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Assessing Sustainable Environmental Technologies for Pollution Control: A Multi-Criteria Decision Making Approach

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A B S T R A C T

We live in a time of severe ecological disaster because of the different issues our ecosystem is experiencing and many of which tend to get worse with time. Thus, its importance in spreading public awareness about such issues to be able to minimize their adverse effects. On the other hand, daily rises in environmental contamination result in the planet experiencing grave and permanent damage. There are many types, such as air, water, soil, noise, and light. Environmental pollution is continuously causing big problems all over the world; we need efficient ways of controlling it. This paper proposes a complete strategy to check eco-friendly technology that helps in fighting against pollution by the MCDM method, which takes into consideration different environmental, money-related, and social factors while checking and ranking various tech options. It considers various desires of different persons and unsure elements in making decisions. The paper also expands on the use of Fuzzy TOPSIS as a strong tool that can deal with tricky and unclear parts normally found in the process of choice over the environment. A case study on this method for selecting the optimal eco-friendly technology for pollution control is well-demonstrated. The results show the critical importance of bringing multiple factors and various stakeholders' considerations onto one platform in order to make a decision for choosing an eco-friendly solution. The output of this study enhances environmental management by giving decision-makers an effective strategy in making intelligent choices for meeting the standards of pollution control with ecological friendliness.

Keywords: Sustainable environmental technologies, pollution control, MCDM, Fuzzy TOPSIS, Environmental management, Decision making

1. Introduction

People often seek out natural settings like parks, beaches, or forests when they feel stressed or disconnected. They look for comfort in nature's soothing presence. This natural tendency shows a str ong link between human health and the health of the environment. Environmental problems cause many health issues around the world. A large number of deaths are tied to environmental factors that we can prevent. To stay healthy and live long, we need clean air clean water, and places free from toxins. As more people are born and we use too much energy and build more factories, we face big challenges. We must tackle these issues to stop more damage to the environment. We have to protect the planet for the people who will live here after us. We need to make sure they get a healthy planet that can last. This means we should cut down on how much we use from nature and protect all the different plants and animals on Earth [1-4].

Environmental sustainability involves decisions made today that ensure a continued quality of life later, while lessening our negative impact on the Earth's ecosystems. It hence involves attaining and finding a balance between human needs and the preservation of the environment through lessening resource depletion and waste. By following this sustainable path, we manage to keep in balance and ensure natural resources are being used responsibly. The increasingly fast population and industrial growth has put pressure on the resources and underlined the urgency of sustainability. It results in increased greenhouse gas emissions, deforestation, and other environmental issues. This is a call to business-impacting sustainable practices like minimizing waste, using clean energy, and following good labor standards that can help resolve these issues. Their actions can contribute considerably to a more sustainable future, which is good for the environment and society as a whole [5, 6].

Among the most critical global challenges in the 21st century, environmental pollution, especially from human health, ecosystem, and economic perspectives, has become a high concern. With increasingly greater industrial activities, urbanization, and agriculture, finding appropriate and sustainable technologies for pollution control is becoming a pressing need. Traditional methods of pollution control, which normally rely on end-of-pipe measures, cannot guarantee solutions for such complex environmental degradation. Therefore, the need for new and efficient sustainable technologies is dire to reduce pollution, but at the same time, they must contribute towards broader environmental objectives, economic, and social. Decisions concerning the choice of appropriate technology for pollution control are extremely complicated due to the large number of relevant factors to consider, which include environmental effectiveness, cost-effectiveness, social acceptability, and technological feasibility-all many factors that represent trade-offs and make decision-making complex to handle. Moreover, the involvement of various stakeholders-from government agencies to industrial players down to local communities and environmental groups-implies complexity because the stakeholder groups might have different priorities and concerns. Therefore, effective evaluation and prioritizing require an integrated systematic approach [7-10].

On the other hand, MCDM methods have gained much recognition as strong strategies with which to deal with these issues of complexity in environmental decision-making. MCDM provides a formal platform for considering multiple criteria, which are often in conflict with one another, to help the decision-maker in balancing the different objectives and to make an informed choice in the presence of different criteria [11-13]. MCDM approaches allow a more integrated evaluation of pollution control technologies for the compliance of a decision with the principle of sustainability by incorporating environmental, economic, and social criteria. Fuzzy TOPSIS is one powerful tool for environmental decisions among the various techniques included within MCDM. Fuzzy logic allows more flexibility and realistic representation of the inherent uncertainties and imprecisions that exist in environmental data and also in stakeholders' preferences. Therefore, fuzzy TOPSIS enhances the decision-making by offering more accurate and reliable evaluation of pollution control technologies.

The paper, therefore, intends to address these very issues in the context of environmental management by presenting a comprehensive framework for assessing sustainable environmental technologies for pollution control. The proposed framework makes use of the strong points of the MCDM approach in general but focuses on the application of Fuzzy TOPSIS for the systematic evaluation and prioritizing of available technologies. In this respect, the present framework can be a useful tool to assist the decision-makers in tackling the relevant environmental decision-making problems that include the stakeholder preferences and deal with uncertainties. The approach proposed is further demonstrated through a case study analysis that follows, where the most appropriate sustainable technologies for pollution control will be selected using the framework. These findings point to the necessity for multi-criteria and multi-stakeholder platforms which could actively and effectively advocate for environmentally sustainable solutions. The research study wants to contribute to a better understanding of environmental technologies and provide a practical guide to decision-makers with the aim of pursuing sustainable pollution control goals.

2. Related Works

Evaluation of sustainable technologies for pollution control is essentially a multidimensional problem, as reflected in recent research through various methodologies. This section reviews some of the key studies done using multi-criteria decision-making approaches to evaluate technologies in various contexts. It will show the effectiveness and application of those methods.

Attri et al. [14] presented a role of MCDM methods in evaluating the wastewater treatment technologies from a viewpoint of sustainability. In their study, they compared six different wastewater treatment technologies using four parameters for sustainability and three MCDM techniques, including FSWARA, FMOORA, and FTOPSIS. FSWARA was used to weight the criteria, while FMOORA and FTOPSIS were used for ranking technologies. This extensive research showed the reliability of MCDM methods for evaluating complex environmental technologies and presented an improved practice of decision-making in wastewater treatment. These results reinforce the need for a structured approach to sustainability assessment, confirming that MCDM techniques are capable of handling the multi-dimensionality of environmental technologies.

An et al. [15] developed one innovative methodology in the evaluation of technologies for the remediation of groundwater, considering eight criteria along economic, environmental, technological, social, and political aspects. Relative priorities of technologies were scored using the Analytic Hierarchy Process (AHP), while ELECTRE was used for the ranking of technology with respect to sustainability performance. The most sustainable technology was represented by monitored natural attenuation (MNA), followed by the pump-treat (P&T) and permeable reactive barriers (PRB). Sensitivity analysis confirmed the results; therefore, showing the effectiveness of the combined AHP and ELECTRE approach in handling diverging evaluation criteria and uncertainties associated with environmental decisions.

It presents Campos-Guzmán et al. [16] with a broad review of methodologies that evaluate the sustainability of renewable energy systems by using integrated LCA and MCDM techniques. This review concludes that while LCA and MCDM alone, on their own merit, can give great insights into specific dimensions, it is their combined use which offers the evaluation in a far more complete way. The study has, in particular, identified a tendency of AHP being frequently used in combination with LCA on the subject of renewable energy systems and underlined the application of integrated frameworks for both quantitative and qualitative sustainability indicators. This work serves to illustrate the advantages of a hybrid approach in capturing the full spectrum of sustainability dimensions.

Zhou et al. [17] discussed the sustainability of municipal sewage sludge disposal systems in China by using a hybrid approach based on AHP and Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR). Six sludge disposal systems were compared in the paper by using environmental, economic as well as social criteria. The results indicated that land application was the most sustainable option, followed by construction materials application as well as pyrolysis. Sensitivity analysis established the sturdiness of results in this study and, therefore, the effectiveness of the combined AHP and VIKOR method in the ranking of alternatives when providing indications of sustainable sludge management practices.

Si et al. [18] analyzed how MCDM methods were applied to choose the main green technologies for retrofitting existing buildings. This work presented a case study in the usage of AHP over technology evaluations concerning environmental and economic criteria, which pointed out that social criteria such as inhabitant satisfaction must also be included. Accordingly, technologies with variable speed drives ranked high because of their efficiency and effectiveness. This paper, therefore, underscores the relevance of MCDM techniques in green technology decision-making by underlining the essentiality of a full multi-criteria evaluation framework.

Carli et al. [19] proposed the AHP method for performing analyses on sustainability at a metropolitan level in energy, water as well as environmental systems. In their paper, 35 indicators were employed using the Sustainable Development of Energy, Water, and Environment Systems Index for four metropolitan parts. The results obtained were very helpful for the local governments while making improvements in their respective sustainability. AHP helped to emphasize targeted actions for the improvement of some dimensions of sustainability, hence underlining the eligibility of MCDM methods within urban sustainability management.

Ali et al. [20] evaluated various wastewater treatment technologies in Pakistan by implementing the fuzzy VIKOR method, based on ten criteria including the three standard dimensions of environmental, economic, and technological factors. Consequently, this study indicated that activated sludge technology ranked first for industrial wastewater treatment, followed by membrane filtration and sequential batch reactor technologies. The obtained results had many practical implications for decision-makers in Pakistan with regard to the effectiveness of the fuzzy VIKOR approach in multi-criteria management for choosing the best technologies.

Maxim [21] applied a weighted sum multi-attribute utility process to provide a ranking of numerous electricity generation systems according to ten indicators related to sustainability. The most sustainable were large hydroelectric projects, followed by small hydro, onshore wind as well as solar photovoltaic technologies, in that order. These results provide emphasis on the importance of structured and strategic approaches within the implementation of sustainable energy policies and also present the usefulness of MCDM approaches within the assessment of diverse energy technologies.

Siksnelyte et al. [22] contributed to a review of applying MCDM approaches in the field of sustainable energy growth by analyzing 105 papers from the Web of Science database. The researched areas were categorized into application and method classes. The authors perform SWOT analysis for MCDM approaches. The review proved that MCDM technique is quite widely adopted and effective for problems of energy sustainability, giving one more proof of its importance regarding decision-making support. Abdel-Basset et al. [23] proposed a hybrid MCDM model for the evaluation of bioenergy production technologies in Egypt by considering DEMATEL and EDAS approaches under a neutrosophic setting. It was observed that adapting agricultural as well as municipal wastes into biogas was the most appropriate technology for bioenergy production. This work introduced a strong methodology to evaluate sustainable bioenergy options, focusing on the contribution of hybrid MCDM techniques in making decisions under complex and uncertain contexts.

These studies collectively demonstrate the utility of MCDM methods for the assessment of a wide variety of environmental technologies and systems and give reason to the powerful synthesis multiple criteria can afford while also affording complex decision-making scenarios. In this respect, the methodologies and findings presented form a sound basis on which to found an evaluation of sustainable pollution control technologies and underpin effective development of assessment frameworks.

3. Materials and Methods

In this study, certain factors were weighed up cautiously in selecting the suite of pollution control technologies under evaluation to make sure that the assessment would be thorough. The selection criteria reflect the multi-faceted nature of pollution control: environmental effectiveness of the technology, economic viability of the technology, and public and stakeholder acceptance. Furthermore, each alternative has been analyzed with respect to technological readiness and regulatory compliance, fitting into current and future environmental standards. These options taken up represent a wide range of approaches that each has its own strengths and weaknesses to handle the issue of pollution. Therefore, the research will attempt to analyze those factors that may give the best available technologies in pollution control, effective and viable for a longer period, thus enabling the decision-makers to make an informed and balanced choice [24-27].

3.1. Criteria for Evaluating Pollution Control Technologies

In this research, several criteria are employed to evaluate the effectiveness of pollution control technologies:

Environmental Impact (EI): The Environmental Impact of a technology evaluates its capability to significantly reduce pollution and be able to mitigate the unwanted effects on the ecosystem. It will involve measures of how well the technology minimizes the emission of harmful substances such as pollutants and greenhouse gases that work toward the overall improvement of the quality of the environment. A higher scored would go to technologies showing major reduction in pollutants and minimization of impact on natural habitats and biodiversity.

Economic Feasibility (EF): It will look at the overall cost-effectiveness of the technology, including the immediate capital investment required to implement it and the operating and maintenance costs over time. This criterion will determine whether the benefits from the technology resonate with the costs of technology and that it represents good value for money. The economic viability of the technology is looked at in terms of such factors as capital costs, life cycle costs, and the possibility of making economic savings or incomes.

Social Acceptability (SA): It would measure public and stakeholder's support for the technology with its impacts on the public health, safety and well-being of the community. This entails how different groups perceive the working of technology to be creating or eliminating jobs, along with its overall effect in the quality of life in communities. A technology that also agrees with the values of society and tries to address the concerns of the public is most likely to achieve wider acceptance and facilitate smooth implementation.

Technological Maturity (TM): Technological maturity refers to the technological maturity with regard to its development for reliability and wide usage. It looks at the track record of the technology, the extent of deployment in real-world situations, and demonstrated performance under a wide range of conditions. Proven technologies, therefore, are well-tested, having been successfully implemented across different settings, making them more mature and thus dependable.

Regulatory compliance (RC): It refers to the degree to which existing environmental regulations are met by the technology and its immediate and future potentials. This criterion makes certain that the technology not only will meet current laws and standards but also will be able to take in stride any future regulations. Technologies that best exhibit regulatory conformance and/or flexibility toward the accommodation of new or evolving regulations are preferred.

Scalability and Flexibility (SF): It is a measure to check how much a technology might be subjected to various scales of operation and different environmental conditions. It involves the ability to scale up or scale down based on application size that may affect its performance in environmental settings. Technologies that offer scalability and flexibility are preferred because they are versatile and can address a wide range of pollution control needs.

3.2. Different Pollution Control Technologies

Alternatives selected in this research study involve the identification of a diverse range of technologies that represent a different approach to pollution control. Each alternative chosen is based on its application with regard to different types of pollutants and also suited to different environmental contexts. Chosen technologies are part of diverse methods: chemical, physical, and biological processes that ensure a wide perspective on available solutions. The list was therefore compiled to include those options that have already proved their effectiveness, scalability, and relevance in regard to present-day challenges of pollution. This process of selection-what ends up in the list and what does not-indicates the variety underlying the technologies involved but at the same time allows a comparative evaluation of strengths and deficiencies in technological options for effective and sustainable control.

Advanced Oxidation Processes (AOPs): These are usually implemented to degrade impurities in water or air by using strong chemical reactions. Most AOPs use chemicals such as ozone or ultraviolet light that destroy the pollutants. Ozone, for instance, is a strong oxidant that reacts with pollutants to break them into smaller, harmless molecules. Similarly, UV light is helpful in producing reactive particles that destroy the pollutants. This method tends to be effective in removing a wide range of harmful substances, making the water or air much cleaner [28, 29].

Electrostatic Precipitators (ESPs): ESPs work by air cleansing through filtration of very small particles amidst the fumes of exhaust, which emanate from factories or power plants. In a model, an electrical field is developed which charges all the particles in the exhaust. These charged particles now feel an attraction for plates carrying the opposite charge. This process helps to minimize the quantity of dust and other particulate matter released in the air, improving air quality [30, 31].

Bioremediation (BR): It utilizes the metabolic capability of living organisms, such as bacteria, fungi, or plants, to detoxify environmental pollutants. These usually consist of harmless bacteria being added directly to the polluted soil or water, where they metabolically break down harmful chemicals into less harmful substances. On the other hand, plants absorb and store pollutants through their roots. The approach generally consists of cleanup methodologies of oil spills, heavy metals, and other contaminants to restore polluted areas to better health conditions [32-34].

Membrane Filtration (MF): It is a water filtration technique, or air, from its pollutants by passing it through a special filter. The filter itself, also known as a membrane, allows clean water or air to pass through its small pores while holding larger particles and contaminants in its pores. Membranes vary in kind and depend upon the kind of particles which have to be filtered. For example, microfiltration removes larger-sized particulates such as sand and dirt while ultra-filtration can remove smaller ones that even include bacteria and viruses.

Carbon Capture and Storage (CCS): One of the main causes of global warming is carbon dioxide emissions, which can be reduced with the use of CCS technology. Before being released into the environment, carbon dioxide (CO_2) emissions from a variety of sources, including power plants and industrial operations, are captured through this process. The acquired carbon dioxide is sent to storage locations, which are frequently found far below ground in geological structures, where it is kept safe for extended periods of time. Additionally, this helps control the release of greenhouse gases and stops CO_2 from contributing to global warming [37, 38].

Catalytic Converters (CC): Catalytic converters are installed in the exhaust systems of automotive vehicles and other related machines to reduce injurious emissions. They have some special materials commonly referred to as catalysts, which accelerate chemical reactions. Such reactions change injurious gases such as carbon monoxide (CO), nitrogen oxides (NO_x) as well as hydrocarbons into less injurious elements such as carbon dioxide (CO_2), nitrogen and water vapor. Thus, catalytic converters help in lowering air pollution and enhancing the quality of air [39, 40].

The presented selection criteria and their alternatives form the basis of a practical, focused approach for decision-makers in evaluating and prioritizing those environmental technologies for sustainable pollution control.

3.3. Fuzzy TOPSIS Methodology:

Fuzzy TOPSIS has been applied for the technique of order preference by similarity to ideal solution in this research work for assessment and ranking of sustainable environmental technologies for pollution control. It started with the identification of important criteria like environmental impact, economic feasibility, and technological maturity, all of which are very crucial in assessing the sustainability of these technologies. The fuzzy nature of the methodology allows the modeling of uncertainty and vagueness inherent in expert judgments and elicits the ability to capture the complexity or even controversy of real-world decision-making. The proposed methodology should, therefore, be able to systematically handle ambiguity in criteria weights and performance ratings by converting qualitative assessments into fuzzy numbers and constructing a fuzzy decision matrix. The final step was to determine the closeness coefficient of each alternative, a measure of how close the chosen technology stands from the ideal solution, thus allowing a more objective comparison and ranking of the technologies.

The suitability of the Fuzzy TOPSIS methodology has something to do with its capability to address multidimensional and uncertain natures of environmental decision-making problems. In each technology related to pollution control, there are various trade-offs among the environmental, economic, and social features involved that make it difficult to derive a clear preference based on conventional methods. This technique, Fuzzy TOPSIS, integrates fuzziness to capture the subjective and imprecise information from the stakeholders and experts. That gives it a particular effectiveness for cases where precise numerical data may not exist or be unreliable. Further, the ability of this method to consider multiple criteria and give a ranking on the relative importance of those criteria meets the objective of the present study, which is to select the most feasible and effective technologies for pollution control. This can enhance the robustness, as well as harmonization with wider sustainability goals in decision-making [44-47].

4. Results

Results of this study present an in-depth analysis of the performance of different environmental technologies for sustainable pollution control. In this research, each technology is systematically compared with a set of well-defined criteria using an MCDM approach by considering stakeholder preferences and accounting for uncertainties inherent in the decision-making process. The outcome of the analysis presenting the comparative performance of the technologies under consideration is presented in this section. These outcomes provide an insight into the relative strengths and weaknesses of each technology. In fact, it is a critical source for any decision-maker desiring to enforce an effective pollution control strategy. This section presents an application of the Fuzzy TOPSIS methodology to rank sustainable environmental technologies by their effectiveness in pollution control. The criteria were defined and weighted, fuzzy decision matrices were built, and closeness coefficients of each alternative were calculated. Such methodology provided a way to compare the technologies with nuances by taking into account inherent uncertainties and diverse criteria relevant to environmental sustainability. The results present the relative performance of each technology and those that are the best to help achieve goals on pollution control in different circumstances.

Step 1: Create a decision matrix

This study has 6 criteria and 6 alternatives which are ranked by the FUZZY TOPSIS method. Table 1 represents the type of criterion-weight assigned to each criterion.

Table 1 Characteristics of Criteria

Name	Type	Weight
EI	+	(0.167,0.167,0.167)
EF	+	(0.167,0.167,0.167)
SA	+	(0.167,0.167,0.167)
TM	+	(0.167,0.167,0.167)
RC	+	(0.167,0.167,0.167)
SF	+	(0.167,0.167,0.167)

The following Table 2 shows the fuzzy scale used in the model.

Table 2 Fuzzy Scale

Code	Linguistic terms	L	M	U
1	Very low	1	1	3
2	Low	1	3	5
3	Medium	3	5	7
4	High	5	7	9
5	Very high	7	9	9

The alternatives are weighted for the various criteria and the outcomes of the decision matrix are shown below. Remember that if several experts are participating in the review, then the matrix below in Table 3 presents the arithmetic mean of all experts.

Table 3 Decision Matrix

	EI	EF	SA	TM	RC	SF
AOPs	(5.000,7.000,8.600)	(6.400,8.400,9.000)	(5.800,7.800,9.000)	(6.000,8.000,8.600)	(5.600,7.600,8.800)	(6.200,8.200,9.000)
ESPs	(4.000,6.000,7.800)	(2.600,4.600,6.600)	(3.600,5.600,7.600)	(3.000,5.000,7.000)	(3.600,5.600,7.600)	(3.000,5.000,7.000)
BR	(2.800,4.600,6.600)	(1.800,3.400,5.400)	(2.600,4.600,6.600)	(1.600,3.400,5.400)	(2.400,4.000,6.000)	(2.000,4.000,6.000)
MF	(3.600,5.600,7.600)	(4.200,6.200,8.200)	(3.400,5.400,7.400)	(3.800,5.800,7.800)	(3.800,5.800,7.800)	(4.400,6.400,8.400)
CCS	(5.200,7.200,9.000)	(4.600,6.600,8.000)	(4.600,6.600,8.200)	(5.400,7.400,8.800)	(5.800,7.800,9.000)	(5.800,7.800,9.000)
CC	(1.600,3.600,5.600)	(2.800,4.800,6.800)	(2.200,4.200,6.200)	(2.400,4.400,6.400)	(2.600,4.600,6.600)	(2.800,4.400,6.400)

Step 2: Create the normalized decision matrix

The following connection can be used to create a normalised choice matrix based on the positive and negative ideal solutions:

$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right)$; $c_j^* = \max_i c_{ij}$; Positive ideal solution

$\tilde{r}_{ij} = (\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}})$; $a_j^- = \min_i a_{ij}$; Negative ideal solution

The normalized decision matrix is shown in the Table 4 below.

Table 4 A normalized decision matrix

	EI	EF	SA	TM	RC	SF
AOPs	(0.556,0.778,0.956)	(0.711,0.933,1.000)	(0.644,0.867,1.000)	(0.682,0.909,0.977)	(0.622,0.844,0.978)	(0.689,0.911,1.000)
ESPs	(0.444,0.667,0.867)	(0.289,0.511,0.733)	(0.400,0.622,0.844)	(0.341,0.568,0.795)	(0.400,0.622,0.844)	(0.333,0.556,0.778)
BR	(0.311,0.511,0.733)	(0.200,0.378,0.600)	(0.289,0.511,0.733)	(0.182,0.386,0.614)	(0.267,0.444,0.667)	(0.222,0.444,0.667)
MF	(0.400,0.622,0.844)	(0.467,0.689,0.911)	(0.378,0.600,0.822)	(0.432,0.659,0.886)	(0.422,0.644,0.867)	(0.489,0.711,0.933)
CCS	(0.578,0.800,1.000)	(0.511,0.733,0.889)	(0.511,0.733,0.911)	(0.614,0.841,1.000)	(0.644,0.867,1.000)	(0.644,0.867,1.000)
CC	(0.178,0.400,0.622)	(0.311,0.533,0.756)	(0.244,0.467,0.689)	(0.273,0.500,0.727)	(0.289,0.511,0.733)	(0.311,0.489,0.711)

Step 3: Create the weighted normalized decision matrix

Since each of those criteria has a different weight attached to it, the weighted normalized decision matrix can be calculated by multiplying each criterion's weight in the normalized fuzzy decision matrix by the following formula.

$\tilde{v}_{ij} = \tilde{r}_{ij}.\widetilde{w}_{ij}$

Where $\widetilde{w}_{ij}$ represents weight of criterion c_j

The following Table 5 shows the weighted normalized decision matrix

Table 5 The weighted normalized decision matrix

	EI	EF	SA	TM	RC	SF
AOPs	0.093,0.130,0.160) (	0.119,0.156,0.167) (	0.108,0.145,0.167) (	0.114,0.152,0.163) (	0.104,0.141,0.163) (	0.115,0.152,0.167) (
ESPs	0.074,0.111,0.145) (	0.048,0.085,0.122) (	0.067,0.104,0.141) (	0.057,0.095,0.133) (	0.067,0.104,0.141) (	0.056,0.093,0.130) (
BR	0.052,0.085,0.122) (	0.033,0.063,0.100) (	0.048,0.085,0.122) (	0.030,0.065,0.102) (	0.045,0.074,0.111) (	0.037,0.074,0.111) (
MF	0.067,0.104,0.141) (	0.078,0.115,0.152) (	0.063,0.100,0.137) (	0.072,0.110,0.148) (	0.071,0.108,0.145) (	0.082,0.119,0.156) (
CCS	0.096,0.134,0.167) (	0.085,0.122,0.148) (	0.085,0.122,0.152) (	0.102,0.140,0.167) (	0.108,0.145,0.167) (	0.108,0.145,0.167) (
CC	0.030,0.067,0.104) (	0.052,0.089,0.126) (	0.041,0.078,0.115) (	0.046,0.084,0.121) (	0.048,0.085,0.122) (	0.052,0.082,0.119) (

Step 4: Determine the fuzzy positive ideal solution (FPIS, A*) and the fuzzy negative ideal solution (FNIS, A^-)

The FPIS and FNIS of the alternatives can be defined as follows:

$$A^* = \{\tilde{v}_1^*, \tilde{v}_2^*, \ldots, \tilde{v}_n^*\} = \left\{\left(\max_j v_{ij} \mid i \in B\right), \left(\min_j v_{ij} \mid i \in C\right)\right\}$$
$$A^- = \{\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-\} = \left\{\left(\min_j v_{ij} \mid i \in B\right), \left(\max_j v_{ij} \mid i \in C\right)\right\}$$

Where $\tilde{v}_i^*$ is the max value of i for all the alternatives and $\tilde{v}_1^-$ is the min value of i for all the alternatives. B and C represent the positive and negative ideal solutions, respectively.

The positive and negative ideal solutions are shown in the Table 6 below.

Table 6 The positive and negative ideal solutions

	Positive ideal	Negative ideal
EI	(0.096,0.134,0.167)	(0.030,0.067,0.104)
EF	(0.119,0.156,0.167)	(0.033,0.063,0.100)
SA	(0.108,0.145,0.167)	(0.041,0.078,0.115)
TM	(0.114,0.152,0.167)	(0.030,0.065,0.102)
RC	(0.108,0.145,0.167)	(0.045,0.074,0.111)
SF	(0.115,0.152,0.167)	(0.037,0.074,0.111)

Step 5: Calculate the distance between each alternative and the fuzzy positive ideal solution $A^*$and the distance between each alternative and the fuzzy negative ideal solution A^-

The distance between each alternative and FPIS and the distance between each alternative and FNIS are respectively calculated as follows:

$S_i^* = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^*)$ i=1,2,…,m

$S_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-)$ i=1,2,…,m

d is the distance between two fuzzy numbers , when given two triangular fuzzy numbers (a_1, b_1, c_1) and (a_2, b_2, c_2), e distance between the two can be calculated as follows:

$$d_v(\tilde{M}_1, \tilde{M}_2) = \sqrt{\frac{1}{3}[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2]}$$

Note that $d(\tilde{v}_{ij}, \tilde{v}_j^*)$ and $d(\tilde{v}_{ij}, \tilde{v}_j^-)$ are crisp numbers.

The Table 7 below shows distance from positive and negative ideal solutions

Table 7 Distance from positive and negative ideal solutions

	Distance from positive ideal	Distance from negative ideal
AOPs	0.011	0.414
ESPs	0.262	0.165
BR	0.397	0.027
MF	0.2	0.229
CCS	0.065	0.362
CC	0.365	0.061

Step 6: Calculate the closeness coefficient and rank the alternatives

The closeness coefficient of each alternative can be calculated as follows:

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-}$$

The best alternative is closest to the FPIS and farthest to the FNIS. The closeness coefficient of each alternative and the ranking order of it are shown in the Table 8 below.

Table 8 Closeness coefficient

	Ci	Rank
AOPs	0.974	1
ESPs	0.386	4
BR	0.064	6
MF	0.534	3
CCS	0.848	2
CC	0.144	5

The following graph in Figure 1 shows the closeness coefficient of each alternative.

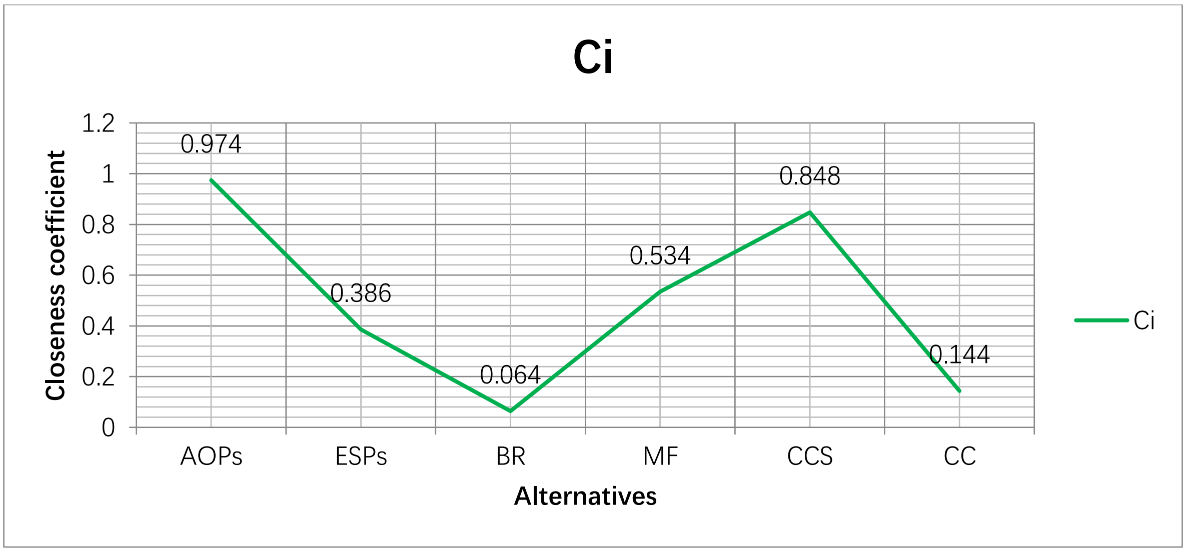

Fig. 1 Closeness coefficient

The findings of this research study reveal a comprehensive ranking of various pollution control technologies based on their effectiveness, as measured by their Closeness coefficient (Ci). Advanced Oxidation Processes (AOPs) emerged as the most effective technology with a high Closeness coefficient of 0.974, indicating its superior performance in pollution control. Carbon Capture and Storage (CCS) followed, with a Closeness coefficient of 0.848, reflecting its strong effectiveness but slightly lower than AOPs. Membrane Filtration (MF) ranked third with a Ci of 0.534, suggesting it is a solid option, though less effective than AOPs and CCS. Electrostatic Precipitators (ESPs) were placed fourth with a Closeness coefficient of 0.386, showing moderate effectiveness. Catalytic Converters (CC) and Bioremediation (BR) ranked lower, with Ci values of 0.144 and 0.064, respectively, indicating that these technologies are less effective in comparison to the higher-ranked alternatives. This ranking provides valuable insights for decision-makers aiming to prioritize technologies based on their pollution control efficacy.

5. Discussion

The results of this research give an in-depth view of the effectiveness of the various applied technologies of pollution control and shed light on the relative performance based upon the Closeness coefficient, Ci. These rankings are critically important with respect to the potential applications and overall efficacy of said technologies in the management of different types of pollutants.

AOPs were rated as the most promising of the technologies evaluated with the highest closeness coefficient of 0.974 [48, 49]. This is indicative of the fact that advanced chemical treatment techniques of AOPs involve the generation of highly active species for a wide range of organic and inorganic pollutants to effectively provide their degradation. This outstanding ranking is especially pronounced when other traditional methods have poor performance. Because of its competence in handling complex contaminants and achieving high levels of pollutant degradation, AOP has become the choice for rigorous pollution control applications. Its effectiveness suggests that AOP technology may be especially valuable in industries with challenging streams and demanding better treatment technologies.

Carbon Capture and Storage (CCS) secured the second position with a Closeness coefficient of 0.848. CCS technologies are designed to capture carbon dioxide emissions from industrial sources and store them securely to prevent their release into the atmosphere. The high ranking of CCS underscores its critical role in mitigating climate change by addressing greenhouse gas emissions. However, the slightly lower effectiveness compared to AOPs may be attributed to the complexity and high costs associated with the implementation of CCS systems. The need for extensive infrastructure and ongoing operational challenges can impact its overall performance. Despite these challenges, CCS remains a crucial technology for reducing carbon footprints and combating global warming.

MF came third with a Closeness coefficient of 0.534. It is an effective technology that uses semi-permeable membranes to separate contaminants from liquids, particularly water. The position of MF in the middle shows the critical application of MF in the water and wastewater treatment train. While MF is effective in removing particulate matter and dissolved substances, this process is somewhat limited as compared to AOPs and CCS in terms of wider applications in pollution controls. This can be particularly true for applications in the area of separations and purifications; thus, its effectiveness may not be that complete with regard to all types of pollutants. Electrostatic Precipitators ranked fourth with a Closeness coefficient of 0.386. In practice, ESPs serve to capture particulate matter from industrial emissions based on electrostatic forces. They are effective in the abatement of particulate pollution but less versatile in handling other types of pollutants. The problem is that performance is limited, as their role is mainly particulate removal rather than a broader spectrum of pollutant control. This ranking would suggest the requirement to complement ESPs with complementary technologies in view of more comprehensive pollution control.

CC and BR scored closely from the fifth to the sixth with 0.144 and 0.064 in their Closeness coefficients, respectively. Catalytic Converters have a major embedding on vehicles to reduce poisonous gases like nitrogen oxides and hydrocarbons by means of catalyst conversion, thus showing lesser effectiveness when applied in larger contexts like pollution control. Since it is a special application, it should be that their general impact is also much lesser than those of the other general technologies. The lowest Closeness coefficient is that of Bioremediation, which applies biological processes for pollutant degradation. Though quite efficient in a number of applications, like soil or water decontamination, Bioremediation is effective in general, as its action is usually slower and depends on favorable environmental conditions. These results once more point to the right selection of pollution control technology depending on needs and site conditions. While AOPs and CCS are, respectively, more effective in their sets, the appropriateness of each technology would again be very different for the type of pollutant or context in which it would be applied. This paper thus provides a useful framework for decision-makers in order to evaluate and prioritize the selected pollution control technologies for any given solution to a certain environmental problem. Results also stress the need for development and improvement of pollution control technologies continuously, so that the emergent environmental challenges could generally be met more effectively.

6. Conclusion

This study successfully assessed and ranked several pollution control technologies in order of AOPs, CCS, and MF. The outcomes showed the potentials of AOPs to work within wide ranges of variables for any given pollutant and the importance of CCS in mitigating greenhouse gas emissions. While this effectiveness holds, Membrane Filtration and Electrostatic Precipitators are applications that are a bit more specialized. Catalytic Converters and Bioremediation reveal limitations for broader applications in general pollution control contexts, since they deal with more limited applications. The importance of this study is that it has given a structured frame in which to appraise and prioritize pollution control technologies for effectiveness, thus helping decisions by all concerned on the basis of effectiveness and application context. This framework is particularly helpful to industries and policymakers in that they can now pin effective pollution control measures helpful in improving environmental sustainability. Nevertheless, there are several limitations to this study. Each of these case studies was defined by a set of selected technologies and selected criteria, which may not be considered fully representative of all facets of pollution control. The ranking of efficiencies will depend upon the particular contexts in which the technologies operate and will alter with different environmental conditions or technologies which provide further improvements. Other future studies should also be involved in an expanded array of technologies and criteria while, at the same time, considering real-world case studies that could further validate such research.

The study of evolving technologies and their integration with other existing ones could go a long way in yielding more findings relating to performance and potential use with respect to emerging environmental challenges. Dynamic and context-specific enhancement of the framework will provide even more holistic and applicable outcomes toward assessments of pollution control technologies.

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