frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 11 December 2024
DOI 10.3389/fenvs.2024.1389639

OPEN ACCESS

EDITED BY
Sushant K. Singh,
CAIES Foundation, India

REVIEWED BY
Xiangyun Gao,
China University of Geosciences, China
Balamurugan M.,
Dayananda Sagar College of Engineering, India

*CORRESPONDENCE
Lixin Tian,
tianlx@ujs.edu.cn

RECEIVED 21 February 2024
ACCEPTED 25 November 2024
PUBLISHED 11 December 2024

CITATION
Ahsan M, Tian L, Du R, Alhussan AA and El-kenawy E-SM (2024) Enhancing environmental sustainability through code-driven process integration in the petrochemical industry.
Front. Environ. Sci. 12:1389639.
doi: 10.3389/fenvs.2024.1389639

Enhancing environmental sustainability through code-driven process integration in the petrochemical industry

Muhammad Ahsan[1], Lixin Tian[1]*, Ruijin Du[1], Amel Ali Alhussan[2] and El-Sayed M. El-kenawy[3,4,5,6]

[1]School of Mathematical Sciences, Jiangsu University, Jiangsu, China, [2]Department of Computer Sciences, College of Computer and Information Sciences, Princess Nourah Bint Abdulrahman University, Riyadh, Saudi Arabia, [3]School of ICT, Faculty of Engineering, Design and Information and Communications Technology (EDICT), Bahrain Polytechnic, Isa Town, Bahrain, [4]Jadara University Research Center, Jadara University, Irbid, Jordan, [5]Applied Science Research Center, Applied Science Private University, Amman, Jordan, [6]Department of Communications and Electronics, Delta Higher Institute of Engineering and Technology, Mansoura, Egypt

Balancing various objectives and navigating uncertainties, reducing CO_2 emissions and enhancing energy efficiency in industry presents a complex challenge. While previous studies primarily focused on conventional optimization methods, this research introduces an innovative approach: a multi-criteria optimization framework tailored to address uncertainties. The primary objective is to optimize energy consumption, minimize emissions, and improve cost efficiency simultaneously within the petrochemical industry. To effectively manage uncertain variables, this study integrates decision-making simulations and expert insights through a hybrid methodology to yield optimal outcomes. Employing three distinct preference categories, the model formulates comprehensive decision-making strategies. Empirical findings underscore the model's efficacy in reducing CO_2 emissions, bridging crucial gaps in existing research, and advocating sustainable practices in the sector. Departing from conventional methodologies, this research leverages advanced decision-making techniques adept at handling uncertainty. The framework identifies pivotal emission sources and advocates economically viable reduction strategies. Its adaptability enriches our comprehension of emission challenges by considering diverse factors and expert perspectives. Professional assessments affirm the model's success and propose a Coding-Based Prototype as a strategic tool for addressing uncertainties. These results underscore the imperative for policy reforms, such as embracing carbon capture technologies, to bolster global sustainability and foster enduring growth in the industrial domain.

KEYWORDS
multi-criteria optimization, decision-making, petrochemical, coding, emission

1 Introduction

The emission of carbon and other greenhouse gases is a critical global issue, significantly affecting the Earth's climate by increasing temperatures and contributing to air pollution, which in turn affects public health (Fang G. et al., 2022). Factors such as rapid population growth, widespread industrialization, and growing energy needs have led countries to focus

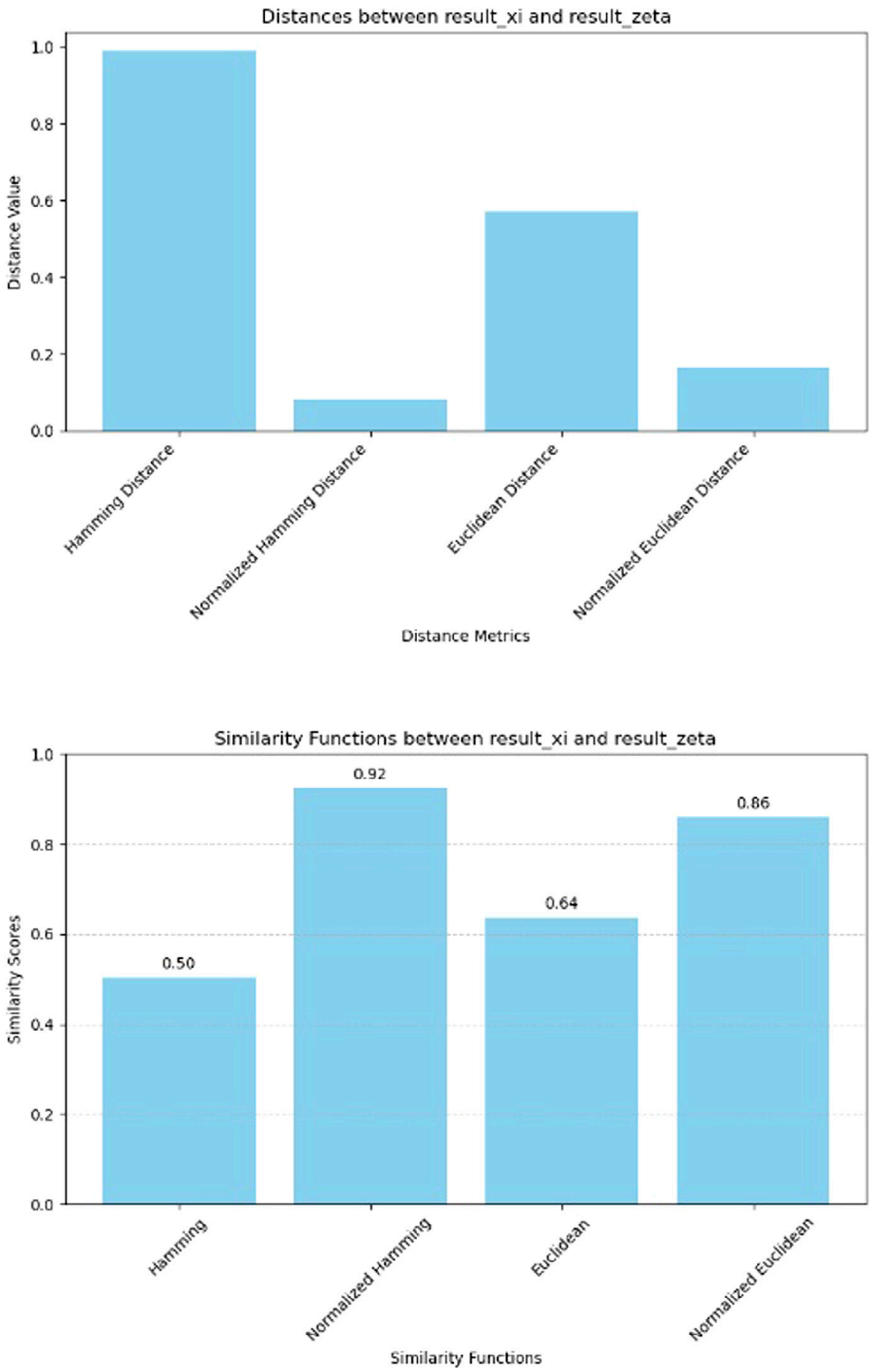

FIGURE 1
Graphical representation of distance measure and similarity measure.

as shown in Figure 1 on renewable energy sources and energy-saving measures (Dong F. et al., 2022). It's essential to recognize that economic expansion, a key component of GDP, fuels energy demand, especially in industrial activities, thereby increasing carbon emissions (Wang et al., 2022). Moreover, globalization, which makes it easier to enter new markets, has led to higher production levels, further boosting energy use and emissions (Fang T. et al., 2022). A lack of environmental consciousness among both companies and individuals exacerbates the issue, with economic motives often overriding the environmental benefits of switching to cleaner energy sources (Zhong et al., 2022; Pan et al., 2022). Tackling carbon emissions effectively calls for a strategic and cost-efficient approach. This necessitates a renewed investigation to enhance resource efficiency and create a detailed framework for decision-making that identifies key factors and their interconnections. The present study aims to reform the management of carbon emissions in the petrochemical sector by employing an innovative hybrid decision-making model. This model overcomes the gap left by previous research, offering a comprehensive strategy that accounts for uncertain data, focuses on cost-effectiveness, and includes expert insights. It promotes sustainable policies, validated through practical applications and expert assessments, and underscores the importance of regulatory measures, highlighting the role of carbon capture technologies in achieving global sustainability.

The main contributions of this paper include:

1. Introduces an innovative fuzzy decision-making model prioritizing financially viable emission reduction strategies.
2. Develops a Python-based prototype assessing factors and techniques in the Petrochemical Industry.
3. Utilizes linguistic terms for precise evaluations, offering heightened originality and efficacy.
4. Exploits Decision Making methodologies for uncertain data analysis and multi-criteria decision-making, improving result accuracy.
5. Introduces a comprehensive approach involving six components to widen the analytical landscape.

The rest of the document is organized in the following manner: The subsequent section involves reviewing the literature. Following that, the second section focuses on the methodologies and findings of the analysis. Ultimately, the concluding section expands upon the discussions and draws conclusions.

2 Literature

The global challenge of rising carbon emissions has spurred worldwide efforts for resolution, marked by intensified research and heightened concerns (Lin and Guan, 2023; Pang et al., 2023; Yu et al., 2023). Studies emphasize a direct link between economic growth, driven by business investments, and increased carbon emissions (Cui et al., 2022). While such investments create employment opportunities, unregulated surges may worsen emissions due to extensive energy consumption in production processes (Li et al., 2022; Lin and Sai, 2022; Liu et al., 2022; Jin et al., 2022; Navidi et al., 2022). Fossil fuel reliance in economic growth amplifies emissions (Akadiri and Adebayo, 2021), observed notably in India and top GDP countries (Zuo et al., 2022). Globalization fuels emissions through increased international trade, enabling multinational investments and necessitating heightened production capacities to meet diverse consumer demands (Xu et al., 2022; Lyu et al., 2022; Dong W. et al., 2022; Ren et al., 2022; Tao, 2022). The global reliance on fossil fuels intensifies emissions, particularly in G20 countries and Argentina (Yuping et al., 2021; Sheraz et al., 2021; Xiaoman et al., 2021; Qamruzzaman, 2022). Studies highlight globalization's reduced environmental sensitivity, leading to heightened production, energy demands, and waste generation (Akram et al., 2022; You and Zhang, 2022; Yunzhao, 2022; Abushamah and Skoda, 2022). Advocating for heightened environmental awareness, studies stress its pivotal role in addressing carbon emission challenges (Zhang et al., 2021; Razmjoo et al., 2021). Financial considerations contribute to emissions, as businesses prioritize cost-effective fossil fuels over renewables (Kuang et al., 2022; He et al., 2022). Mitigating this requires enhancing the cost competitiveness of renewable energy through research, development, and governmental incentives (de Oliveira and Moutinho, 2022; Gu et al., 2022; Sun and Zhang, 2022; Aihua et al., 2022; Guo et al., 2021). Efficient strategies, employing fuzzy decision-making models, can minimize carbon emissions (Guo et al., 2021). Refinery-chemical integration, particularly focusing on reducing oil usage while increasing the production of value-added chemicals, has emerged as a pivotal direction for the sustainable advancement of the petrochemical sector (Wong et al., 2023; Statista, 2023). While this integration offers the advantage of efficient crude oil utilization, it presents challenges in balancing increased petrochemical output with decreased environmental impact. Following the US, China is recognized as the second-largest nation in terms of oil refining capacity and chemical consumption. By 2030, the number of refineries in China is projected to rise from 220 in 2018 to 245, with processing capacity escalating from 611.68 million tons to 956.30 million tons (Simayi et al., 2021; Independent Commodity Intelligence Service, 2023). This underscores the tension between sustainable development goals and industry expansion. Furthermore, in 2021, petrochemical production contributed to approximately 25.5% of the total industrial VOC emissions and 20.0% of the total industrial carbon emissions (United Nations Environment Programme, 2023). The situation concerning wastewater and solid waste generation remains concerning. Additionally, China has enacted a series of regulations aiming for the petrochemical industry to reduce its energy intensity and CO_2 emissions by 10.0% and 12.5%, respectively, from the 2020 levels (National Development and Reform Commission of the People's Republic of China, 2022). Consequently, there is a pressing need for collaborative reduction and optimization, given the homologous nature of multiple pollutants and carbon emissions. Petrochemical processes exhibit an inseparable elemental relationship across various units due to energy-intensive production and feedstocks that act as energy carriers. This complexity complicates the quantification of material or energy loss, as well as waste emissions, because of their intrinsic role in material-energy coupling (Deng et al., 2023; Alazaiza et al., 2022). Therefore, a precise integrated analysis is crucial for managing complex systems and guiding pollution abatement. To elucidate the coupling relationship within an integrated system, several studies have been conducted on petrochemical production, especially in refineries (Sun et al., 2020; Sarwer et al., 2022; Thanigaivel et al., 2022). Ye et al. (2022) developed a simulation model that established an inherent relationship between delayed coking and hydrotreating in a refinery, quantifying the impact of upstream reaction condition changes on downstream products. Mohseni et al. (2019) employed an interpretive structural modeling technique to identify interrelations between different refining production modes, including setup reduction and pull production. These models, within a multi-factor management framework, enable the tracking of reaction pathways and synergistic material-energy transformations. Nevertheless, with the trend towards refinery-chemical integration, it is insufficient to explore the refinery alone, as petrochemical manufacturing also significantly influences material-energy interactions and system stability (Zhang et al., 2023).

2.1 Motivation/research gap

Previous investigations (Ignatius et al., 2016), (Yu et al., 2014), (Dinçer et al., 2023), and (Ubando et al., 2013) have encountered obstacles in identifying and implementing precise methods for curbing carbon emissions, prompting the need for this study to predict feasible reduction strategies and assess their efficacy accurately. The cited works lack sufficient granularity for thorough data analysis, hampering comprehensive understanding and effective decision-making. Moreover, their models struggle with managing non-membership values and falter when parameters are subdivided into sub-parameters. To overcome these limitations, we introduce an advanced framework integrating intuitionistic fuzzy set theory with hypersoft set theory, resulting in the Intuitionistic Fuzzy Hypersoft Set (IFHSS) approach. This methodology offers two key advancements: first, it expands the spectrum of membership (truth) and non-membership (falsity) values, and second, it enhances the management of parameters with nested sub-parameters, enabling more nuanced and accurate analysis. Our research focuses on devising effective emission reduction strategies within the petrochemical sector by targeting energy consumption, optimizing CO2 mitigation, and minimizing operational costs. The objective is to pinpoint the most economically viable solutions for achieving these goals. The findings aim to provide actionable insights for policymakers and industry stakeholders, empowering them to make informed decisions on carbon reduction initiatives.

3 Methodology

Addressing carbon emissions, highlighted by globalization and economic expansion (Fang G. et al., 2022; Ren et al., 2022; Tao, 2022), necessitates considering environmental awareness and financial factors (Qamruzzaman, 2022; Yunzhao, 2022). However, simultaneous resolution proves impractical due to associated costs, prompting a fresh investigation utilizing three programming-based decision-making techniques (Al-Kasasbeh et al., 2022). These methodologies offer a comprehensive exploration of emission management, introducing each with code demonstrations adaptable to real-world scenarios. The study focuses on prioritizing contributors to carbon emissions in the petrochemical sector, starting with the Entropy-based approach. This method utilizes entropy to identify significant emission contributors and recommends cost-effective mitigation strategies across three phases (Al-Kasasbeh et al., 2022). The study aims to guide further research in integrating decision-making with artificial intelligence and machine learning in emission reduction within the petrochemical industry. In this study, three methodologies are employed. First, a coding-based IHSS entropy approach is used to identify the primary sources of carbon emissions. Second, similarity measure techniques are applied to determine the most cost-effective and beneficial carbon emission reduction strategies. Lastly, a parametric TOPSIS method is utilized to rank various carbon emission reduction techniques.

Definition 1: (Saqlain et al., 2023) An Entropy (EN) function on the IHSS (Intuitionistic Hypersoft Set), denoted by E: IHSS$(\mathcal{U}) \rightarrow \mathbb{R}^+ \cup 0$, satisfies:

- $E(\varrho) = 0$ if and only if $\varrho \in$ IHSS$(\mathcal{U})$.
- $E(\varrho) = mn$ if $u_{\Psi(g)}(x) = 0$ for all $g \in E$ and $x \in \mathcal{U}$.
- $E(\varrho) = E(\varrho^c)$ for all $\varrho \in$ IHSS$(\mathcal{U})$.
- $E(\varrho) \leq E(\varsigma)$ if $\varsigma \subseteq \varrho$, where $\varrho = (\Psi_1, G_1)$ and $\varsigma = (\Psi_2, G_2)$.

The expression for $E(\varrho)$, the IHSS entropy for $\varrho = (\Psi_1, G_1)$, is given by:

$$E(\varrho) = \sum_{j=1}^{n} \sum_{i=1}^{m} (1 - \left(u_{\Psi_1(g_j)}(x_i) \right)$$

This formula defines the IHSS entropy for the specified IHSS $\varrho = (\Psi_1, G_1)$. Consider a universal set X. Define $G = Q_1 \times Q_2 \times \cdots \times Q_n$, where $n \geq 1$, and Q_i represents sets of valuable features. The steps for the IHSS-based EN are as follows as shown in Algorithm 1:

1: Express data linguistically.
2: Input each IHSS.
3: Transform IHSS using $\frac{1}{2}(1 + \frac{T_s^\epsilon(r) - F_s^\epsilon(r)}{T_s^\epsilon(r) + F_s^\epsilon(r) + 1})$ (Atanassov, 1986), where T and F denote truth and non-membership respectively.
4: Compute IHSS values for factors related to carbon emissions in the petrochemical industry.
5: Utilize Table 1 to interpret factors contributing to carbon emissions.
6: Determine entropy (EN) for each IHSS using 3.
7: Select IHSS with minimum entropy for optimal outcome.
8: If multiple IHSS exhibit low entropy, choose any.

Algorithm 1. IHSS entropy based algorithm.

Factors' IHSS computation using $\frac{1}{2}(1 + \frac{T_s^\epsilon(r) - F_s^\epsilon(r)}{T_s^\epsilon(r) + F_s^\epsilon(r) + 1})$ (Atanassov, 1986), yields: Fuel = 0.5, Processes = 0.1, Efficiency = 0.3, Compliance = 0.75.

In Table 1, values (0.5, 0.4) relate to carbon emissions for g_1 = (Investment, Processes Market Dynamics, Process Safety Incidents):

Note: Feedstock Processing contributes 50% to carbon emissions for g_1.
Feedstock Processing does not contribute in 40% of g_1 cases.

3.1 Example

In the petrochemical industry, rising carbon emissions pose challenges amid increasing global demand driven by population growth and technological advancements. Current methods fall short in addressing the need for sustainable solutions. Identifying primary emission factors and proposing effective reduction techniques is crucial, despite complex implementation risks. Six carbon emission factors $(X = a, b, c, d, e, f)$ are studied: Feedstock Processing (a), Energy Consumption (b), Combustion of Fossil Fuels (c), Chemical Reactions (d), Waste Management (e), and Transportation (f). These factors are

TABLE 1 Experts' views on feedstock processing using IHSS and sub-parameters.

Expert evaluation/ Parameters	g_1	g_2	g_3	g_4
∂_1	(0.5,0.3)	(0.1,0.5)	(0.9,0.1)	(0.1,0.4)
∂_2	(0.9,0.1)	(0.4,0.2)	(0.7,0.1)	(0.1,0.5)
∂_3	(0.6,0.2)	(0.2,0.1)	(0.1,0.1)	(0.3,0.2)
∂_4	(0.5,0.3)	(0.1,0.4)	(0.7,0.2)	(0.7,0.3)

TABLE 2 Experts' views on feedstock processing using IHSSES and sub-parameters.

Expert evaluation/Parameters	g_1	g_2	g_3	g_4
∂_1	0.5	0.37	0.7	0.4
∂_2	0.7	0.56	0.66	0.37
∂_3	0.61	0.53	0.5	0.53
∂_4	0.55	0.4	0.63	0.6

examined alongside unique attributes (Q_1, Q_2, Q_3), such as Economic Development, Industrial Structure, and Operational Risk. A combination space G_1 results from $Q_1 \times Q_2 \times Q_3$. Expert opinions $(\partial_1, \partial_2, \partial_3, \partial_4)$ are sought to determine influential emission factors. Management plans to integrate evidence using IHSS implementations outlined in Tables (Fang G. et al., 2022; Dong F. et al., 2022; Wang et al., 2022; Fang T. et al., 2022; Zhong et al., 2022; Pan et al., 2022). IHSS will be transformed into fuzzy hypersoft sets, denoted by $\frac{1}{2}(1+\frac{T_s^\varepsilon(r)-F_s^\varepsilon(r)}{T_s^\varepsilon(r)+F_s^\varepsilon(r)+1})$ (Atanassov, 1986). Entropy values for different sources (e.g., Feedstock Processing, Energy Consumption) are calculated using Python programming. For instance, the entropy of Feedstock Processing is 13.10. The optimal solution with the least entropy (E(Feedstock Processing)= 13.10) suggests it as the primary contributor to carbon emissions in the petrochemical industry. Although only a limited number of Tables 1, 2 have been depicted here, the remaining ones will be managed with the aid of programming. Please see the supplementary material for the Python code as shown in Algorithm 2.

```
1: Insert each IHSS.
2: Establish similarity for each IHSS using a
   defined method.
3: Choose the IHSS with the most similarities.
4: Select one optimal if multiple are obtained.
```

Algorithm 2. IHSS similarity measure based algorithm.

3.2 Carbon emission reduction technique selection based on similarity measure

Discussion revolves around IHSS distance measures and a specific definition for similarity measure in IHSS.

Definition 2: (Saqlain et al., 2023) Defines IHSS $\xi = (\Psi_1, G_1)$ and $\zeta = (\Psi_2, G_2)$ within an initial universe development $\mathcal{U}$.

Distances for ξ and ζ are determined as follows:

1. Hamming distance
2. Normalized Hamming distance
3. Euclidean distance
4. Normalized Euclidean distance

Properties:

- For Hamming and normalized Hamming distances: $0 \le d_{IHSS}^{H}(\xi,\zeta) \le mn$, $0 \le d_{IHSS}^{nH}(\xi,\zeta) \le 1$
- For Euclidean and normalized Euclidean distances: $0 \le d_{IHSS}^{E}(\xi,\zeta) \le \sqrt{mn}$, $0 \le d_{IHSS}^{nE}(\xi,\zeta) \le 1$

The proposed DM can define similarity measure between Fuzzy Hypersoft sets, characterizing various similarity measure between IHSS ξ and ζ.

- $S_{IHSS}^{H}(\xi,\zeta) = \frac{1}{1+d_{IHSS}^{H}(\xi,\zeta)}$
- $S_{IHSS}^{E}(\xi,\zeta) = \frac{1}{1+d_{IHSS}^{E}(\xi,\zeta)}$
- $S_{IHSS}^{nH}(\xi,\zeta) = \frac{1}{1+d_{IHSS}^{nH}(\xi,\zeta)}$
- $S_{IHSS}^{nE}(\xi,\zeta) = \frac{1}{1+d_{IHSS}^{nE}(\xi,\zeta)}$

3.2.1 Example

In the realm of petrochemical industries: The pursuit of techniques to curtail carbon emissions has become paramount. Innovative technologies like Carbon Capture and Storage (CCS), Renewable Feedstocks, and Energy Efficiency measures are revolutionizing the sector. CCS involves capturing carbon dioxide emissions from industrial processes and storing them underground to prevent their release into the atmosphere. Process Intensification aims to optimize chemical processes to minimize energy consumption and waste generation. Renewable Feedstocks focus on using sustainable raw materials instead of fossil fuels to produce chemicals. Energy Efficiency measures concentrate on reducing energy consumption during petrochemical production processes. Embracing these advancements holds immense potential to significantly mitigate carbon footprints in the petrochemical industry, fostering sustainability and environmental responsibility. To simplify, we provide data solely for two Carbon Capture Storage and ideal carbon emission reduction technique. Detailed materials related to these methods are available in the supplementary files for further review. Python programming can facilitate this process; please see 1 and the supplementary material for the Python code for the specific code involved.

1. Our objective is to identify the ideal sustainable energy source based on established standards within the petrochemical industry. Within this framework, the concept of IHSS plays a pivotal role in our exploration and evaluation of potential carbon emission reduction techniques.

Carbon Capture and Storage $\xi = (\varphi, \mathcal{F}) =$
$\Psi_1(g_1) = \{\langle u_1, (0.3, 0.1)\rangle, \langle u_2, (0.2, 0.4)\rangle, \langle u_3, (0.6, 0.4)\rangle\}$,
$\Psi_1(g_2) = \{\langle u_1, (0.2, 0.3)\rangle, \langle u_2, (0.5, 0.1)\rangle, \langle u_3, (0.6, 0.4)\rangle\}$,
$\Psi_1(g_3) = \{\langle u_1, (0.7, 0.3)\rangle, \langle u_2, (0.3, 0.2)\rangle, \langle u_3, (0.5, 0.2)\rangle\}$,

$\Psi_1(g_4) = \{\langle u_1, (0.2, 0.4)\rangle, \langle u_2, (0.4, 0.2)\rangle, \langle u_3, (0.2, 0.1)\rangle\}$,
and ideal carbon emission reduction technique in the form of IHSS is $\zeta = (\psi, \mathcal{F}) =$
$\Psi_2(g'''_1) = \{\langle u_1, (0.5, 0.2)\rangle, \langle u_2, (0.5, 0.4)\rangle, \langle u_3, (0.2, 0.1)\rangle\}$,
$\Psi_2(g'''_2) = \{\langle u_1, (0.5, 0.4)\rangle, \langle u_2, (0.5, 0.1)\rangle, \langle u_3, (0.1, 0.4)\rangle\}$,
$\Psi_2(g'''_3) = \{\langle u_1, (0.4, 0.5)\rangle, \langle u_2, (0.1, 0.6)\rangle, \langle u_3, (0.4, 0.1)\rangle\}$,
$\Psi_2(g'''_4) = \{\langle u_1, (0.3, 0.5)\rangle, \langle u_2, (0.1, 0.6)\rangle, \langle u_3, (0.2, 0.5)\rangle\}$,

Using Programming,

(a) Hamming distance: 4.8
(b) Normalized Hamming distance: 0.39999999999999997
(c) Euclidean distance: 1.2328828005937953
(d) Normalized Euclidean distance: 0.3559026084010437
(e) Similarity function (Hamming): 0.1724137931034483
(f) Similarity function (Normalized Hamming): 0.7142857142857143
(g) Similarity function (Euclidean): 0.4478515396034525
(h) Similarity function (Normalized Euclidean): 0.7375160972507133

2. Select the options that exhibit the highest similarity measure, consequently identifying the most effective technique for reducing carbon emissions in the petrochemical industry. Although only a limited amount of data is provided here, additional data will be processed using programming tools.

3.3 Using a TOPSIS-Based optimised IHSS classifier for evaluations of carbon emissions in the petrochemical industry

The petrochemical industry faces a critical challenge in reducing carbon emissions to combat climate change. To address this, a multifaceted approach is crucial, exploring various strategies from energy-efficient practices to technological advancements. The introduction of a Multi-Criteria Decision Making (MCDM) system centered on the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) offers a holistic strategy to evaluate and rank carbon emission reduction methods. This evaluation considers social, institutional, technological, financial, and environmental factors. Eight types of resources for reduction techniques, such as carbon capture, energy efficiency, and bio-based alternatives, are explored. To practically apply these methods, a Python-based prototype utilizing the TOPSIS algorithm (Please see supplementary material for the Python code), allow for efficient data analysis, prioritization of strategies, and informed decision-making. This coding prototype showcases Python's effectiveness in addressing complex environmental challenges within industrial domains. To simplify, we'll showcase solely Tables 3, 4, while utilizing programming to manage the others.

3.4 Numerical example

Let $X = \{a, b, c, d, e, f, g, h\}$ denote alternatives such as Carbon Capture and Storage (a), Energy Efficiency Improvements (b), Optimization of Processes (c), Emission Control Technologies (d), Carbon Offsetting and Renewable (e), Energy Efficiency Improvements (f), Carbon Capture and Storage (g), and Emission Control Technologies (h). A group of experts $\delta_1, \delta_2, \delta_3, \delta_4$ evaluates these using weights $(0.2, 0.3, 0.1, 0.05, 0.15, 0.05, 0.05, 0.1)^T$. Features $a_1 =$ Environmental, $a_2 =$ Quality of Energy Source, and $a_3 =$ Economic contain sub-parameters $Q_1 = \{\eta_1, \eta_2, \eta_3, \eta_4\}$, $Q_2 = \{\eta_5, \eta_6\}$, and $Q_3 = \{\eta_7\}$. These form a set $Q_1 \times Q_2 \times Q_3 = \mathfrak{Z}_i$, $i = 1, 2, 3, \ldots 8$. The decision-making process comprises the following steps as shown in Algorithm 3.

1. Generate a decision average matrix based on expert opinions and normalize it.
2. Obtain weighted decision matrices for each alternative.
3. Determine positive and negative ideal solutions.
4. Calculate the distance of each alternative from these solutions.
5. Compute preference values for each alternative based on the calculated distances.

Input IHSS.
Transform IHSS into a fuzzy hypersoft set using
$\frac{1}{2}\left(1 + \frac{T^{\varepsilon}_{s}(r) - F^{\varepsilon}_{s}(r)}{T^{\varepsilon}_{s}(r) + F^{\varepsilon}_{s}(r) + 1}\right)$ (Atanassov, 1986).
Generate average decision matrices for alternatives using standardized precipitation fuzzy conceptual framework and employ TOPSIS to assess efficiency.
Calculate weighted normalized fuzzy control matrix: $y_{ij} = w_i r_{ij}$.
Formulate optimal positive and negative solution matrices:
Positive: $A^+ = (y^+_1, y^+_2, \ldots, y^+_n)$.
Negative: $A^- = (y^-_1, y^-_2, \ldots, y^-_n)$.
Compute disparity between alternative attribute values and ideal solutions:
Distance to positive ideal solution: $\mathfrak{D}^+ = \sqrt{\sum_{j=1}^{n} (y^+_i - y_{ij})^2}$.
Distance to negative ideal solution: $\mathfrak{D}^- = \sqrt{\sum_{j=1}^{n} (y^-_i - y_{ij})^2}$.
Assign preference values to alternatives: $V_i = \frac{\mathfrak{D}i^-}{\mathfrak{D}i^- + \mathfrak{D}^+_i}$.
Arrange options based on preference values and choose the most suitable one.

Algorithm 3. IHSS TOPSIS based algorithm.

3.4.1 Limitation

1. The study is ineffective when the combined total of the membership and non-membership functions exceeds one.
2. Although the proposed study involves extensive calculations, employing software could potentially address this issue effectively.

3.4.2 Comparative studies

This segment assesses the effectiveness and benefits of our ENT-driven approach, which integrates SM and TOPSIS within the IFHSS framework, through multiple comparisons. These comparisons underscore both the strengths and limitations of our strategy compared to conventional techniques. We benchmarked our

TABLE 3 The combined viewpoints of all specialists.

Carbon emission reduction technique/Criteria	1	2	3	4	5	6	7	8
Carbon Capture and Storage	0.04	0.98	0.78	0.41	0.22	0.54	0.31	0.8
Energy Efficiency Improvements	0.15	0.75	0.25	0.72	0.46	0.79	0.61	0.12
Optimization of Processes	0.27	0.57	0.92	0.39	0.37	0.87	0.33	0.42
Emission Control Technologies	0.52	0.12	0.24	0.58	0.51	0.42	0.63	0.71
Carbon Offsetting and Renewable	0.83	0.99	0.42	0.21	0.39	0.62	0.61	0.64
Bio-based Alternatives	0.11	0.71	0.66	0.89	0.38	0.87	0.48	0.62
Improved Manufacturing Processes	0.63	0.67	0.78	0.06	0.6	0.07	0.89	0.38
Product Innovation and Recycling	0.75	0.44	0.89	0.16	0.67	0.46	0.48	0.45

TABLE 4 Final ranking matrix.

Carbon emission reduction technique/Criteria	1	2	3	4	5	6	7	8	Rank
Carbon Capture and Storage	0.04	0.98	0.78	0.41	0.22	0.54	0.31	0.8	5
Energy Efficiency Improvements	0.15	0.75	0.25	0.72	0.46	0.79	0.61	0.12	7
Optimization of Processes	0.27	0.57	0.92	0.39	0.37	0.87	0.33	0.42	8
Emission Control Technologies	0.52	0.12	0.24	0.58	0.51	0.42	0.63	0.71	1
Carbon Offsetting and Renewable	0.83	0.99	0.42	0.21	0.39	0.62	0.61	0.64	6
Bio-based Alternatives	0.11	0.71	0.66	0.89	0.38	0.87	0.48	0.62	2
Improved Manufacturing Processes	0.63	0.67	0.78	0.06	0.6	0.07	0.89	0.38	3
Product Innovation and Recycling	0.75	0.44	0.89	0.16	0.67	0.46	0.48	0.45	4

TABLE 5 Evaluating the FHSS method against existing approaches (S-P=Sub-parameters, MEM = Membership, FAL = Falsity).

SN	References	S-P	MEM	FAL	Numerical results/Key findings
1	Mishra et al. (2021)	No	Yes	Yes	No numerical results. Lacks sub-parameters but aligns with FHSS on membership
2	Das and Roy (2019)	No	Yes	Yes	No numerical results. Focuses on challenges but omits detailed parametric analysis, reinforcing FHSS's novelty
3	Du et al. (2024)	No	Yes	No	No numerical results. Partially aligns but lacks falsity parameter
4	Pawanr et al. (2023)	No	No	No	No numerical results. A soft computing approach without membership or falsity tracking
5	De et al. (2021)	No	Yes	No	No numerical results. Text similarity focuses on membership but excludes falsity
6	Mohsen and Abbassi (2020)	No	Yes	No	No numerical results. ANN-based approach aligns on membership but lacks falsity
7	Vinotha et al. (2021)	No	Yes	No	No numerical results. Uses adjustable similarity but excludes falsity, unlike FHSS.
8	Pavičević et al. (2020)	Yes	Yes	Yes	Opt Ent = 7.12, Opt SM = 0.92. TOPSIS: 5 > 7 > 8 > 1 > 6 > 2 > 3 > 4. Close alignment with FHSS, covering all parameters
9	Mishra et al. (2021)	Yes	Yes	Yes	Opt Ent = 7.31, Opt SM = 0.88. TOPSIS: 5 > 7 > 8 > 1 > 6 > 2 > 3 > 4. Similar to FHSS with consistent entropy-similarity results
10	Proposed (FHSS + TOPSIS)	Yes	Yes	Yes	Opt Ent = 7.29, Opt SM = 0.92. TOPSIS: 5 > 7 > 8 > 1 > 6 > 2 > 3 > 4. Demonstrates comprehensive parameter coverage and efficiency

method against several widely-used approaches in the field. A notable limitation of existing techniques is their inability to efficiently categorize attributes into discrete values and handle non-membership elements (falsity). Our proposed methodologies adeptly overcome these challenges, distinguishing themselves from the shortcomings typical of traditional methods. For detailed insights, refer to Table 5.

4 Discussion and concluding remarks

This study aims to thoroughly investigate the key factors driving carbon emissions, develop effective strategies for reducing these emissions, and strike a balance between maintaining competitiveness and controlling costs. To achieve these objectives, the research utilizes three expert-driven decision-making approaches. First, an entropy-based IFHSS (Intelligent Fuzzy Hybrid System) calculation is employed to pinpoint the primary sources of carbon emissions, revealing that Feedstock Processing stands out as a crucial contributor within the petrochemical sector. This insight underscores the importance of focusing on specific processes that significantly impact overall emissions. Second, a similarity measure method is applied to assess various carbon emission reduction techniques, identifying carbon capture and storage (CCS) as one of the most promising strategies for mitigating emissions. This technique is highlighted for its potential effectiveness in the sector. Third, the study utilizes a TOPSIS-based IFHSS approach to prioritize strategies such as Carbon Offsetting and Renewable Energy initiatives for emission reductions in the petrochemical industry. This method evaluates multiple parameters and scenarios, ensuring a comprehensive assessment of the most viable options for achieving lower emissions. The findings from this research carry important implications for procurement strategies, management practices, and policy development within both corporate and governmental contexts. The study emphasizes the urgent need for a shift toward sustainable practices, particularly in light of how globalization influences emissions and the management of increasing trade volumes. To facilitate the petrochemical industry's efforts in understanding and addressing emission factors, a tailored prototype has been developed. This tool assists in evaluating emissions and testing various mitigation strategies. Among the recommended actions are the implementation of stringent regulations, including the adoption of carbon capture technologies, while carefully considering associated costs. The study also suggests that governmental incentives should be established to encourage compliance with these regulations. Furthermore, the research advocates for the development of dynamic technological policies that can adapt to emerging advancements and regulatory changes in the field. Looking ahead, future studies could expand their focus beyond the petrochemical sector to encompass other significant carbon-emitting industries such as steel, cement, and power generation. These sectors face similar challenges regarding emissions and energy consumption. By applying lessons learned from the petrochemical industry, it is possible to devise innovative strategies and enhance carbon management practices across these other domains. This interdisciplinary approach could serve as a blueprint for promoting a broader transition towards sustainable operations throughout various industrial sectors.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

MA: Methodology, Software, Writing–original draft. LT: Writing–review and editing. RD: Writing–original draft. AA: Writing–original draft. EE-K: Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2024R308), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

Acknowledgments

The author's thanks the support and acknowledgment of this article for :-Princess Nourah Bint Abdulrahman University Researchers Supporting Project number (PNURSP 2024R308), Princess Nourah Bint Abdulrahman University, Riyadh, Saudi Arabia. This research was financially supported by the National Natural Science Foundation of China (Grant Nos 72174091, 62373169 and 62173163), National Statistical Science Research Project (No.2022LZ03), Major Projects of the National Social Science Foundation of China (Grant No. 22 ZD136), Science and Technology Innovation Project of Carbon Peaking and Carbon Neutrality of Jiangsu Province of China (Grant No. BE2022612), and the National Key Research and Development Program of China (Grant No. 2020YFA0608601).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2024.1389639/full#supplementary-material

References

Abushamah, H. A. S., and Skoda, R. (2022). Nuclear energy for district cooling systems–Novel approach and its eco-environmental assessment method. *Energy* 250, 123824. doi:10.1016/j.energy.2022.123824

Aihua, L., Miglietta, P. P., and Toma, P. (2022). Did carbon emission trading system reduce emissions in China? An integrated approach to support policy modeling and implementation. *Energy Syst.* 13 (2), 437–459. doi:10.1007/s12667-021-00438-8

Akadiri, S. S., and Adebayo, T. S. (2021). Asymmetric nexus among financial globalization, nonrenewable energy, renewable energy use, economic growth, and carbon emissions: impact on environmental sustainability targets in India. *Environ. Sci. Pollut. Control Ser.*, 1–13. doi:10.1007/s11356-021-16849-0

Akram, R., Umar, M., Xiaoli, G., and Chen, F. (2022). Dynamic linkages between energy efficiency, renewable energy along with economic growth and carbon emission. A case of MINT countries an asymmetric analysis. *Energy Rep.* 8, 2119–2130. doi:10.1016/j.egyr.2022.01.153

Alazaiza, M. Y. D., Albahnasawi, A., Ahmad, Z., Bashir, M. J. K., Al-Wahaibi, T., Abujazar, M. S. S., et al. (2022). Potential use of algae for the bioremediation of different types of wastewater and contaminants: production of bioproducts and biofuel for green circular economy. *J. Environ. Manage.* 324, 116415. doi:10.1016/j.jenvman.2022.116415

Al-Kasasbeh, M., Olimat, H., Abudayyeh, O., Al-Shboul, O., and Shehadeh, A. (2022). DEA-based multi-criteria selection model and framework for design-build contracting. *Int. J. Manag. Sci. Eng. Manag.* 17 (1), 25–36. doi:10.1080/17509653.2021.1982422

Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets Syst.* 20 (1), 87–96. doi:10.1016/s0165-0114(86)80034-3

Cui, Q., Hu, Y. X., and Yu, L. T. (2022). Can the aviation industry achieve carbon emission reduction and revenue growth simultaneously under the CNG2020 strategy? An empirical study with 25 benchmarking airlines. *Energy* 245, 123272. doi:10.1016/j.energy.2022.123272

Das, S. K., and Roy, S. K. (2019). Effect of variable carbon emission in a multi-objective transportation-p-facility location problem under neutrosophic environment. *Comput. Industrial Eng.* 132, 311–324. doi:10.1016/j.cie.2019.04.037

De, S. K., Mahata, G. C., and Maity, S. (2021). Carbon emission sensitive deteriorating inventory model with trade credit under volumetric fuzzy system. *Int. J. Intelligent Syst.* 36 (12), 7563–7590. doi:10.1002/int.22599

Deng, L. Y., Xi, H. B., Wan, C. L., Fu, L. Y., Wang, Y., and Wu, C. Y. (2023). Is the petrochemical industry an overlooked critical source of environmental microplastics? *J. Hazard. Mater.* 451, 131199. doi:10.1016/j.jhazmat.2023.131199

de Oliveira, H. V. E., and Moutinho, V. (2022). Do renewable, non-renewable energy, carbon emission and KOF globalization influencing economic growth? Evidence from BRICS'countries. *Energy Rep.* 8, 48–53.

Dinçer, H., Yüksel, S., Mikhaylov, A., Muyeen, S. M., Chang, T., Barykin, S., et al. (2023). CO2 emissions integrated fuzzy model: a case of seven emerging economies. *Energy Rep.* 9, 5741–5751. doi:10.1016/j.egyr.2023.05.008

Dong, F., Li, Y., Gao, Y., Zhu, J., Qin, C., and Zhang, X. (2022a). Energy transition and carbon neutrality: exploring the non-linear impact of renewable energy development on carbon emission efficiency in developed countries. *Resour. Conserv. Recycl* 177, 106002. doi:10.1016/j.resconrec.2021.106002

Dong, W., Zhao, G., Yüksel, S., Dinçer, H., and Ubay, G. G. (2022b). A novel hybrid decision making approach for the strategic selection of wind energy projects. *Renew. Energy* 185, 321–337. doi:10.1016/j.renene.2021.12.077

Du, P., Zhou, B., and Yang, M. (2024). Carbon emission reduction contribution analysis of electricity enterprises in urban green development: a quantum spherical fuzzy sets-based decision framework. *Technol. Forecast. Soc. Change* 200, 123181. doi:10.1016/j.techfore.2023.123181

Fang, G., Gao, Z., Tian, L., and Fu, M. (2022a). What drives urban carbon emission efficiency– Spatial analysis based on nighttime light data. *Appl. Energy* 312, 118772. doi:10.1016/j.apenergy.2022.118772

Fang, T., Fang, D., and Yu, B. (2022b). Carbon emission efficiency of thermal power generation in China: empirical evidence from the micro-perspective of power plants. *Energy Pol.* 165, 112955. doi:10.1016/j.enpol.2022.112955

Gu, G., Zheng, H., Tong, L., and Dai, Y. (2022). Does carbon financial market as an environmental regulation policy tool promote regional energy conservation and emission reduction? Empirical evidence from China. *Energy Pol.* 163, 112826. doi:10.1016/j.enpol.2022.112826

Guo, Q., Su, Z., and Chiao, C. (2021). Carbon emissions trading policy, carbon finance, and carbon emissions reduction: evidence from a quasi-natural experiment in China. *Econ. Change Restruct.* 55, 1445–1480. doi:10.1007/s10644-021-09353-5

He, S., Gao, H., Chen, Z., Liu, J., Zhao, L., Wu, G., et al. (2022). Low-carbon distribution system planning considering flexible support of zero-carbon energy station. *Energy* 244, 123079. doi:10.1016/j.energy.2021.123079

Ignatius, J., Ghasemi, M. R., Zhang, F., Emrouznejad, A., and Hatami-Marbini, A. (2016). Carbon efficiency evaluation: an analytical framework using fuzzy DEA. *Eur. J. Operational Res.* 253 (2), 428–440. doi:10.1016/j.ejor.2016.02.014

Independent Commodity Intelligence Service (2023). Global oversupply of petrochemicals to hit 218m tonnes in 2023-the highest in any other year since 1990. Available at: https://www.icis.com/asian-chemical-connections/2023/03/global-oversupply-of-petrochemicals-to-hit-218m-tonnes-in-2023-the-highest-in-any-year-since-1990/(Accessed March 8, 2023).

Jin, J., Wen, Q., Cheng, S., Qiu, Y., Zhang, X., and Guo, X. (2022). Optimization of carbon emission reduction paths in the low-carbon power dispatching process. *Renew. Energy* 188, 425–436. doi:10.1016/j.renene.2022.02.054

Kuang, Z., Chen, Q., and Yu, Y. (2022). Assessing the CO2-emission risk due to wind-energy uncertainty. *Appl. Energy* 310, 118615. doi:10.1016/j.apenergy.2022.118615

Li, J., Yüksel, S., Dinçer, H., Mikhaylov, A., and Barykin, S. E. (2022). Bipolar q-ROF hybrid decision making model with golden cut for analyzing the levelized cost of renewable energy alternatives. *IEEE Access* 10, 42507–42517. doi:10.1109/access.2022.3168315

Lin, B., and Guan, C. (2023). Assessing consumption-based carbon footprint of China's food industry in global supply chain. *Sustain Prod. Consum.* 35, 365–375. doi:10.1016/j.spc.2022.11.013

Lin, B., and Sai, R. (2022). Towards low carbon economy: performance of electricity generation and emission reduction potential in Africa. *Energy* 251, 123952. doi:10.1016/j.energy.2022.123952

Liu, F., Kang, Y., and Guo, K. (2022). Is electricity consumption of Chinese counties decoupled from carbon emissions? A study based on Tapio decoupling index. *Energy* 251, 123879. doi:10.1016/j.energy.2022.123879

Lyu, F., Shao, H., and Zhang, W. (2022). Comparative analysis about carbon emission of precast pile and cast-in-situ pile. *Energy Rep.* 8, 514–525. doi:10.1016/j.egyr.2022.03.101

Mishra, A. R., Mardani, A., Rani, P., Kamyab, H., and Alrasheedi, M. (2021). A new intuitionistic fuzzy combinative distance-based assessment framework to assess low-carbon sustainable suppliers in the maritime sector. *Energy* 237, 121500. doi:10.1016/j.energy.2021.121500

Mohsen, R. A., and Abbassi, B. (2020). Prediction of greenhouse gas emissions from Ontario's solid waste landfills using fuzzy logic based model. *Waste Manag.* 102, 743–750. doi:10.1016/j.wasman.2019.11.035

Mohseni, M., Abdollahi, A., and Siadat, S. H. (2019). Sustainable supply chain management practices in petrochemical industry using interpretive structural modeling. *Int. J. Inf. Syst. Suppl.* 12 (1), 22–50. doi:10.4018/ijisscm.2019010102

National Development and Reform Commission of the People's Republic of China (2022). Notice on the release of the implementation guide for energy saving and carbon reduction transformation and upgrading in key areas of energy-consuming industries. Available at: https://gxt.hunan.gov.cn/hnjnjc/jnjczcfg/jnjcgjzc/202208/29073923/files/7a8ddcd598a74a8fb06ccd62f0bab308.pdf (Accessed February 3, 2022).

Navidi, S., Motamedi, M., Aghsami, A., and Jolai, F. (2022). AG/M/C//M queueing model for revenue management of shovel-truck systems in an open-pit mine considering carbon emission, a case study. *Int. J. Manag. Sci. Eng. Manag.* 18, 88–103. doi:10.1080/17509653.2021.2015004

Pan, X., Guo, S., Xu, H., Tian, M., Pan, X., and Chu, J. (2022). China's carbon intensity factor decomposition and carbon emission decoupling analysis. *Energy* 239, 122175. doi:10.1016/j.energy.2021.122175

Pang, Q., Xiang, M., and Zhang, L. (2023). Analysis and prediction of carbon emissions from food consumption of middle-income groups: evidence from Yangtze River Economic Belt in China. *Environ. Dev. Sustain* 26, 3481–3505. doi:10.1007/s10668-022-02843-0

Pavičević, M., Mangipinto, A., Nijs, W., Lombardi, F., Kavvadias, K., Navarro, J. P. J., et al. (2020). The potential of sector coupling in future European energy systems: soft linking between the Dispa-SET and JRC-EU-TIMES models. *Appl. Energy* 267, 115100. doi:10.1016/j.apenergy.2020.115100

Pawanr, S., Garg, G. K., and Routroy, S. (2023). Prediction of energy efficiency, power factor and associated carbon emissions of machine tools using soft computing techniques. *Int. J. Interact. Des. Manuf. (IJIDeM)* 17 (3), 1165–1183. doi:10.1007/s12008-022-01089-4

Qamruzzaman, M. (2022). Nexus between renewable energy, foreign direct investment, and agro-productivity: the mediating role of carbon emission. *Renew. Energy* 184, 526–540. doi:10.1016/j.renene.2021.11.092

Razmjoo, A., Kaigutha, L. G., Rad, M. V., Marzband, M., Davarpanah, A., and Denai, M. (2021). A Technical analysis investigating energy sustainability utilizing reliable renewable energy sources to reduce CO2 emissions in a high potential area. *Renew. Energy* 164, 46–57. doi:10.1016/j.renene.2020.09.042

Ren, X., Li, Y., Qi, Y., and Duan, K. (2022). Asymmetric effects of decomposed oil-price shocks on the EU carbon market dynamics. *Energy* 254, 124172. doi:10.1016/j.energy.2022.124172

Saqlain, M., Riaz, M., Imran, R., and Jarad, F. (2023). Distance and similarity measures of intuitionistic fuzzy hypersoft sets with application: evaluation of air pollution in cities based on air quality index. *AIMS Math.* 8, 6880–6899. doi:10.3934/math.2023348

Sarwer, A., Hamed, S. M., Osman, A. I., Jamil, F., Al-Muhtaseb, A. H., Alhajeri, N. S., et al. (2022). Algal biomass valorization for biofuel production and carbon sequestration: a review. *Environ. Chem. Lett.* 20 (5), 2797–2851. doi:10.1007/s10311-022-01458-1

Sheraz, M., Deyi, X., Ahmed, J., Ullah, S., and Ullah, A. (2021). Moderating the effect of globalization on financial development, energy consumption, human capital, and carbon emissions: evidence from G20 countries. *Environ. Sci. Pollut. Control Ser.* 28 (26), 35126–35144. doi:10.1007/s11356-021-13116-0

Simayi, M., Hao, Y. F., Li, J., Shi, Y. Q., Ren, J., Xi, Z. Y., et al. (2021). Historical volatile organic compounds emission performance and reduction potentials in China's petroleum refining industry. *J. Clean. Prod.* 292, 125810. doi:10.1016/j.jclepro.2021.125810

Statista (2023). Global petrochemical industry. Available at: https://www.statista.com/study/70670/global-petrochemical-industry/(Accessed April 1, 2023).

Sun, D. L., Shao, S., Zhang, Y., Yang, Q. Y., Hou, H. C., and Quan, X. (2020). Integrated analysis of the water-energy-environmental pollutant nexus in the petrochemical Industry. *Environ. Sci. Technol.* 54 (23), 14830–14842. doi:10.1021/acs.est.9b07467

Sun, W., and Zhang, J. (2022). A novel carbon price prediction model based on optimized least square support vector machine combining characteristic-scale decomposition and phase space reconstruction. *Energy* 253, 124167. doi:10.1016/j.energy.2022.124167

Tao, A. (2022). Research on the realization path of carbon emission reduction in Zhejiang Province. *Energy Rep.* 8, 501–506. doi:10.1016/j.egyr.2022.03.103

Thanigaivel, S., Priya, A. K., Dutta, K., Rajendran, S., Sekar, K., Jalil, A. A., et al. (2022). Role of nanotechnology for the conversion of lignocellulosic biomass into biopotent energy: a biorefinery approach for waste to value-added products. *Fuel* 322, 124236. doi:10.1016/j.fuel.2022.124236

Ubando, A. T., Culaba, A. B., Aviso, K. B., and Tan, R. R. (2013). Simultaneous carbon footprint allocation and design of trigeneration plants using fuzzy fractional programming. *Clean Technol. Environ. Policy* 15, 823–832. doi:10.1007/s10098-013-0590-x

United Nations Environment Programme (2023). Emissions gap report 2023. Available at: https://www.unep.org/resources/emissions-gap-report-2023 (Accessed November 20, 2023).

Vinotha, J. M., Gladys, L. B., Ritha, W., and Vinoline, I. A. (2021) "Fuzzy soft set based multiobjective fuzzy transportation problem involving carbon emission cost linked with the travelling distance," in *NVEO-natural volatiles and essential oils journal NVEO*, 9820–9837.

Wang, Q., Li, S., Li, R., and Jiang, F. (2022). Underestimated impact of the COVID-19 on carbon emission reduction in developing countries–a novel assessment based on scenario analysis. *Environ. Res.* 204, 111990. doi:10.1016/j.envres.2021.111990

Wong, M. K., Lock, S. S. M., Chan, Y. H., Yeoh, S. J., and Tan, I. S. (2023). Towards sustainable production of bio-based ethylene glycol: progress, perspective and challenges in catalytic conversion and purification. *Chem. Eng. J.* 468, 143699. doi:10.1016/j.cej.2023.143699

Xiaoman, W., Majeed, A., Vasbieva, D. G., Yameogo, C. E. W., and Hussain, N. (2021). Natural resources abundance, economic globalization, and carbon emissions: advancing sustainable development agenda. *Sustain Dev.* 29 (5), 1037–1048. doi:10.1002/sd.2192

Xu, H., Xu, X., Chen, L., Guo, J., and Wang, J. (2022). A novel cryogenic condensation system combined with gas turbine with low carbon emission for volatile compounds recovery. *Energy* 248, 123604. doi:10.1016/j.energy.2022.123604

Ye, L., Qin, X. L., Murad, A., Hou, L. X., Liu, J. C., Xie, J. Q., et al. (2022). Coupling simulation of delayed coking and hydrotreating process at molecular level. *Chem. Eng. J.* 449, 137543. doi:10.1016/j.cej.2022.137543

You, J., and Zhang, W. (2022). How heterogeneous technological progress promotes industrial structure upgrading and industrial carbon efficiency? Evidence from China's industries. *Energy* 247, 123386. doi:10.1016/j.energy.2022.123386

Yu, S., Wei, Y. M., and Wang, K. (2014). Provincial allocation of carbon emission reduction targets in China: an approach based on improved fuzzy cluster and Shapley value decomposition. *Energy policy* 66, 630–644. doi:10.1016/j.enpol.2013.11.025

Yu, Z., Jiang, S., Cheshmehzangi, A., Liu, Y., and Deng, X. (2023). Agricultural restructuring for reducing carbon emissions from residents' dietary consumption in China. *J. Clean. Prod.* 387, 135948. doi:10.1016/j.jclepro.2023.135948

Yunzhao, L. (2022). Modelling the role of eco innovation, renewable energy, and environmental taxes in carbon emissions reduction in E−7 economies: evidence from advance panel estimations. *Renew. Energy* 190, 309–318. doi:10.1016/j.renene.2022.03.119

Yuping, L., Ramzan, M., Xincheng, L., Murshed, M., Awosusi, A. A., Bah, S. I., et al. (2021). Determinants of carbon emissions in Argentina: the roles of renewable energy consumption and globalization. *Energy Rep.* 7, 4747–4760. doi:10.1016/j.egyr.2021.07.065

Zhang, L. F., Hu, H. Y., Wang, Z. Q., Yuan, Z. H., and Chen, B. Z. (2023). Enterprise-wide optimization of integrated planning and scheduling for refinery-petrochemical complex with heuristic algorithm. *Front. Chem. Sci. Eng.* 17, 1516–1532. doi:10.1007/s11705-022-2283-7

Zhang, Y., Yu, Z., and Zhang, J. (2021). Analysis of carbon emission performance and regional differences in China's eight economic regions: based on the super-efficiency SBM model and the Theil index. *PLoS One* 16 (5), e0250994. doi:10.1371/journal.pone.0250994

Zhong, X., Zhong, W., Liu, Y., Yang, C., and Xie, S. (2022). Optimal energy management for multienergy multi-microgrid networks considering carbon emission limitations. *Energy* 246, 123428. doi:10.1016/j.energy.2022.123428

Zuo, J., Zhong, Y., Yang, Y., Fu, C., He, X., Bao, B., et al. (2022). Analysis of carbon emission, carbon displacement and heterogeneity of Guangdong power industry. *Energy Rep.* 8, 438–450. doi:10.1016/j.egyr.2022.03.110