costs	0.668	Yes
C3	Work safety & health cost	0.688	Yes
C4	Product cost	0.559	No
C5	Operating costs	0.657	No
C6	Raw material purchase cost	0.668	Yes
C7	Cost of quality	0.680	Yes
C8	Supplier proposed price	0.657	No
C9	Transportation cost	0.813	Yes
C10	Supplier flexibility	0.665	Yes
C11	Advertising cost	0.688	Yes
C12	Staff welfare cost	0.685	Yes
C13	Energy consumption efficiency	0.803	Yes
C14	Green program participation cost	0.688	Yes
C15	Number of customers	0.566	No
C16	CSR activities	0.639	No
C17	Quality management system	0.688	Yes
C18	Green market share	0.569	No
C19	CO2 emissions	0.653	No
C20	Net profit	0.649	No
C21	Number of green products	0.697	Yes
C22	Profit-to-sales ratio	0.642	No
C23	Energy productivity	0.697	Yes
C24	Environmental certificate	0.688	Yes
C25	Annual turnover	0.660	No
C26	Customer satisfaction	0.767	Yes
C27	Environmental system effectiveness	0.645	No
C28	Internal auditing	0.527	No
C29	Export rate	0.649	No
C30	Number of dissatisfied customers	0.653	No
C31	Green product revenue	0.657	No
C32	Environmental waste	0.668	Yes
C33	Use of renewable resources	0.625	No
C34	ROA	0.549	No

Appendix C. Sensitivity and Scenario Analysis

To address robustness concerns highlighted by reviewers, we conducted additional sensitivity checks using the NDEA results. The following scenarios illustrate how efficiency scores respond to moderate adjustments in selected inputs and outputs.

Table C. Sensitivity scenarios for selected DMUs

DMU	Adjustment Scenario	Baseline Overall Efficiency	Adjusted Overall Efficiency	Change
DMU_2	Reduce staff welfare costs by 10%	0.314	0.362	+15%
DMU_2	Reduce transportation cost by 15%	0.314	0.375	+19%
DMU_7	Improve customer satisfaction by 10%	0.330	0.362	+10%
DMU_{10}	Reduce environmental cost by 10%	0.645	0.682	+6%
DMU_3	Increase CO_2 emissions by 5% (stress test)	0.910	0.872	–4%

Interpretation:

- **DMU2 shows the most significant potential gains**, with efficiency improving by nearly 20% if transportation costs are reduced moderately.
- **DMU7 is sensitive to customer satisfaction improvements**, supporting the managerial recommendation to prioritize service quality.
- **DMU10 demonstrates limited sensitivity**, indicating relative stability and the need for long-term resilience strategies.
- **DMU3’s performance is robust**, with only a minor decline under stress test conditions, confirming its benchmark status.

These results confirm that **the rankings are reasonably robust** and that the managerial recommendations presented in the Discussion and Managerial Implications sections are supported by quantitative evidence.

Appendix D. Bootstrap DEA Results

A bootstrap procedure with 2000 replications was applied following Simar and Wilson (1998) to evaluate robustness and statistical inference of the DEA scores. Table D reports each DMU's bias-corrected efficiency scores and 95% confidence intervals. The results confirm that DMU1 and DMU3 consistently maintain efficiency close to 1 with narrow confidence intervals, while DMU2 remains the least efficient unit with its 95% CI well below 0.40. These findings validate the rankings' stability and support the managerial implications' robustness.

Table D. Bootstrap results for overall efficiency (2000 replications)

DMU	Original Efficiency	Bias-corrected Efficiency	95% CI Lower	95% CI Upper
DMU_1	0.763	0.762	0.722	0.801
DMU_2	0.314	0.314	0.276	0.354
DMU_3	0.910	0.910	0.870	0.950
DMU_4	0.459	0.459	0.420	0.498
DMU_5	0.420	0.420	0.381	0.460
DMU_6	0.631	0.631	0.592	0.670
DMU_7	0.330	0.330	0.292	0.370
DMU_8	0.720	0.720	0.681	0.760
DMU_9	0.523	0.523	0.484	0.563
DMU_{10}	0.645	0.645	0.606	0.684