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Assessment of the Logistics Performance of OPEC Countries with Integrated MCDM Methods

OPEC Ülkelerinin Lojistik Performanslarının Birleşik ÇKKV Yöntemleri ile Değerlendirilmesi

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ABSTRACT

For OPEC member states—whose economies heavily rely on oil exports—effective logistics systems are critical for maintaining stability and growth. While many studies analyze logistics performance using composite indices or econometric models, few have examined the impact of different MCDM weighting and ranking techniques on the evaluation results. This study aims to fill this gap by comparing two objective weighting methods—Entropy and CRITIC—and integrating them with two widely used MCDM ranking techniques, TOPSIS and CoCoSo. In the first stage, Entropy and CRITIC methods were applied to determine the weights of logistics performance indicators. The results show that Entropy prioritizes structural, information-intensive criteria such as infrastructure, while CRITIC gives more weight to performance-based indicators like shipment efficiency and on-time delivery due to its sensitivity to standard deviation and correlation. In the second stage, TOPSIS and CoCoSo methods were used to generate country rankings. CoCoSo results demonstrated more stable and balanced performance.

Keywords: Logistics Performance Index, Entropy Method, CRITIC Method, CoCoSo Method, TOPSIS Method.

ÖZ

Ekonomileri büyük ölçüde petrol ihracatına dayanan OPEC üyesi ülkeler için, etkili lojistik sistemleri istikrar ve büyümeyi sürdürmek için kritik öneme sahiptir. Birçok çalışma lojistik performansı bileşik endeksler veya ekonometrik modeller kullanarak analiz ederken, çok azı farklı ÇKKV ağırlıklandırma ve sıralama tekniklerinin değerlendirme sonuçları üzerindeki etkisini incelemiştir. Bu çalışma, iki nesnel ağırlıklandırma yöntemini (Entropy ve CRITIC) karşılaştırarak ve bu metotları yaygın olarak kullanılan iki ÇKKV sıralama yöntemlerinden olan TOPSIS ve CoCoSo ile entegre ederek bu boşluğu doldurmayı amaçlamaktadır. İlk aşamada, Entropy ve CRITIC yöntemleri lojistik performans göstergelerinin ağırlıklarını belirlemek için uygulanmaktadır. Sonuçlar, Entropy'nin altyapı gibi yapısal, bilgi yoğun kriterlere öncelik verdiğini, CRITIC'in ise standart sapmaya ve korelasyona duyarlılığı nedeniyle sevkiyat verimliliği ve zamanında teslimat gibi performansa dayalı göstergelere daha fazla ağırlık verdiğini göstermektedir. İkinci aşamada, ülke sıralamaları oluşturmak için TOPSIS ve CoCoSo yöntemleri kullanılmıştır. Analiz sonuçları, CoCoSo metodunun daha istikrarlı ve dengeli bir performansa sahip olduğunu göstermektedir.

Anahtar Kelimeler: Lojistik Performans Endeksi, Entropy Yöntemi, CRITIC Yöntemi, CoCoSo Yöntemi, TOPSIS Yöntemi.

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1. INTRODUCTION

The Organization of the Petroleum Exporting Countries (OPEC) is a global institution that plays a pivotal role in maintaining oil market stability and supporting a sustainable energy supply. Established in 1960 in Baghdad, OPEC currently includes 13 member countries: Algeria, Angola, Congo, Equatorial Guinea, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, Saudi Arabia, the United Arab Emirates (UAE), and Venezuela. The organization's core mission is to coordinate petroleum policies among member states and balance the interests of producers and consumers (OPEC, 2024).

As of 2023, OPEC countries collectively hold 79.1% of the world's proven crude oil reserves, produce approximately 35.1% of global oil, and account for nearly 46.7% of global oil exports (OPEC, 2024; IEA, 2024; BP, 2023). Additionally, their share in global merchandise and energy trade is estimated between 12% and 15% for the period 2017-2021 (OPEC, 2022, p. 49) and between 44% and 47% % for the period 2019-2023 (OPEC, 2024, p. 49). This economic footprint makes OPEC not only a dominant energy supplier but also a significant actor in shaping trade flows, infrastructure development, and macroeconomic stability in resource-rich regions. While many studies have focused on macroeconomic indicators such as GDP, energy consumption, and fiscal performance (Apergis & Paynes, 2009; Jian et al., 2019), relatively limited research has assessed logistics performance, which is a strategic factor in global supply chain efficiency and competitiveness.

Logistics performance is a critical determinant of trade facilitation, affecting transportation costs, supply chain reliability, and economic stability. A well-developed logistics sector improves trade efficiency, supports industrial growth, and strengthens global supply chains, whereas poor logistics infrastructure can create barriers to trade, increase operational costs, and disrupt economic activities (Devlin & Yee, 2005; Rashidi & Cullinane, 2019). Given that OPEC member countries rely heavily on international trade, particularly in oil and gas exports, their logistics efficiency plays a fundamental role in sustaining economic stability and competitiveness in global markets. However, there is a research gap in assessing the logistics performance of OPEC nations, making it essential to conduct a comprehensive evaluation using scientific methods.

The World Bank has been publishing the Logistics Performance Index (LPI) since 2007 to assess logistics capabilities across more than 160 countries. The LPI evaluates national logistics performance based on six key dimensions:

- Customs efficiency
- Infrastructure quality
- International shipping capabilities
- Logistics competence and quality
- Tracking and tracing systems
- Timeliness of shipments

This index serves as a benchmark for trade logistics efficiency, offering insights into the strengths and weaknesses of different nations' supply chain networks. The LPI is based on both qualitative data (expert surveys from logistics professionals, freight forwarders, and express carriers) and quantitative trade data, providing a well-rounded evaluation of logistics performance (Arvis et al., 2013).

Due to the multi-dimensional nature of logistics evaluation, the analysis is approached using Multi-Criteria Decision-Making (MCDM) methods, which provide structured decision-making models for complex evaluations. MCDM techniques have been widely applied in logistics and economic studies to develop quantitative ranking systems, integrating multiple logistics indicators into a single framework. However, since a consensus cannot be achieved about which is the best method of MCDMs, different weight calculation methods and alternative selection methods are included in this study.

This study evaluates LPI of OPEC countries using an integrated MCDM approach. Specifically, two objective weighting methods, Entropy and CRITIC, are employed to determine the relative importance of logistics performance criteria. These weighting methods are then applied within the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and CoCoSo (Combined Compromise Solution) methods to rank OPEC countries based on their logistics efficiency.

Evaluation of logistics performance is a multi-dimensional analysis process using MCDMs. In recent years, new generation techniques such as Entropy, CRITIC, TOPSIS and CoCoSo have come to the fore among MCDM methods. Therefore, in this study, these methods were used to evaluate the logistics performance of OPEC countries.

The reason for choosing these methods is that they have been used intensively in logistics performance evaluation in recent years and provide high accuracy. In the literature, it has been shown that these methods provide effective results in logistics efficiency analysis. It evaluates the information content of the data objectively and gives high weight to information-intensive criteria. This method offers an effective solution especially in multi-criteria problems where data diversity is high (Alinezhad & Khalili, 2019). It gives weight to more discriminative criteria by taking into account the variation and correlation between the criteria. In this way, the bias brought by high correlation is minimized (Diakoulaki et al., 1995). It ranks the alternatives based on their closeness to the ideal solution, gives a reward to the one close to the good solution and a penalty to the one close to the bad solution. This feature provides more realistic results in logistics performance analysis (Hwang & Yoon, 1981). It produces more robust and balanced rankings by combining different multi-criteria decision-making methods. It is especially preferred in complex logistics performance problems. For this reason, these methods were selected in this study to fill the gap in the literature.

The research aims to analyze the logistics capabilities of OPEC nations using data from 2018 to 2023, providing insights into trade efficiency, infrastructure quality, and supply chain effectiveness. The findings contribute to a deeper understanding of logistics performance variations among OPEC countries, offering valuable insights for policymakers, trade analysts, and economic researchers.

2. LITERATURE REVIEW

This section provides an overview of previous studies on logistics performance assessment and the methodologies used in evaluating (LPI). In recent years, researchers have increasingly focused on applying (MCDM) methods to assess and compare the logistics capabilities of different countries. These studies employ various techniques, including objective weighting methods, hybrid MCDM models, and fuzzy logic-based approaches to improve the accuracy and reliability of rankings.

Several studies have analyzed the logistics performance of economic blocs such as the European Union (EU), the Organization for Economic Co-operation and Development (OECD), and the Balkan, utilizing a range of decision-making techniques. Table 1 presents a summary of relevant studies that have applied different MCDM methodologies to LPI evaluations. Akandere (2021) examined the the belt road countries' logistics and environmental performance using the Entropy based TOPSIS.

As demonstrated in Table 1, a wide range of methodologies has been used to assess logistics performance across different regions and economic groups, extending with findings. While various MCDM methods have been applied to evaluate the LPI of EU, OECD, and Balkan countries, no previous study has specifically examined the LPI of OPEC nations using an integrated Entropy and CRITIC based TOPSIS, and CoCoSo approach.

Table 1. Previous Studies on LPI Evaluation

Author(s)	Year	Methods	Topic	Findings
Yazdani et al.	2017	Fuzzy QFD and Fuzzy TOPSIS	Group decision support for logistic and supply chain	Weights of the decision criteria are determined using fuzzy QFD and ranking of alternatives are generated for logistic providers using fuzzy TOPSIS.
Öztürk & Kaya	2020	CRITIC-WASPAS	OECD logistics comparison	CRITIC method is more robust than subjective methods.
Abara	2021	Relation Analysis	Investigating the relationship between logistics performance and foreign trade volume.	The result of the analysis indicated that the impact of logistics performance on foreign trade volume is statistically and highly significant.
Akandere	2021	Entropy-TOPSIS	Examining the Belt Road countries' logistics and environmental performance.	Singapore in 2014 and Greece in 2016 and 2018 ranked first among the countries with the best environmental and logistics performance.

Özekenci	2023	SWARA-CRITIC Based CoCoSo	LPI in developing economies	The findings indicate that business fundamentals [BF] is the most significant criterion, followed by international logistics opportunities [ILO] and digital readiness.
Ju et al.	2024	Fuzzy ROV	Assessment of Logistics Performance Index of EU Countries	The defined model is reflected in a comparison with the World Bank report in which many countries share the same position.
Keleş & Kahveci	2025	WENSLO +ARTASI	The logistics performance of the EU candidates and members.	EU countries that have high-income economy, were ranked at top, and Cyprus, although it is an island country and may have logistical connections with many countries, was ranked last among EU countries
Özekenci	2025	SD, CRITIC, LOPCOW, MEREC + CRADIS	Evaluation of OECD countries' LPI with hybrid MCDM	Finland had the highest LPI score, Costa Rica the lowest
Yazar Okur et al.	2025	Fermatean Fuzzy Entropy + WASPAS	Evaluating logistics sector sustainability indicators	The study found that, according to experts, the most important sustainability dimension was economic, followed by environmental and social.
Yildirim, B. F., Adiguzel Mercangoz, B.	2020	Fuzzy AHP + ARAS-G	Evaluating the logistics performance of OECD countries	The results show that the rankings calculated by ARAS-G have the strongest relationship with years.

Given the absence of such an analysis, this study aims to fill this research gap by introducing a novel MCDM framework to assess the logistics performance of OPEC countries. By combining objective weighting methods (Entropy and CRITIC) with two ranking techniques (TOPSIS and CoCoSo), this study provides a comprehensive and data-driven assessment of logistics performance in OPEC nations between 2018 and 2023.

3. MATERIALS AND METHODS

In this study, LPI data published by the World Bank was used to evaluate the logistics performance of OPEC member countries. LPI data is updated every two years, and the most up-to-date data from 2018 and 2023 were taken into account in this study. The reason for choosing the data is that 2018 reflects the pre-pandemic logistics performance, while 2023 reflects the change in logistics efficiency in the post-pandemic period. LPI data consists of "Customs" (C1), which shows customs efficiency and border transactions, "Infrastructure" (C2), which measures the quality of trade and transportation infrastructure, "International Shipments" (C3), which expresses the ease of arranging shipments at competitive prices, "Logistics Quality & Competence" (C4), which is related to the quality and adequacy of logistics services, "Tracking & Tracing" (C5), which evaluates the traceability of shipments, and "Timeliness" (C6), which shows the frequency of shipments reaching their destination within the planned time.

The data sources are based on the LPI reports published by the World Bank, and the data are numerical and statistical logistic performance indicators. Since the LPI data is published every two years, there are some restrictions on data continuity. Therefore, in order to reach the most up-to-date and accurate results in the study, data from both 2018 and 2023 were analyzed comparatively. The alternatives used were determined as OPEC members Algeria, Angola, Congo, Equatorial Guinea, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, Saudi Arabia, United Arab Emirates (UAE) and Venezuela.

In this study, MCDM methods were used for logistic performance evaluation. Entropy, CRITIC, TOPSIS and CoCoSo methods, which have become prominent in recent years, were preferred. The Entropy method analyzes the information content of the data and gives high weight to more information-intensive criteria, thus providing an objective evaluation. The CRITIC method, on the other hand, gives weight to more distinctive criteria by considering the variation and correlation between the criteria. The use of these two methods is important to ensure that the criteria are weighted correctly. For the logistics performance ranking, TOPSIS and CoCoSo methods were used. While the TOPSIS method ranks the alternatives according to their degree of closeness to the ideal solution, the CoCoSo method combines multiple compromise solutions to obtain more balanced and stable rankings.

Table 2. Summary of the Criteria Table

Criterion	Code	Definition
Customs	C1	The efficiency of customs and borders
Infrastructure	C2	The quality of trade and transport infrastructure
International Shipments	C3	The ease of arranging competitively priced shipments
Logistics Quality & Competence	C4	The competence and quality of logistics services
Tracking & Tracing	C5	The ability to track and trace consignments
Timeliness	C6	The frequency with which shipments reach consignees within scheduled or expected delivery times

Source: Adapted from World Bank, 2018

Using these methods together allows for a more comprehensive and reliable assessment of logistics performance. The results show that the United Arab Emirates has the highest logistics performance among OPEC countries, while countries such as Angola and Venezuela stand out with low logistics efficiency. In this context, it was concluded that strategic planning should be made for infrastructure investments and modernization of customs processes in order to improve the logistics performance of OPEC countries.

3.1. Entropy Method

The Entropy method, introduced by Rudolf Clausius in 1865, is a fundamental concept initially developed within the field of thermodynamics. In decision-making studies, it has been widely adapted to determine the significance of various criteria by analyzing their information content. The method objectively assigns weights by evaluating the dispersion of data among different indicators, ensuring that more informative criteria receive greater weight. This approach helps to minimize subjective bias in the decision-making process, making it especially useful in logistics performance evaluation. The Entropy method's application in decision analysis is well-documented and highlighted its effectiveness in quantifying information content and its relevance in multi-criteria decision-making contexts (Diakoulaki et al., 1995). Steps of Entropy model's algorithm are indicated as following (Zhu et al., 2020).

Step 1: Data standardization processing.

$$P_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \quad i=1,2,.n \quad \text{and} \quad j=1,2,..m \tag{1}$$

where $x_{ij}$is the value of jth sample (alternative) under the criterion i.

Step 3. Computation of the Entropy of each indicator by applying Eq. (2).

$$E_i = -k \sum_{i=1}^{n} P_{ij} \ln P_{ij} \tag{2}$$

where $k = \frac{1}{\ln(n)}$

Step 3. Calculating the weight for each indicator by Eq. (3).

$$W_i = \frac{1-E_i}{\sum_{k=1}^{m}(1-E_i)} \tag{3}$$

The Entropy method is particularly useful in logistics performance evaluation as it eliminates redundancy in data and highlights the most influential factors in trade and transport efficiency. Previous studies have successfully applied Entropy in logistics and transportation research, demonstrating its effectiveness in objective weight determination (Diakoulaki et al., 1995; Alinezhad & Khalili, 2019).

3.2. CRITIC Method

The CRITIC method, introduced in 1995 (Diakoulaki et al., 1995), is another objective weighting technique used to measure the relative importance of decision-making criteria.

Unlike Entropy, which focuses on the information content, CRITIC evaluates both the contrast intensity and correlation between criteria. The method assigns greater weights to indicators that show high variability and low correlation, ensuring that the most discriminative factors have a stronger influence on the decision-making process (Diakoulaki et al., 1995). The CRITIC method process is as follows (Diakoulaki et al., 1995; Özdağoğlu et al., 2022):

Step 1. Initial data matrix is prepared with Eq. (5).

$$X = \begin{vmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nj} & \cdots & x_{nm} \end{vmatrix} \tag{5}$$

Step 2. Normalize the raw data matrix with Eq. (6) and Eq. (7).

$$r_{ij} = \frac{x_{ij} - X_j^{worst}}{X_j^{best} - X_j^{worst}} \quad \text{for cost criterion} \tag{6}$$

$$r_{ij} = \frac{X_j^{best} - x_{ij}}{X_j^{best} - X_j^{worst}} \quad \text{for benefit criterion} \tag{7}$$

While calculating the Eq. (6) and Equation (7), X_j^{worst} represents the minimum value at the related criterion and X_j^{best} represents the maximum value.

Step 4. Calculate the criteria standard deviations by Eq. (8):

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}(r'_{ij} - \bar{r}_j)^2}{m}} \tag{8}$$

Step 5. Calculate the correlation between criteria pairs using Eq. (9):

$$t_{jk} = \frac{\sum_{i=1}^{m}\left(r'_{ij} - \bar{r}_j\right)\left(r'_{ik} - \bar{r}_k\right)}{\sqrt{\sum_{i=1}^{m}(r'_{ij} - \bar{r}_j)^2 \sum_{i=1}^{m}(r'_{ik} - \bar{r}_k)^2}} \tag{9}$$

Step 6. Calculate the quantity of information of each criterion as follows.

$$C_j = \sigma_j \sum_{k=1}^{n}\left(1 - t_{jk}\right) \tag{10}$$

The larger the C_j is, the more information a certain criterion contains, so the weight of this evaluation criterion is greater than that of other criteria.

Step 5: Determination of the criteria weights (W_j). To calculate the final criteria weights (W_j) the c_j values of the criteria are used. Increase in the c_j value increases the relative importance for the decision-making process. To calculate W_j value the Eq. (11) is used.

$$W_j = \frac{c_j}{\sum_{k=1}^{m} c_k} \tag{11}$$

In logistics research, the CRITIC method has been employed to assess supply chain performance, trade logistics efficiency, and transport infrastructure quality (Diakoulaki et al., 1995).

3.3. TOPSIS and CoCoSo Methods

Once the Entropy and CRITIC methods determine the weights of LPI indicators, the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and CoCoSo (Combined Compromise Solution) methods are applied to rank OPEC countries based on their logistics performance. TOPSIS ranks alternatives by calculating their distance from an ideal best and an ideal worst solution. This method ensures that the country with the closest logistics performance to the optimal solution ranks the highest (Hwang & Yoon, 1981). The TOPSIS score, C_i^* is being within the interval [0,1] and the best score must be nearest to the 1.

CoCoSo is an advanced ranking technique that integrates multiple compromise decision-making approaches to improve ranking accuracy. By incorporating both summation and multiplication aggregation functions, CoCoSo enhances the stability of ranking results and provides a more robust evaluation of logistics performance (Yazdani et al., 2019).

By integrating these methods, this study aims to compare and rank the logistics performance of OPEC countries between 2018 and 2023, identifying strengths and weaknesses in their transport and trade efficiency. This approach not only fills a gap in logistics research but also contributes to the ongoing discourse on logistics optimization in resource-rich economies.

This integrated approach enhances the robustness of the analysis by reflecting both the discriminative power of the criteria and the relative performance of alternatives. Integrated MCDM models have increasingly been adopted in recent years to improve the accuracy and reliability of performance evaluations across complex decision-making. The integration with the Entropy method enables a comprehensive weighting framework, ensuring a more accurate and objective evaluation of logistics performance in OPEC countries. Moreover, this study employs a novel decision-making model by combining objective weighting techniques (Entropy and CRITIC) with alternative selection methods (TOPSIS and CoCoSo). TOPSIS steps are indicated as the following (Hwang & Yoon, 1981).

Step 1. Decision matrix is prepared using Eq. (12).

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \tag{12}$$

Step 2. Normalized matrix is created with the Eq. (13).

$$N = \begin{bmatrix} n_{11} & \cdots & n_{1n} \\ \vdots & \ddots & \vdots \\ n_{m1} & \cdots & n_{mn} \end{bmatrix} n_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \; i = 1,2, \dots \dots m, \; j = 1,2, \dots \dots n \tag{13}$$

Step 3. The normalisation of criteria values is accomplished based on compromise normalisation equation.

$$V = \begin{bmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{bmatrix} \text{where } v_{ij} = w_{ij} * n_{ij} \tag{14}$$

Step 4. Positive and negative ideal solutions are computed by applying Eq. (15).

$$A^* = \{v_1^*, v_2^*, \dots \dots v_n^*\} \quad A^- = \{v_1^-, v_2^-, \dots \dots v_n^-\} \tag{15}$$

Step 5. Distances from ideal solutions are calculated.

$$S_i^* = \sqrt{\sum (v_{ij} - v_j^*)^2} \quad S_i^- = \sqrt{\sum (v_{ij} - v_j^-)^2} \tag{16}$$

Step 6. TOPSIS score is computed for each alternative applying Eq. (17) and evaluated.

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*} \tag{17}$$

Alternatively, the steps of CoCoSo method are given as below (Yazdani et al., 2019).

Step 1. Form the initial decision matrix X for m alternatives with respect to n criteria.

$$X = \begin{vmatrix} x_{12} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{vmatrix} \quad i = 1,2,.m. j = 1,2,.n. \tag{18}$$

Step 2. The normalisation of criteria values is accomplished based on compromise normalisation equation.

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad \text{for benefit criterion} \tag{19}$$

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad \text{for cost criterion} \tag{20}$$

Step 3. The total of the weighted comparability sequence and the whole of the power weight of comparability sequences for each alternative sum of the weighted comparability sequence and an amount of the power weight of comparability sequences for each alternative as S_i and P_i, respectively:

$$S_i = \sum_{j=1}^{n} (w_j r_{ij}) \tag{21}$$

this S_i value is achieved based on grey relational generation approach:

$$P_i = \sum_{j=1}^{n} (r_{ij})^{w_j} \tag{22}$$

This P_i value is also achieved according to the WASPAS multiplicative attitude.

Step 4. compute the relative priorities of alternatives by the aggregation strategies shown as Eqs. (23)-(25).

$$\mathrm{k}_{ia} = \frac{P_i+S_i}{\sum_{i=1}^{m}(P_i+S_i)}, \quad i = 1,2,\ldots\ldots m. \tag{23}$$

$$\mathrm{k}_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i}, \quad i = 1,2,\ldots\ldots m. \tag{24}$$

$$\mathrm{k}_{ic} = \frac{\lambda(S_i)+(1-\lambda)(P_i)}{\lambda \max_i S_i+(1-\lambda)\max_i P_i}, \quad i = 1,2,\ldots m \tag{25}$$

In Eq. (48), the value of λ (usually $\lambda = 0{,}5$) is determined by decision-makers and $0 \leq \lambda \leq 1$.

Step 5. The ranking of all alternatives is determined in descending order of the performance scores of the alternatives.

$$\mathrm{k}_i = (\mathrm{k}_{ia}, \mathrm{k}_{ib}, \mathrm{k}_{ic})^{\frac{1}{3}} + \frac{1}{3}(\mathrm{k}_{ia} + \mathrm{k}_{ib} + \mathrm{k}_{ic}) \tag{26}$$

4. RESULTS

This section presents the findings of the Entropy and CRITIC weighting methods combined with the TOPSIS and CoCoSo ranking techniques for evaluating the logistics performance of OPEC countries**.** First, the Entropy and CRITIC methods were applied separately to determine the weight of each criterion. Once the criteria weights were established, the logistics performance of OPEC countries was ranked using TOPSIS and CoCoSo methods. Below, Table 3 shows the data for 2018, and Table 4 shows the data for 2023.

Table 3. The Decision Matrix of OPEC Countries (2018)

Country	C1	C2	C3	C4	C5	C6
Algeria	2.13	2.42	2.39	2.39	2.6	2.76
Angola	1.57	1.86	2.2	2	2	2.59
Congo	2.27	2.07	2.87	2.28	2.38	2.95
Equatorial Guinea	1.91	1.88	2.88	2.25	2.13	2.75
Gabon	1.96	2.09	2.1	2.07	2.07	2.67
Iran	2.63	2.77	2.76	2.84	2.77	3.36
Iraq	1.84	2.03	2.32	1.91	2.19	2.72
Kuwait	2.73	3.02	2.63	2.8	2.66	3.37
Libya	1.95	2.25	1.99	2.05	1.64	2.77
Nigeria	1.97	2.56	2.52	2.4	2.68	3.07
Saudi arabia	2.66	3.11	2.99	2.86	3.17	3.3
United Arab Emirates	3.63	4.02	3.85	3.92	3.96	4.38
Venezuela	1.79	2.1	2.38	2.21	2.29	2.58

Table 4. The Decision Matrix of OPEC Countries for (2023)

Country	C1	C2	C3	C4	C5	C6
Algeria	2.3	2.1	3	2.2	2.5	2.6
Angola	1.7	2.1	2.4	2.3	2.3	2.1
Congo	2.3	2.1	2.6	2.9	2.7	2.9
Equatorial Guinea	2.4	2.4	2.2	2.7	2.7	2.5
Gabon	2.7	2.4	2.4	2.5	2.2	2.7
Iran	2.2	2.4	2.4	2.1	2.4	2.7
Iraq	2.1	2.2	2.5	2.2	2.4	3
Kuwait	3.2	3.6	3.2	2.9	3.3	2.8
Libya	1.9	1.7	2	1.9	1.8	2.2
Nigeria	2.4	2.4	2.5	2.3	2.7	3.1
Saudi arabia	3	3.6	3.3	3.3	3.5	3.6
United Arab Emirates	3.7	4.1	3.8	4	4.1	4.2
Venezuela	2.1	2.4	2	2.5	2.3	2.5

4.1. Results of the Entropy and CRITIC Method

The Entropy and CRITIC methods used in MCDM applications allow objective determination of criteria weights. Although both methods adopt an objective approach, they differ in terms of the basic evaluation paradigm:

Entropy analyzes the diversity (degree of uncertainty) in the data based on the information content of the criteria. Since criteria with high diversity carry more information, it assigns higher weights to these criteria.

The CRITIC method, on the other hand, determines weights for criteria with more effective discriminatory power by considering both variance (criterion's distinctiveness) and correlation (level of relationship with other criteria). These methodological differences are clearly evident in the application results, in Table 5.

Table 5. CRITIC and Entropy Weights (for 2018 and 2023)

Weights	C1	C2	C3	C4	C5	C6
Weights of $CRITIC_{2018}$	0,14	0,18	0,27	0,10	0,16	0,12
Weights of $Entropy_{2018}$	0,21	0,22	0,12	0,16	0,19	0,09
Weights of $CRITIC_{2023}$	0,15	0,15	0,20	0,17	0,10	0,20
Weights of $Entropy_{2023}$	0,17	0,25	0,14	0,15	0,17	0,13

Infrastructure (C2) stands out as the criterion with the highest weight (0.25) in 2023 according to the Entropy method. This shows that the infrastructure criterion has become more decisive in terms of information diversity. The same criterion has decreased in

CRITIC compared to 2018, suggesting that infrastructure is now more highly correlated with other criteria. International Shipping (C3) had the highest weight (0.27) in the CRITIC method in 2018, but this weight decreased to 0.20 in 2023. This can be explained by the decrease in differences between countries in shipment data or the fact that this criterion has become correlated with others. On-Time Delivery (C6) showed a big jump in the CRITIC method in 2023, increasing its weight from 0.12 to 0.20. This shows that the time factor has become more discriminatory in the post-pandemic period and that differentiation between countries has increased in this regard. Tracking & Tracing (C5) received the lowest weight (0.10) in 2023 according to CRITIC. This indicates that differences between countries have narrowed and the discriminatory power of the criterion has weakened due to the general digitalisation of systems.

4.2. Results of the Entropy Based TOPSIS Method

The TOPSIS method ranks alternatives based on their similarity to an ideal solution. The following tables present the normalized decision matrix, the weighted decision matrix, and the final ranking of OPEC countries based on their logistics performance. The results highlight variations in logistics efficiency, with countries performing differently across the six logistics criteria.

Table 6 presents the normalized decision matrix, where each criterion value has been transformed into a comparable scale. Normalization ensures that all logistics indicators contribute equally to the analysis, regardless of their original units.

Table 6. The Normalized Decision Matrix (2023)

Country	C1	C2	C3	C4	C5	C6
Algeria	0.2533	0.2184	0.3095	0.2296	0.2522	0.2496
Angola	0.1872	0.2184	0.2476	0.2401	0.2320	0.2016
Congo	0.2533	0.2184	0.2682	0.3027	0.2724	0.2783
Equatorial Guinea	0.2643	0.2496	0.2270	0.2818	0.2724	0.2400
Gabon	0.2973	0.2496	0.2476	0.2610	0.2220	0.2591
Iran	0.2422	0.2496	0.2476	0.2192	0.2421	0.2591
Iraq	0.2312	0.2288	0.2579	0.2296	0.2421	0.2879
Kuwait	0.3524	0.3743	0.3301	0.3027	0.3329	0.2687
Libya	0.2092	0.1768	0.2063	0.1983	0.1816	0.2112
Nigeria	0.2643	0.2496	0.2579	0.2401	0.2724	0.2975
Saudi arabia	0.3303	0.3743	0.3405	0.3445	0.3531	0.3455
United Arab Emirates	0.4074	0.4263	0.3920	0.4175	0.4136	0.4031
Venezuela	0.2312	0.2496	0.2063	0.2610	0.2320	0.2400
W_j	0.17	0.25	0.14	0.15	0.17	0.13

Table 7 displays the weighted decision matrix obtained by multiplying each normalized value with its corresponding Entropy-based weight. Higher values indicate greater importance of that criterion in determining the logistics performance of each country.

Table 7. Weighting of Decision Matrix (2023)

Country	C1	C2	C3	C4	C5	C6
Algeria	0.0431	0.0546	0.0433	0.0344	0.0429	0.0324
Angola	0.0318	0.0546	0.0347	0.0360	0.0394	0.0262
Congo	0.0431	0.0546	0.0376	0.0454	0.0463	0.0362
Equatorial Guinea	0.0449	0.0624	0.0318	0.0423	0.0463	0.0312
Gabon	0.0505	0.0624	0.0347	0.0391	0.0377	0.0337
Iran	0.0412	0.0624	0.0347	0.0329	0.0412	0.0337
Iraq	0.0393	0.0572	0.0361	0.0344	0.0412	0.0374
Kuwait	0.0599	0.0936	0.0462	0.0454	0.0566	0.0349
Libya	0.0356	0.0442	0.0289	0.0297	0.0309	0.0275
Nigeria	0.0449	0.0624	0.0361	0.0360	0.0463	0.0387
Saudi arabia	0.0562	0.0936	0.0477	0.0517	0.0600	0.0449
United Arab Emirates	0.0693	0.1066	0.0549	0.0626	0.0703	0.0524
Venezuela	0.0393	0.0624	0.0289	0.0391	0.0394	0.0312
Max (A^+)	0.0693	0.1066	0.0549	0.0626	0.0703	0.0524
Min (A^-)	0.0318	0.0442	0.0289	0.0297	0.0309	0.0262

Table 8 provides the final ranking of OPEC countries based on their logistics performance using the TOPSIS method. The C_i^* value represents the closeness coefficient, with higher values indicating better logistics efficiency. The UAE ranks highest, demonstrating superior logistics performance, while Angola and Venezuela are among the lowest-ranked countries.

Table 8. Order of Closeness to Solution (2023)

Country	A^+	A^-	C_i^*	Ranking
Algeria	0.0740	0.0255	-0.5249	8
Angola	0.0828	0.0159	-0.2384	5
Congo	0.0695	0.0299	-0.7544	10
Equatorial Guinea	0.0672	0.0305	-0.8312	12
Gabon	0.0684	0.0301	-0.7865	11
Iran	0.0724	0.0250	-0.5272	9
Iraq	0.0745	0.0230	-0.4475	6
Kuwait	0.0335	0.0672	1.9945	1
Libya	0.0947	0.0039	-0.0435	4
Nigeria	0.0661	0.0314	-0.9064	13
Saudi arabia	0.0260	0.0712	1.5748	2
United Arab Emirates	0.0000	0.0964	1.0000	3
Venezuela	0.0740	0.0240	-0.4784	7

4.3. Results of the CRITIC based CoCoSo Method

The CoCoSo method is used to evaluate the logistics performance of OPEC countries by integrating different decision-making models into a single ranking system. This method is particularly effective in dealing with trade-offs between multiple criteria, making it a robust approach for analyzing logistics performance.

In this section, we present a series of tables that outline the normalized values, computed rankings, and final logistics performance assessments based on the CRITIC weighting method. These results provide a comparative analysis of how each country performed across various logistics indicators.

Table 9 displays the normalized values for each logistics criterion (C1-C6) for OPEC countries in 2023. Normalization is essential to standardize the data, ensuring that all values fall within a comparable range. By doing so, the influence of scale differences among criteria is minimized, allowing for a fair assessment of logistics performance.

Table 9. Creating the Normalization Matrix (2023)

Country	C1	C2	C3	C4	C5	C6
Algeria	0.3000	0.1667	0.5556	0.1429	0.3043	0.2381
Angola	0.0000	0.1667	0.2222	0.1905	0.2174	0.0000
Congo	0.3000	0.1667	0.3333	0.4762	0.3913	0.3810
Equatorial Guinea	0.3500	0.2917	0.1111	0.3810	0.3913	0.1905
Gabon	0.5000	0.2917	0.2222	0.2857	0.1739	0.2857
Iran	0.2500	0.2917	0.2222	0.0952	0.2609	0.2857
Iraq	0.2000	0.2083	0.2778	0.1429	0.2609	0.4286
Kuwait	0.7500	0.7917	0.6667	0.4762	0.6522	0.3333
Libya	0.1000	0.0000	0.0000	0.0000	0.0000	0.0476
Nigeria	0.3500	0.2917	0.2778	0.1905	0.3913	0.4762
Saudi arabia	0.6500	0.7917	0.7222	0.6667	0.7391	0.7143
United Arab Emirates	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Venezuela	0.2000	0.2917	0.0000	0.2857	0.2174	0.1905

The S_i values in Table 10 represent the sum of weighted normalized values for each country across all criteria. A higher S_i value indicates better overall logistics performance based on the weight assigned to each criterion. The P_i values given in Table 10 represent the geometric mean of weighted normalized values. Unlike S_i, which relies on summation, P_i values incorporate multiplicative aggregation, enhancing ranking stability.

Table 10. Calculation of S_i Values (2023)

Country	C1	C2	C3	C4	C5	C6	S_i	P_i
Algeria	0.045	0.026	0.114	0.024	0.033	0.048	0.293	4.814
Angola	0.000	0.026	0.046	0.033	0.024	0.000	0.129	3.088
Congo	0.047	0.026	0.069	0.081	0.043	0.077	0.343	4.989
Equatorial Guinea	0.054	0.046	0.023	0.065	0.043	0.039	0.269	4.776
Gabon	0.078	0.046	0.046	0.049	0.019	0.058	0.295	4.866
Iran	0.039	0.046	0.046	0.016	0.028	0.058	0.233	4.673
Iraq	0.032	0.033	0.058	0.024	0.028	0.087	0.260	4.752
Kuwait	0.117	0.124	0.138	0.081	0.071	0.067	0.598	5.477
Libya	0.016	0.000	0.000	0.000	0.000	0.010	0.025	1.241
Nigeria	0.054	0.046	0.057	0.033	0.043	0.096	0.329	4.959
Saudi arabia	0.101	0.124	0.149	0.114	0.081	0.144	0.718	5.670
United Arab Emirates	0.155	0.157	0.206	0.171	0.109	0.202	1.000	6.000
Venezuela	0.031	0.046	0.000	0.049	0.024	0.039	0.188	3.973

Table 11 presents the final results of the CoCoSo method for evaluating the logistics performance of OPEC countries in 2023. The table includes four key indicators for each country. They are the aggregate score of the weighted normalized matrix (S_i+ P_i), the first compromise score $K_i^{(1)}$, the second compromise score $K_i^{(2)}$, the final combined compromise score $K_i^{(3)}$, and the final weighted index *k* which determines the ultimate ranking of the alternatives. The results show that Saudi Arabia, Kuwait, and UAE achieved the highest rankings across all CoCoSo indicators. Specifically, Saudi Arabia ranked 2nd in all scoring columns with a high cumulative score of k =11.3179, reflecting consistent superiority in both additive and multiplicative criteria evaluations. Kuwait follows closely in 3rd place, with strong scores across $K_i^{(1)}$, $K_i^{(2)}$, and $K_i^{(3)}$, indicating balanced performance in logistics infrastructure, timeliness, and trade facilitation. In contrast, Libya consistently ranks the lowest across all indicators, reflecting its critical logistical shortcomings. Its final weighted score k= 0.7335 is significantly lower than other countries, suggesting serious infrastructural and systemic limitations in its supply chain capabilities. Middle-tier countries such as Nigeria, Congo, and Gabon display moderate performance with consistent rankings (4th–6th place). These results highlight some strength in logistics operations, though still behind the top three performers. The use of multiple CoCoSo components in this table—especially $K_i^{(3)}$, which averages both additive and relative rankings—ensures a well-rounded assessment. It combines both the relative superiority (via $K_i^{(2)}$) and absolute normalized performance (via $K_i^{(1)}$) to yield the most reliable final ranking, shown in the kk column. This approach strengthens the objectivity and validity of the evaluation process, particularly in diverse and economically asymmetric groups like OPEC.

Table 11. Relative Weights of Alternatives (2023)

Country	S_i+P_i	$K_i^{(1)}$	Rank	$K_i^{(2)}$	Rank	$K_i^{(3)}$	Rank	k	Rank
Algeria	5.107	0.080	7	15.538	7	0.730	7	5.449	7
Angola	3.216	0.050	12	7.594	12	0.460	12	2.701	12
Congo	5.331	0.083	4	17.651	4	0.762	4	6.165	4
Equatorial Guinea	5.045	0.079	8	14.567	8	0.721	8	5.122	8
Gabon	5.1604	0.081	6	15.651	6	0.737	6	5.490	6
Iran	4.906	0.077	10	13.034	10	0.701	10	4.604	10
Iraq	5.013	0.078	9	14.196	9	0.716	9	4.9979	9
Kuwait	6.074	0.095	3	28.211	3	0.868	3	9.724	3
Libya	1.266	0.020	13	2.000	13	0.181	13	0.734	13
Nigeria	5.287	0.083	5	17.082	5	0.755	5	5.973	5
Saudi Arabia	6.382	0.100	2	32.942	2	0.912	2	11.318	2
United A.E.	7.000	0.110	1	44.647	1	1.000	1	15.252	1
Venezuela	4.160	0.065	11	10.680	11	0.594	11	3.780	11

According to the Table 12, United Arab Emirates and Saudi Arabia ranked high in all of four hybrit methods which demonsrates the continuity of strong infrastructure and logistics systems. Gabon, Nigeria ve Congo, CRITIC yöntemine göre daha yukarıda yer alırken, Entropy sonuçlarında daha düşük puan almıştır. Bu da bu ülkelerde belirli kriterlerin (örneğin zamanında teslimat gibi) daha fazla varyans gösterdiğini işaret eder. Venezuela, LPI puanlamasında en üst sırada yer alırken diğer tüm MCDM yöntemlerinde son sıralardadır. Bu çelişki, LPI endeksinin bazı bileşenlerinin burada farklı ağırlıkla değerlendirilmiş olabileceğini gösterir. Libya ve Algeria, genel olarak her yöntemde alt sıralarda yer almaktadır.

Table 12. The Ranks of OPEC Countries for the year 2018

Country	CRITIC–TOPSIS	Entropy–TOPSIS	CRITIC–COCOSO	Entropy – COCOSO	LPI
United Arab E.	1	2	1	1	2
Saudi Arabia	2	1	2	2	3
Kuwait	3	3	3	3	8
Gabon	4	7	4	5	7
Nigeria	5	8	5	4	4
Congo	6	9	6	6	11
Equatorial Guinea	7	10	7	7	10
Algeria	8	13	8	8	13
Iran	9	11	9	9	9
Iraq	10	5	10	10	6
Venezuela	11	6	11	11	1
Angola	12	4	12	12	12
Libya	13	12	13	13	5

Figure 1 presents the logistics performance rankings of OPEC member countries for the year 2018, based on four integrated multi-criteria decision-making (MCDM) approaches: CRITIC–TOPSIS, Entropy –TOPSIS, CRITIC– CoCoSo, and Entropy – CoCoSo. The consistency observed in the top three rankings—United Arab Emirates, Saudi Arabia, and Kuwait—across all methods indicates their superior logistics infrastructure and operational efficiency within the OPEC region. These countries benefit from strategic investments in transport networks, customs modernization, and logistics service quality. In contrast, nations such as Libya, Venezuela, and Angola occupy the lowest positions in all four methods, reflecting persistent deficiencies in logistics systems and institutional capacity. Notably, the CRITIC– CoCoSo method exhibits the most coherent and balanced ranking distribution, effectively capturing performance variations by leveraging both statistical variance and compromise-based aggregation. This suggests that CRITIC–CoCoSo is better suited for identifying subtle differences in performance among mid-tier countries such as Gabon and Nigeria, whose rankings vary significantly between Entropy- and variance-based models. Overall, the 2018 rankings provide a foundational benchmark for longitudinal logistics performance evaluation within OPEC.

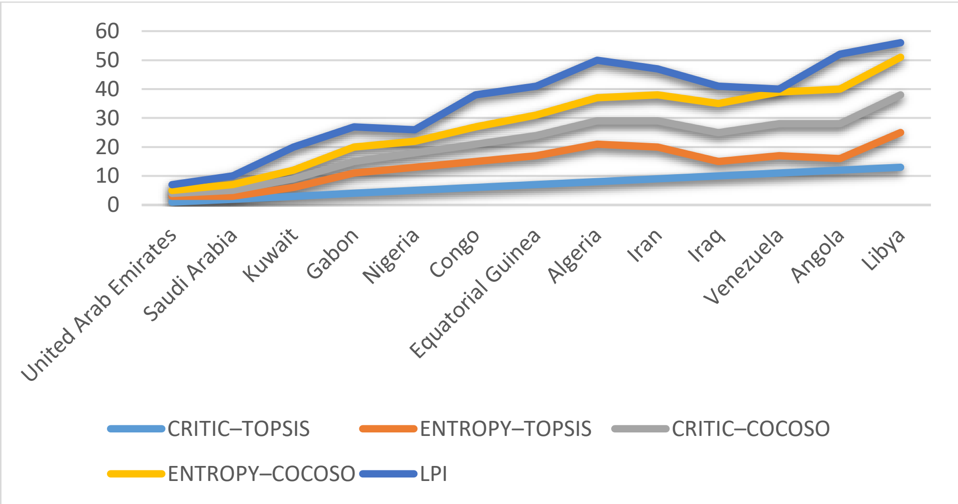

Figure 1. The ranks of OPEC countries for the year 2018

In Table 13, United Arab Emirates ranked highest in all methods, making it the country with the highest logistics performance in OPEC in 2023. Despite the different criteria weightings of the Entropy and CRITIC methods, the top three countries (United Arab Emirates, Saudi Arabia, Kuwait) remained generally stable in the rankings. Gabon, Congo, and Nigeria performed better in the CRITIC-weighted rankings, while their performance was lower in the Entropy-weighted rankings. This reflects the impact of data variance and information density on country performance. Libya and Angola rank last in all four methods, indicating serious weaknesses in their logistics infrastructure and processes.

Table 13. The Ranks of OPEC Countries for the year 2023

Country	CRITIC–TOPSIS	Entropy–TOPSIS	CRITIC–COCOSO	Entropy – COCOSO	LPI
United Arab E.	1	3	1	1	1
Saudi Arabia	2	2	2	2	2
Kuwait	3	1	3	3	3
Gabon	4	11	4	6	7
Nigeria	5	13	5	5	4
Congo	6	10	6	4	11
Equatorial Guinea	7	12	7	8	10
Algeria	8	8	8	7	8
Iran	9	9	9	10	9
Iraq	10	6	10	9	6
Venezuela	11	7	11	11	12
Angola	12	5	12	12	13
Libya	13	4	13	13	5

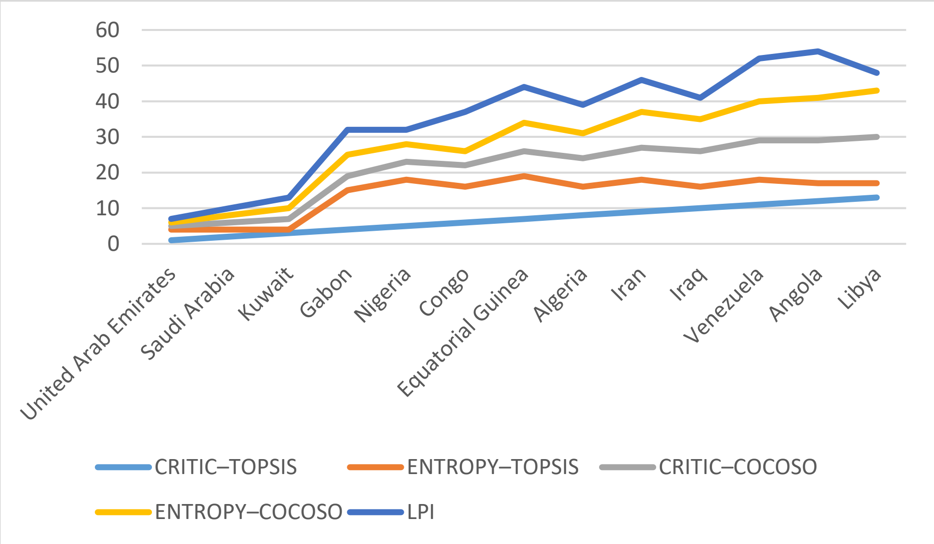

Figure 2. The ranks of OPEC countries for the year 2023

In Figure 2, logistics performance of OPEC countries for the year 2023 is assessed. The results derived from four hybrid MCDM models—CRITIC–TOPSIS, Entropy –TOPSIS, CRITIC– CoCoSo, and Entropy – CoCoSo —demonstrate a consistent pattern among top-performing nations while also highlighting methodological sensitivities in mid-tier and low-performing countries. The United Arab Emirates, Saudi Arabia, and Kuwait rank at the top across all models, underscoring their sustained investment in logistics infrastructure, digital customs operations, and trade facilitation. Among these methods, CRITIC– CoCoSo emerges as the most analytically robust, offering greater stability and consistency in rankings due to its dual focus on variance-based weighting and compromise aggregation. Conversely, Entropy –TOPSIS reveals higher volatility, particularly in the rankings of countries such as Angola and Venezuela, which are positioned relatively high despite clear infrastructural limitations. This discrepancy suggests that Entropy-based weighting may overemphasize criteria with uniform distribution while underrepresenting variance-based distinctiveness. Overall, the CRITIC– CoCoSo method provides the most balanced and decision-relevant results for evaluating logistics performance in heterogeneous and resource-dependent economic blocs like OPEC.

4.4. Decision Matrix for 2018 and 2023

In order to assess the changes in logistics performance among OPEC countries over the years, a comparative analysis of the Logistics Performance Index (LPI) scores for the years 2018 and 2023 has been conducted. This comparison aims to highlight the progress or decline in logistics efficiency within these countries, focusing on critical aspects such as customs efficiency, infrastructure quality, international shipments, logistics competence, tracking and tracing, and timeliness. The LPI scores are essential indicators reflecting the countries' capabilities in handling trade and logistics activities effectively.

The following table (Table 14) presents the LPI scores of OPEC countries for both 2018 and 2023. The comparison provides insights into how each country has evolved in terms of logistics performance over the selected period. Specifically, the analysis identifies improvements driven by infrastructure investments and logistics modernization, as well as potential challenges linked to economic and political factors affecting logistics efficiency.

Table 14. LPI Scores of OPEC Countries (2018 vs. 2023)

Country	C1 (Customs)	C2 (Infrastruc.)	C3 (International Shipments)	C4 (Logistics Quality)	C5 (Tracking & Tracing)	C6 (Timeliness)
Algeria	2.13 → 2.3	2.42 → 2.1	2.39 → 3.0	2.39 → 2.2	2.60→ 2.5	2.76 → 2.6
Angola	1.57 → 1.7	1.86 → 2.1	2.20 → 2.4	2.00 → 2.3	2.00 → 2.3	2.59 → 2.1
Saudi Arabia	2.66 → 3.0	3.11 → 3.6	2.99 → 3.3	2.86 → 3.3	3.17 → 3.5	3.3 → 3.6
UAE	3.63 → 3.7	4.02 → 4.1	3.85 → 3.8	3.92 → 4.0	3.96 → 4.1	4.38 → 4.2

The table clearly shows that United Arab Emirates (UAE) maintains its leading position in logistics performance, indicating sustained investment in logistics infrastructure and process optimization. Saudi Arabia also demonstrates significant improvements, particularly in infrastructure and customs efficiency. On the other hand, countries like Algeria and Angola show marginal improvements or slight declines, reflecting challenges related to infrastructure development and trade facilitation.

This comparative analysis provides a deeper understanding of how logistics performance has evolved within the OPEC bloc, emphasizing the need for targeted investments and policy reforms to enhance trade efficiency and global competitiveness.

5. COMPARATIVE ANALYSIS

The comparative analysis of logistics performance among OPEC countries for the year 2023, using four different MCDM method combinations (CRITIC–TOPSIS, Entropy – TOPSIS, CRITIC– CoCoSo, Entropy – CoCoSo), reveals several important patterns and divergences in ranking outcomes. Notably, United Arab Emirates (UAE), Saudi Arabia, and Kuwait consistently occupy the top three positions across all four methods. This consistency reflects their sustained investments in logistics infrastructure, advanced customs systems, and digital transformation in supply chain management. UAE, in particular, maintains its position as the logistics leader within OPEC, benefiting from world-class ports, seamless customs clearance procedures, and high levels of transport connectivity.

Saudi Arabia and Kuwait also demonstrate strong logistics capabilities, with both countries showing a marked improvement compared to earlier years. Their rankings are reinforced by consistent scores in both additive (TOPSIS) and compromise-based (CoCoSo) models, indicating balanced performance across all six LPI components.

In contrast, countries such as Libya, Venezuela, and Angola rank consistently low in all applied models. These results reflect persistent structural and institutional weaknesses, including outdated infrastructure, limited digitalization, and logistical bottlenecks. For instance, Libya occupies the bottom position in all CoCoSo rankings, signaling critical deficiencies in logistics efficiency and an urgent need for systemic reforms.

Another important observation is the discrepancy in rankings for mid-tier countries such as Gabon, Nigeria, and Congo. These nations tend to score better under CRITIC-weighted methods compared to Entropy -based models. This suggests that their logistics performance shows greater variance and distinctiveness in specific criteria (e.g., timeliness or competence), which is more effectively captured by CRITIC due to its emphasis on contrast intensity and low correlation. Entropy, in contrast, favors criteria with higher information Entropy, which may dilute the impact of standout performance in isolated metrics.

Additionally, Venezuela exhibits an interesting anomaly: while it holds a relatively higher LPI score according to the World Bank, it ranks poorly under all four MCDM models. This divergence could indicate that some LPI components are overrepresented or misaligned in weight under traditional LPI scoring, highlighting the importance of objective weighting schemes like Entropy and CRITIC in revealing underlying performance realities.

Overall, the comparative analysis underscores the value of a hybrid MCDM approach in capturing both the diversity and relative significance of logistics criteria. It provides a more comprehensive and balanced evaluation framework, revealing structural strengths in countries like UAE and Saudi Arabia, and pinpointing systemic weaknesses in countries such as Libya and Angola. These insights can guide policy recommendations and infrastructure strategies for enhancing logistics competitiveness across the OPEC bloc.

6. CONCLUSION

This study applied a hybrid multi-criteria decision-making (MCDM) framework combining the Entropy and CRITIC objective weighting methods with the TOPSIS and CoCoSo ranking approaches to evaluate the logistics performance of OPEC member countries for the years 2018 and 2023. The findings offer a comprehensive overview of how logistics efficiency has evolved among these resource-rich nations in a post-pandemic context.

The results consistently highlight the United Arab Emirates as the top performer across all four methodological combinations. This superior performance is attributed to its continuous investment in advanced infrastructure, efficient customs procedures, and high logistics competence. Saudi Arabia and Kuwait also maintain strong rankings, reflecting their growing emphasis on digital transformation, regional connectivity, and trade facilitation reforms. The stability of their top-three positions across all models validates the effectiveness of their long-term logistics strategies.

Conversely, countries such as Libya, Venezuela, and Angola rank consistently at the bottom. Their low scores across different methods signal significant systemic challenges, including underdeveloped infrastructure, outdated customs operations, and limited integration into global supply chains. Notably, Venezuela’s sharp contrast between its relatively higher LPI score and lower MCDM-based rankings underscores the limitations of conventional index-based assessments and emphasizes the importance of objective and holistic evaluation models.

Mid-tier countries like Gabon, Nigeria, and Congo exhibit variation in performance depending on the weighting method used. These differences reveal how specific criteria such as timeliness and shipment efficiency can disproportionately affect rankings under variance-based methods like CRITIC. This further demonstrates the analytical strength of combining different MCDM approaches to uncover nuanced insights into national logistics systems.

The analysis provides actionable insights for policymakers in OPEC countries:

- Infrastructure Development: Countries with consistently low performance should prioritize investment in transport infrastructure, including roads, ports, and logistics hubs, to reduce trade bottlenecks.
- Digital Transformation: Adopting advanced tracking, tracing, and customs automation technologies can enhance logistics efficiency, reduce delays, and improve transparency.

- Regional Collaboration: OPEC nations can benefit from harmonizing logistics standards and collaborating on cross-border initiatives to improve overall trade facilitation within the region.
- Data-Driven Policy Design: The application of objective and hybrid MCDM models enables evidence-based decision-making, helping governments allocate resources more effectively and evaluate the impact of reforms over time.

Future studies may expand upon this research by:

- Integrating qualitative factors, such as political stability or institutional quality, into the MCDM framework to better reflect real-world logistics constraints.
- Evaluating the impact of emerging technologies, including artificial intelligence (AI), blockchain, and the Internet of Things (IoT), on logistics performance in OPEC and other developing economies.
- Extending the scope of analysis to include non-OPEC oil-exporting countries for a broader benchmarking perspective on logistics performance in energy-driven economies.

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