Rapid sustainability assessment of sludge management technologies for industrial scale-up

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Abstract

Sludge reduction technologies have advanced significantly because of their potential in sustainable development and effective waste management. However, the need for scalable, sustainable wastewater treatment technologies is critical in addressing the challenges posed by population growth and environmental concerns. These technologies still lack a comprehensive framework that can evaluate the relationships between techno-economic, environmental life cycle, socio-policy, and reliability as well as sensitivity, and uncertainty analysis. Furthermore, the reliance on expert judgment, in evaluating new technologies, while valuable, often is slow, costly, and sometimes hindered by a lack of familiarity with disruptive innovations due to experts' knowledge gaps and constrained future outlooks. Hence, this study introduces an integrated rapid sustainability assessment framework designed to evaluate pilot sludge reduction technologies across technical, economic, reliability, environmental, and socio-political dimensions. The framework leverages a data-driven, scenario-based multi-criteria decision-making approach, incorporating rigorous sensitivity and uncertainty analyses to enhance the reliability of evaluations. This framework is validated through a case study involving three alternatives: (1) Anoxic/Oxic Membrane bioreactor, (2) Anaerobic Side-Stream Reactor, and (3) Anaerobic Main-Stream Reactor. Using the proposed approach, 145,530 potential future scenarios were analysed, incorporating five key criteria and 20 vital indices. The results indicate that the second alternative outperforms the other options in 86% of the evaluated scenarios. However, its performance may be sensitive to any changes in pollutant removal efficiency, operational costs, and global warming potential

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when scaled to full industrial applications. With comparison with current approaches, this user-friendly framework not only shows its ability to capture a broader range of uncertainties but also identifies trends and potential challenges that may not be readily apparent through expert intuition alone. This method also provides a holistic view of the environmental, technical, reliability and socio-policy impacts, facilitating informed decision-making for scaling pilot technologies to industrial applications.

Keywords: Data-driven scenario analysis; Industrial full scaling; Life cycle assessment; Multi-criteria decision-making; Rapid sustainability assessment; Sludge reduction

1. Introduction

Membrane bioreactor technologies (MBR) have been recommended over the last decade as a sustainable potential to address various challenges in municipal or industrial wastewater treatment systems i.e., increasing population growth, urbanisation, industrialisation, and the need for more efficient and environmentally friendly wastewater treatment processes (Piadeh *et al.*, 2014). Although MBR technology offers advantages such as higher removal efficiencies for pollutants, a smaller footprint compared to conventional treatment systems, and the ability to produce high-quality effluent suitable for reuse or discharge into sensitive environments (Rahman *et al.*, 2023). Despite the recognised efficiency of MBR systems, the challenge of managing high concentrations of waste-activated sludge (WAS) remains a critical issue, impacting both operational costs and sustainability, membrane fouling, energy consumption, chemical usage, and limited flexibility in handling fluctuations (Zhang *et al.*, 2023).

Recent studies have highlighted the critical importance of integrating sludge reduction technologies into MBR systems to address these challenges effectively. Various sludge management approaches, such as aerobic digestion, anaerobic digestion, and advanced oxidation processes, have been explored, with each demonstrating specific benefits and limitations. For instance, anaerobic digestion has been recognised for its potential to generate biogas as a renewable energy source, enhancing the sustainability of wastewater treatment processes (Ren *et al.*, 2023; Zielińska & Bułkowska, 2024). However, issues such as complex microbial dynamics and high sensitivity to operational conditions limit its widespread adoption (Kim *et al.*, 2021). On the other hand, advanced oxidation processes offer rapid sludge reduction capabilities but are often energy-intensive and require careful management of by-products (Wang *et al.*, 2022). Emerging processes, such as hydrothermal carbonisation, have also shown promise in reducing sludge volumes while producing valuable by-products like biochar, although scalability remains a concern (Smith *et al.*, 2020).

Furthermore, recent advancements in integrated frameworks, such as combining MBR systems with sludge reduction technologies, have shown promise in enhancing operational efficiency and sustainability. The life cycle sustainability assessment (LCSA) framework has emerged as a robust tool for evaluating the environmental, economic, and social impacts of these integrated systems, providing valuable insights into their long-term viability (Finkbeiner *et al.*, 2020). Tools like material flow analysis and resource circularity metrics have further contributed to understanding resource efficiency in wastewater treatment systems (Girotto *et al.*, 2021). However, challenges remain in incorporating these tools into decision-making processes due to data gaps and uncertainties in complex operational environments (Zhou *et al.*, 2022).

Scalability of pilot sludge reduction technologies faces challenges such as variability in wastewater characteristics, which can impact reliability and performance at an industrial scale, and high operational costs, particularly for energy-intensive processes like anaerobic digestion and advanced oxidation (Ren *et al.*, 2023). Membrane fouling and retrofitting existing systems for technology integration further complicate large-scale implementation, demanding innovative strategies and adaptive frameworks (Wang *et al.*, 2022). Addressing these issues requires extensive pilot trials and field validations to ensure performance under diverse real-world conditions (Zielińska & Bułkowska, 2024).

2. Literature Review

The integration of a sludge retention reactor (SRR) has been proposed as a pivotal innovation in modern wastewater treatment strategies (Oliveira *et al.*, 2018). The SRR significantly enhances sludge management by optimising the retention time of sludge within the system, thereby reducing the volume of WAS requiring disposal and enhancing the overall process stability (Johnson *et al.*, 2022). Furthermore, SRR can improve the biodegradation efficiency of organic pollutants, leading to a more effective reduction in sludge production while maintaining high-quality effluent standards (Anderson and Li, 2021). The role of SRR in MBR systems is thus instrumental, not only in extending membrane life by reducing fouling rates but also in contributing to the energy efficiency of wastewater treatment plants by lowering the energy demands associated with sludge handling and disposal (Chen *et al.*, 2024).

Current studies have primarily focused on the technical aspects of these methods, such as their effectiveness in reducing WAS, retention time optimisation, and evaluation of operational indices (Corsino *et al.*, 2020a; Cosenza *et al.*, 2024a). However, other vital aspects such as environmental life cycle assessment (ELCA) and techno-economic analysis have been mainly explored within MBR systems, which often results in a neglect of the specific contributions of the SRR component (Chen *et al.*, 2024). For instance, detailed insights into the role and impact of SRR systems have been lacking while cost implications and profitability of operating MBR systems exist (Gao *et al.*, 2021). Similarly, ELCA of MBR systems have emphasised factors such as chemical usage and energy consumption yet have not been deepened into the specific influence of SRR systems (Krzeminski *et al.*, 2017). However, the role of SRR systems in Life Cycle Costing (LCC) and cost-benefit analyses often remains obscured within the broader context of MBR systems (ISO 15686-5:2017; Pretel *et al.*, 2016).

The significance of SRR systems warrants further in-depth investigation, particularly as these technologies transition from experimental pilot models to full-scale operations. Understanding of their economic and operational impacts is essential (Yang *et al.*, 2021). To achieve widespread adoption and effectiveness, SRR systems must be user-friendly, scalable, and adaptable to diverse global conditions (Chen *et al.*, 2024). Despite advancements in the evaluation of emerging technologies, a significant gap remains in how future scenarios are incorporated into these frameworks. Current approaches often rely heavily on expert judgment, which can be constrained by limited knowledge and familiarity with disruptive innovations or market shifts as well as tends to be time-consuming, high-risk, and slow to promote (Karaca *et al.*, 2021).

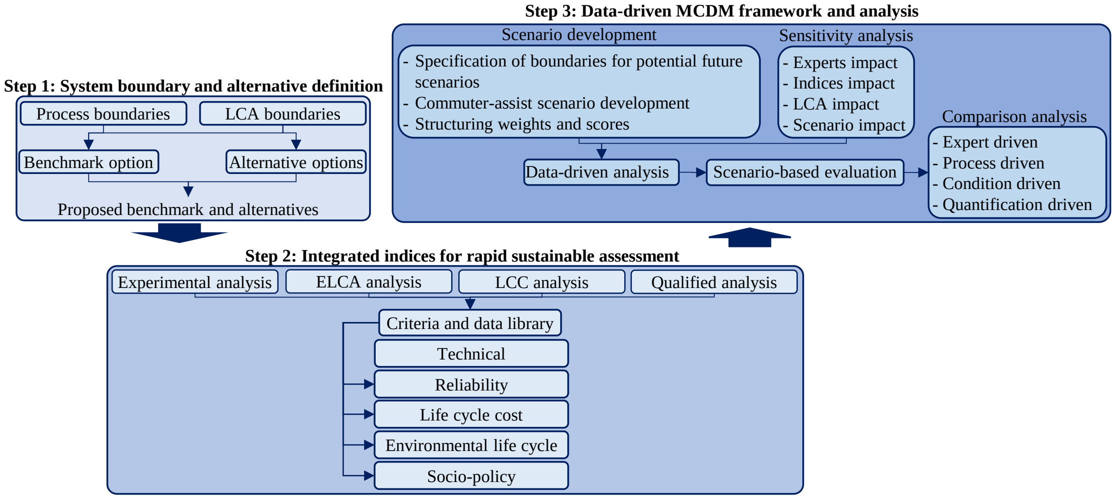
Furthermore, the future scenarios considered within these frameworks are typically limited, and the associated weights and definitions often rest on the knowledge of experts who may lack a complete understanding of the future potential of these emerging technologies (Naghesi *et al.*, 2020; Ahmad *et al.*, 2021). On the other hand, considering a wide range of scenarios may not be practical when they need to be assessed by decision makers. The complexity and volume of information required to explore numerous future possibilities can overwhelm decision-making processes, making it difficult to focus on actionable insights (Zhou *et al.*, 2024). Finally, decision makers often have limited time and resources to evaluate each scenario in detail, potentially leading to analysis paralysis or superficial assessments (Qureshi, 2024). Hence, the balance between comprehensiveness and practicality is critical, where frameworks must provide enough depth to capture key uncertainties without overwhelming the decision-making process. This highlights the challenge of creating adaptive models that are both robust and manageable for real-world applications.

This study aims to develop the Integrated Rapid Sustainability Assessment Framework (IRSAF), a user-centric, data-driven Multi-Criteria Decision-Making (MCDM) methodology to assess the scalability of advanced sludge reduction technologies within membrane bioreactor (MBR) systems and bridging the gap between laboratory research and real-world applications. By incorporating scenario-based analysis and sensitivity modelling, the framework addresses key challenges in evaluating sustainability. More specifically, the primary objectives of this study are to (1) develop a rapid framework designed to address the challenges raised during the industrialisation of pilot RSS technologies. This framework aims to minimise risks associated with unforeseen challenges during the installation and operation of these technologies at an industrial scale; (2) use data-driven, scenario-based MCDM to analyse and mitigate uncertainties associated with transitioning lab-scale sludge reduction technologies to industrial applications; (3) address key challenges related to technical, economic, socio-political, environmental, and reliability dimensions, thereby facilitating informed decision-making for full-scale implementation. To achieve this, the following research questions are addressed through the application of the proposed methodology to a real case study: (1) How effective is the proposed IRSAF framework in identifying and addressing the barriers to the industrial scaling of sludge reduction technologies? (2) What are the primary technical, economic, environmental, and socio-political challenges associated with scaling advanced sludge reduction technologies from lab-scale to industrial applications? (3) How does the integration of data-driven scenario analysis and sensitivity modelling enhance decision-making compared to traditional expert-driven approaches?

The study's novelty lies in its innovative approach to sustainability assessment: (1) It introduces a systematic and holistic framework that integrates data-driven MCDM modelling with scenario-based analysis to provide robust evaluations of pilot sludge reduction technologies for industrial scaling, (2) The framework reduces over-reliance on expert judgment by offering a computer-assisted assessment that captures a broader range of future possibilities, improving decision-making accuracy and adaptability; (3) Unlike traditional methodologies, the study focuses on the complex interactions between diverse sustainability metrics, such as operational costs, environmental impacts, and socio-political factors, while maintaining a user-friendly structure; (4) The sensitivity analysis highlights critical dependencies on specific metrics (e.g., energy consumption and nutrient removal), offering actionable insights for improving the scalability of promising but pilot technologies

3. Methodology

This study follows a three-step framework, as shown in flowchart of methodology in Figure 1a, which comprises the following steps: (1) alternative and system boundary definition establishing the process and Life Cycle Assessment (LCA) boundaries of the options; (2) conducting data analysis and defining integrated indices through both quantitative (such as technical analysis, ELCA, LCC) and qualitative (reliability and socio-policy) data surveys; (3) establishing data-driven MCDM framework to analyse the options throughout possible future-space scenarios considering sensitivity analysis. This MCDM framework is coupled with new and novel scenario analysis and codding to support analysis on the provided big data. Further details are provided in the following sections. This framework is not limited to a particular wastewater treatment application and can be adapted for use in municipal, industrial, or agricultural contexts. Additionally, while this framework is applied explicitly to SRR systems, its principles can encompass various physical, chemical, and biological main or side processes.



(a)

Inputs: Score of alternative for in each index (S_A), Weight of each index (W_I) & min and max weight of each criteria (W_C)

For: o = Normal condition, Analysis on W_I, Analysis on W_C, Analysis on expert

| For j=1: number of criteria

| | For i=min W_{Cj} to max W_{Cj}

| | | Assign Cell_scenario(i,k) = i

| | End for

| End for

| Remove similar Cell_scenario

| Classify the scenarios into all, core, and extreme

| For j=1: number of scenarios

| | For m=1: number of alternatives

| | | Score $A_i = \sum_{n=1}^{number\ of\ sub-criteria} S_{Ani} \times W_{In} \times \mathrm{Cell\_scenarios}\ (n, j)$

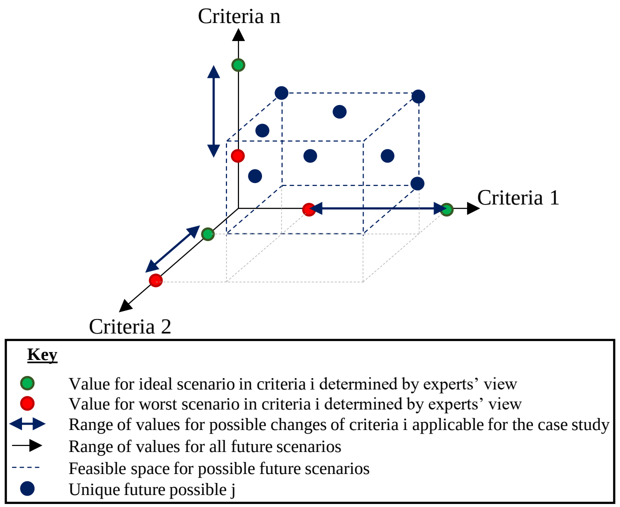
| | | Presence A_i = 1 if A_i is the highest score, 0 if not

| | End for

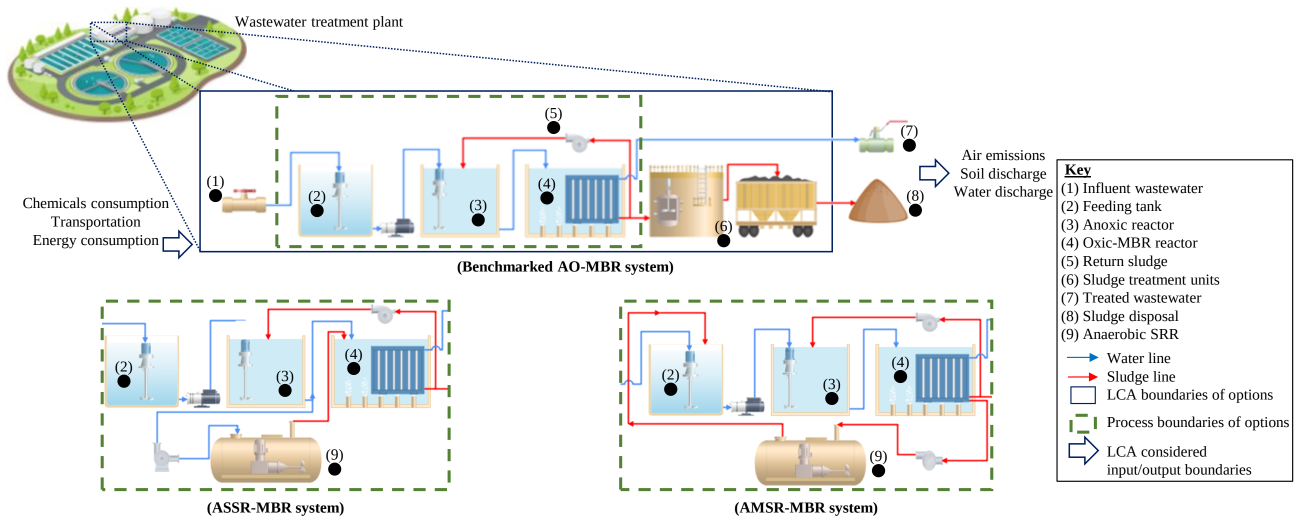
| End for

End for

(b)



(c)



(d)

Figure 1. Schematic components of the IRSAF framework: (a) Flowchart of proposed methodology, (b) Pseudocode of scenario development and sensitivity analysis, (c) Schematic overview of proposed scenario development demonstrated for three criteria assessments, (d) System boundary of the targeted MBR processes

3.1. Step 1: System boundaries and an alternative definition

System boundaries are established here using two categories of process boundaries and LCA. Process boundaries refer to the scope of including all physical equipment, technologies, and treatment processes that differentiate between various options. These can be categorised into two classes of water lines and sludge lines (see Figure 1d for more details). The water line includes the feeding tank, anoxic tank, and MBR reactor, while the sludge line includes the thickening, anaerobic digestion, and dewatering processes of a typical sludge treatment unit. This study follows the recommendations of ISO 14040 (2006) for LCA boundaries. However, to simplify but keep effectiveness, the building phase has been excluded based on the recommendations of Fan *et al.* (2024) and Ren *et al.* (2024). Furthermore, the LCA boundaries did not cover primary treatments such as screening units or post-treating processes such as disinfection to focus more on differences in options introduced for main treatment processes.

The present study tested the framework for the three alternatives. These alternatives are selected from a range of biological wastewater treatment systems designed for sludge reduction directly in the waterline of wastewater treatment plants (Morello *et al.*, 2022; Cosenza *et al.*, 2024b). Three options were selected and developed by Oliveira *et al.* (2018) due to their outstanding sludge reduction efficiency. The anoxic/oxic MBR system was used as a baseline and includes a feeding tank, an anoxic reactor used for denitrification, an oxic MBR reactor used for aerobic treatment and membrane filtration, and a return sludge line used for recycling activated sludge back into the system to maintain microbial activity and enhance sludge reduction.

Two pre-denitrification methods are introduced as alternatives including an anaerobic side-stream reactor (ASSR) and an anaerobic main-stream reactor (AMSR). ASSR deploys an anaerobic reactor in the return activated sludge line of the MBR plant whereas AMSR in a standard pre-denitrification strategy, an anaerobic reactor would be positioned between the anoxic and the aerobic reactors. In this system, some activated sludge flow would be sent from the anoxic reactor to the anaerobic SRR and then to the aerobic reactor. These alternatives have been introduced as practical ways for enhancing nutrient removal and sludge reduction (Corsino *et al.*, 2020b; Hu *et al.*, 2022).

The system boundaries did not consider the disposal of sludge. However, the sludge might be carried to fields and used as fertiliser, and impacts environmentally, regarding in terms of pathogen contamination or eutrophication of nearby freshwaters (Cucina *et al.*, 2021). Finally, the LCA boundary defined the relationships between the system's inputs, products, outputs, life cycles, energy consumption, transportation, and eventual decomposition, and direct and indirect impacts of the plant's operational water and sludge lines were assessed (Sabeen *et al.*, 2018).

3.2. Step 2: Feature extraction and indices definition

While wastewater treatment involves multiple interdependent variables, five main concepts are considered here (See Figure 1a): (1) experimental analysis (C1), which delves into technical aspects; (2) Reliability of systems for full-scaling (C2); (3) ELCA (C3) focusing on environmental impacts; (4) LCC (C4) providing an economic analysis; and (5) Socio-policy aspects (C5) for future industrial applicability. The framework primarily assesses the macro impacts of upscaling the project in terms of engineering aspects. Therefore, considerations for factors such as marketing potentials are felled outside of scope. Nonetheless, certain aspects, such as the impact of alternatives on human health, are still considered. Although these aspects remain consistent regardless of alternative definitions, indices are selected based on the differences among proposed alternatives introduced in the previous step, highlighting disparities between these options for further analysis through MCDM modelling.

Experimental analysis is crucial for validating theoretical models used in simulations and predictions about wastewater treatment processes, playing a vital role in the rapid assessment of laboratory pilot systems intended for industrial scaling (Jones and Brown, 2019). This analysis provides real-world data essential for understanding the actual performance of treatment processes under various conditions (Loosdrecht *et al.*, 2016). Several indices are recommended for technical analysis to ensure adequate assessment, including minimising sludge production and their associated total suspended solids, effective removal of total phosphorus (TP) and total nitrogen (TN), chemical oxygen demand (COD), and heavy metals removal (Wang *et al.*, 2017; Zhou *et al.*, 2022; Cosenza *et al.*, 2024b). Here, heavy metal removal is excluded due to high measurement costs and the frequent lack of required data, which can pose challenges for a rapid assessment framework (Smith and Brown, 2020).

The LCA process is a combination of scope, life cycle inventory, impact assessment, and interpretation of the results (Sabet *et al., 2023*). ECLA is followed here based on recommendations of ISO 14040 (2006) and implemented by SimaPro software V9.0.0. Various concepts, as shown in Figure S1 in the Supplementary information, are included here and a total of 22 indices are quantified. For rapid assessment and providing a minimal MCDM model, these indices are combined tighter in the form of three core indices i.e. ecosystems, human health, and resources. For this purpose, the ReCipe endpoint impact assessment methodology was used based on the recommendations of Pintilie *et al.* (2016) and Karolinczak *et al.* (2024).

LCC determined encompasses four main concepts: (1) material sourcing, (2) direct capital costs, (3) direct operational costs, and (4) end-of-life costs (Liu *et al.,* 2022). Material sourcing including raw material extraction, manufacturing assembly/production, and transportation/distribution are applied for chemical and energy consumption as a source of inputs system (Mohamed *et al.*, 2023). Direct capital costs include expenses related to a plant's infrastructure, such as buildings, machinery, and auxiliary components. However, they are not considered here because they are mostly the same for all alternatives and do not make significant differences in a rapid assessment (Karolinczak *et al.*, 2024). Instead, the focus is on direct operating costs, which accumulate over the plant's lifetime and potentially surpass the initial capital expenditure (Rahman *et al.*, 2023). Here, routine, preventive, and corrective maintenance costs and costs of energy, fuel, and chemical consumption are considered. Furthermore, labour costs are excluded as they do not present a meaningful difference between alternatives.

Finally, eight additional qualified indices crucial for deciding on the full scaling of lab technologies are included here to ensure the rapid assessment covers all vital aspects. These indices are inspired by sustainability assessment frameworks used in water and wastewater treatment processes. Five of these indices focus on the reliability and resilience of the processes to shocks and unforeseen conditions that may be controlled in labs but are inevitable during operations. The first index is the resilience to wastewater quality shocks, which involves the system's ability to handle fluctuations in wastewater quality, such as over or underloading of COD, TP, and TN, due to legal or illegal discharges of surface runoff or municipal, industrial or agricultural wastewater into the collection system (Albtoosh *et al.,* 2024; Zhou *et al.,* 2024). The second index is the shock of wastewater quantity, which is similar to the first but addresses instances when similar sources of wastewater are discharged without notice. This situation that may arise especially after several years when area development causes sudden connections of some wastewater collection networks to the input system (Jato *et al.,* 2022). The third index is the required level and time of direct monitoring and maintenance, representing the system's capability to be automated or self-healing, thereby minimising the need for human monitoring or direct intervention (Piadeh *et al*., 2018b). The fourth index is the fouling tendency, which assesses the system's susceptibility to fouling, affecting its long-term operational stability and efficiency (Piadeh *et al.,* 2018a). Finally, the fifth index is system complexity. Simpler systems with fewer physical, mechanical, and operational complexities are generally more reliable and user-friendly, reducing the risk of system failure at full scale. While it is understandable that some of these indices can be tested and quantified, it is important to note that such tests may not always be feasible due to time and cost constraints (Naghedi *et al.,* 2020).

Furthermore, three social/policy indices are added to include crucial aspects of engagement and acceptance of the new technologies. The first index is the impact of sanctions and restrictions on the sustainable operation of the process (Piadeh *et al.,* 2018b). This can be viewed as part of localisation and includes challenges and barriers beyond the operators' control. For example, in the wastewater industry, procuring ultrafiltration UF filters can be complicated for some countries due to their applications in other industries, such as nuclear energy (Naghedi *et al.,* 2020). Another hot-topic example is the conflict between the US and China over policies related to producing materials for electric vehicle batteries, which results in delays in production or significant cost increases (Naumanen *et al.*, 2019). This index provides general but crucial insights into the potential challenges of scaling new lab processes. The third index is stakeholder collaboration, which reflects the willingness of various stakeholders to support or accept new technologies in treatment plants. Positive collaboration is vital, significantly when non-technical staff, neighbourhood residents, or stakeholders in the financial ecosystem of old technologies might negatively impact the sustainable development of new technologies (Zhou *et al.*, 2024).

3.3. Step 3. Multi-criteria decision making

Table 1 summarised the selected criteria and indices, their data collection or calculation method used for MCDM model. Selected indices have different relative weights, importance, and units, making them difficult to aggregate. Therefore, among the various suggested approaches such as risk management and normalisation/standardisation, MCDM modelling is used based on the recommendations of Torkayesh *et al.* (2022) and Das *et al.* (2024a). For this purpose, the modified analytic hierarchy process method, recommended by Piadeh *et al.* (2018b), is selected for rapid assessments. This method is chosen primarily because of its user-friendly structure, its ability to handle diverse and non-homogeneous indices, its ease in conducting sensitivity analysis, and its adaptability for scenario-based analysis. Instead of traditional scenario development, where a fixed number of scenarios are defined, this approach introduces a novel method. This new technique effectively addresses the limitations of predefined scenarios, such as their lack of flexibility and the difficulty in accommodating unexpected changes or new information over time. As a result, scenarios can quickly become outdated (Das *et al.*, 2024b), but this novel method enhances adaptability and relevance. planning (Hersi et al., 2023). On the other hand, when too many scenarios are predefined, stakeholders may become overwhelmed and less engaged, reducing the effectiveness of scenario planning efforts (Rogy *et al.*, 2022).

Table 1. List of selected sustainability indices and their specifications

Criteria/Index	Code	Nature	Calculation method	Unit	Applied data resource/collection method
Technical	C1				
TP removal	I1	Quantitative	Analytical determination based on experimental data[1]	%	Oliveira *et al*. (2018)
TN removal	I2	Quantitative	Analytical determination based on experimental data[1]	%	Oliveira *et al*. (2018)
COD removal	I3	Quantitative	Analytical determination based on experimental data[1]	%	Oliveira *et al*. (2018)
Sludge production	I4	Quantitative	Analytical determination based on experimental data[1]	Kg TSS/Kg COD removal	Oliveira *et al*. (2018)
Reliability	C2				
Shock of wastewater quality	I5	Qualitative	Quantification of experts' opinion[2]	Unitless	Albtoosh *et al*. (2024); Zhou *et al*. (2024)
Shock of wastewater quantity	I6	Qualitative	Quantification of experts' opinion[2]	Unitless	Jato *et al*. (2022)
O&M requirement	I7	Qualitative	Quantification of experts' opinion[2]	Unitless	Piadeh *et al*. (2018b)
Total resistance	I8	Qualitative	Quantification of experts' opinion[2]	Unitless	Piadeh *et al*. (2018a)
Complexity	I9	Qualitative	Quantification of experts' opinion[2]	Unitless	(Naghedi *et al*., (2020
LCC	C3				
Infrastructure replacement costs	I10	Quantitative	Analytical determination based on experimental data[1]	$/lifespan	Bhmem (2023)
Chemicals	I11	Quantitative	Analytical determination based on experimental data[1]	$/g	Made-in-China (2023)
Electricity	I12	Quantitative	Analytical determination based on experimental data[1]	$/Wh	Climate Change (2022)
Sludge and chemical transportation	I13	Quantitative	Analytical determination based on experimental data[1]	$/Kg.Km	Turkmenler and Aslan (2017)
ELCA	C4				
Human health	I14	Quantitative		10^6 DALY	Ecoinvent v3.5 database
Resources	I15	Quantitative	Outputs of LCA software[3]	10^6 Species.Y	Ecoinvent v3.5 database
Ecosystem	I16	Quantitative	Outputs of LCA software[3]	10^3 US$ 2013	Ecoinvent v3.5 database
Odor pollution	I17	Quantitative	Outputs of LCA software[3]	Unitless	Ecoinvent v3.5 database
Socio-Policy	C5				
Sanctions/Restrictions	I18	Qualitative	Quantification of experts' opinion[2]	Unitless	Piadeh *et al*., (2018b)
Industrial use acceptance	I19	Qualitative	Quantification of experts' opinion[2]	Unitless	Naumanen *et al*., (2019)
Stakeholder collaboration	I20	Qualitative	Quantification of experts' opinion[2]	Unitless	Zhou *et al*., (2024)

1: Experimental data obtained from relevant literature and determined locally for $1m^3$ treated wastewater of the selected alternative

2: 5-level qualitative method is applied for data collection. Data is turned into the quantified data through neutrosophic logic method.

3: Inputting data inventories into the SimaPro software employing ReCipe endpoint impact assessment for $1m^3$ treated wastewater

These changes can be reflected in the relative importance of each index. Additionally, predefined scenarios often reflect the biases and perspectives of their creators, hereafter referred to as experts, leading to a narrow view that can overlook alternative possibilities or emerging trends (Qin *et al.*, 2024). This narrow perspective might not cover the full spectrum of possible futures, especially extreme or highly uncertain outcomes, resulting in gaps in preparedness and strategic

To address these issues, as shown schematically in Figure 1b, the role of experts is limited to determine the boundaries of possible future visions, while all possible future scenarios are generated and analysed by codding provided by MATLAB 2024a (See Figure 1c). For this purpose, two extreme scenarios - worst and ideal conditions - are defined in which different roles of direct stakeholders and possible future conditions are drawn to illustrate how these indices can either promote or prevent the scaling of laboratory-scale systems to full scale (Definitions are provided in Table S1 in the Supplementary information). To analyse the ideal and worst-case scenarios, PESTEL, 7S McKinsey, and SWOT analyses are conducted based on the methods recommended by Naghedi *et al.* (2020).

Expert opinions are used to quantify this data, assign relative weights to criteria, and evaluate the scores of qualified data for different options. Ensuring a sufficient number of credible experts involves several vital steps that blend quantitative and qualitative approaches. First, experts are identified and selected by clearly defining the expertise pre-requirements and creating a diverse pool that encompasses various geographic regions, demographics, and professional backgrounds. This diversity helps to avoid biases and provides multiple perspectives, including those from different relevant sectors (Piadeh *et al.*, 2022). Next, credentials are verified by evaluating the experts' credibility and domain knowledge through peer reviews and endorsements to confirm their expertise (Naghedi *et al.*, 2020). Finally, ensuring an adequate number of experts requires conducting a saturation analysis to determine the necessary number of participants and considering margins of error to ensure the robustness of the expert panel (Rhakho *et al.*, 2024).

During the consultation process, disagreements among experts were resolved through a structured consensus-building approach, such as facilitated workshops and iterative feedback sessions. This ensured that diverse perspectives were integrated without bias, fostering balanced and informed outcomes.

To develop the scenarios, the code begins by initialising sets of weights, with each weight starting at its minimum value. Using an iterative loop, one criterion is adjusted at a time by defined intervals. These intervals are determined based on the scoring systems used, such as the Saaty metric system (e.g., a scale of 1 to 10) or the US metric system (e.g., a scale of 1 to 4), where experts provide their ratings. Each offset generates a new combination of criteria, representing a potential future scenario. All generated scenarios are then reviewed to eliminate duplicate or highly similar weight combinations, ensuring no scenario is assessed more than once, thereby avoiding bias. The final set of unique scenarios is integrated into the MCDM model. In this model, the scores for each index, the performance of each alternative against each index, and the relationships between alternatives, indices, and criteria are predefined. By integrating these elements, the total score for each alternative is calculated for every scenario. Two performance metrics are then measured. The first is the superiority of each alternative in a given scenario (its presence as the best option), and the second is the score of the superior alternative in that scenario. These values are stored in a data library for final analysis, where the best alternatives are determined based on the highest average score and the most frequent occurrences as the superior option across all developed scenarios.

3.4. Step 4: Sensitivity analysis

Sensitivity analysis plays a crucial role in MCDM as it assesses the robustness of decision outcomes in the face of variations in input parameters or criteria weights (Munier, 2024). This study considers five types of sensitivity analysis: (1) uncertainty analysis of quantified data. This analysis, especially for LCA, investigates potential uncertainties and variations in decision outcomes. This is crucial for understanding how data uncertainties can impact the final decision. (2) impact of core scenarios: This involves scenarios where one criterion is given the highest weight compared to others. This analysis is essential because it helps identify the influence of dominant criteria on the decision-making process (Piadeh *et al.*, 2018); (3) extreme scenarios: In these scenarios, one criterion is assigned at least half of the total weight. This is important because it helps to understand the effects of extreme prioritisation of a single criterion on the decision outcomes. It provides insight into the robustness of the decision when one factor overwhelmingly influences the result (Naghedi *et al.*, 2020); (4) weight of indices: This analysis focuses on the impact of variations in the weights of different indices. It is significant because weighting impacts denote the relative importance assigned to various indices in decision-making processes, reflecting their influence on the desired outcomes (Smith and Brown, 2020); (5) weight of stakeholders: This analysis examines how the influence of expert judgment or knowledge can alter the outcomes of the analysis. This is measured by adjusting the experts' weights based on their educational level, service time, and role (Kadlec and Knight, 2020).

3.5. Step 5: Comparison with well-explored methods

To illustrate the differences between the proposed framework and conventional approaches, the identified criteria were re-applied to the case study using widely recognised expert-based scenario analysis methods. These methods were selected through a systematic search of terms such as "sustainability assessment," "MCDM," and "sludge" in the Scopus database. The search results were then reviewed to identify the most suitable methods for expert-based scenario analysis.

Four methods were selected for the study (More details listed in Table S2 in the Supplementary information): (1) expert-driven: This method defines only one scenario, where a set of weights is assigned to each criterion based on expert knowledge, providing a single viewpoint (Eliyan *et al.*, 2023). The scenario reflects the subjective judgment of experts who use their domain-specific knowledge to prioritise the criteria (Agarwal and Singh, 2022); (2) process-driven: Multiple scenarios are created based on the different alternative flow processes introduced. Each scenario represents a unique process flow, and the scenarios are customised according to the shared conditions that apply to all alternatives (Zhou *et al.*, 2020). This approach emphasises the operational and functional aspects of the alternatives, considering variations in process design, performance, and outcomes under different operating conditions, making it ideal for comparative analysis of technological pathways (Yange *et al.*, 2015); (3) condition driven: This method narrows the focus by considering a specific set of conditions, such as predefined economic, environmental, and technical factors (Naghedi *et al.*, 2020). It operates within tightly controlled parameters, assessing the alternatives' performance under specific boundary conditions. This approach is particularly useful when stakeholders or policymakers are concerned with a limited set of critical factors, enabling the evaluation of the alternatives under targeted, real-world conditions that reflect practical constraints (Piadeh *et al.*, 2018b); (4) Quantification driven: In this approach, a single scenario is defined based on the quantification of weights for each index. This method involves a rigorous statistical or mathematical evaluation of the relative importance of each criterion, providing an objective and data-driven basis for the decision-making process (Twagirayezu *et al.*, 2024).

4. Results and Discussion

4.1. Case study description

This study follows the experimental condition of introduced SRR systems proposed by Oliveira *et al.* (2018), which are listed in Table S3 in the Supplementary information. The system description contains an MBR reactor that was fed synthetic wastewater at a flow rate of 2.3 L/h for the duration of the experiment. The sludge retention time was not controlled. In other words, no dedicated wasting operations of sludge were carried out, except for the samples withdrawn to perform chemical-physical analyses. The functional unit for this research was determined to be one cubic meter of wastewater.

Although these alternatives are universally applicable, they are illustrated with a real case study from one wastewater treatment plant located in Tehran. Therefore, the planned dump site was expected to be located 30 km from the facility, and small vehicles (weighing less than 10 tons) were considered for transporting sludge and chemical components. Table S4 provides a thorough inventory of the LCC and ELCA data. Table S5 in the Supplementary information contains the raw data. Inspired by the recommendations of Naghedi et al. (2020), the expert weights are normalised based on three factors: academic knowledge, job title, and service years. This scoring process employs neutrosophic logic and relative benchmarking techniques, as outlined by Piadeh *et al.* (2018b) and Fan *et al.* (2024). The characteristics of the selected experts and their relative weights are detailed in Table 2.

Table 2. Weighting factors and constitution of different experts*

Constitution / Classification	Responsible role	Responders (No)	Criteria weight in aspect				
			C1	C2	C3	C4	C5
1.Job position:							
• Government:	Sludge management and potential source of funding						
- Ministry of power		3	1	1	2	3	3
- Water company manager		4	2	2	3	1	1
- WWTPs' staff		4	3	3	1	1	1
• Consultant	Design and future upgrading						
- Manager		2	2	2	2	2	2
- Designer		4	3	3	3	2	1
• Contractor	Operation and maintenance						
- Manager		2	2	2	1	1	1
- Temporary operator		4	3	3	1	1	1
• University boards:	Pilot scaling and R&D						
- Assistant professor		2	1	1	1	2	1
- Associated professor		2	2	2	2	2	2
- Professor		2	2	2	3	2	3
• End-Users/others	Potential direct or indirect affecting						
- Farmers		5	2	1	1	2	3
- Neighborhood residents representees		3	3	1	2	1	3
- Neighborhood Borad of trustees of industries		3	2	1	2	2	3
Sum		40					
2.Educational level:	Theorical knowledge of domain						
- Diploma or lower		9			1		
- BSc		12			1.5		
- MSc		11			2		
- PhD		8			2.5		
Sum		40					
3.Professional experience:	Practical knowledge of domain						
<10 years		13			1		
≥10 years		27			2		
Sum		40					

C1: Technical C2: Reliability C3: LCA C4: LCC C5: Socio-policy

* For example, weighting score of a professor with over 10-year experience for technical criteria is determined according to 2+2.5+2=6.5

4.2. Index analysis

Figure 2 presents the data and relative normalised scores of each alternative across the evaluated indices. Out of the twenty indices, A3, A2, and A1 outperform in 7, 9, and 4 indices, respectively. The operation and maintenance requirements and complexity are identical for A2 and A3, while the indices related to COD removal and sanctions have equal impacts across all alternatives. Among the indices, four – O&M requirements (Figure 2g), human health (Figure 2n), resources (Figure 2o), and odour pollution (Figure 2q) - are particularly critical as they are the only ones where A1 outperforms the other alternatives. While the two new alternatives include additional systems such as tanks, leading to a reasonable increase in O&M costs, reducing these costs is critical for industrial scaling. Lowering O&M expenses is essential because it directly influences the interest and willingness of investors and operators to adopt and implement these alternatives on a larger scale. The other three indices, however, are all from the environmental perspective and highlight significant shortcomings of the newer processes compared to A1. This suggests that improvements in these areas could present challenges, especially when considering industrial-scale implementation.

To delve deeper, the ELCA analysis indicates that the root of these deficiencies can be traced back to the meta parameters of LCA analysis (see MP1 to MP4 in Figure 3), specifically concerning the global warming potential's impact on health, terrestrial ecosystems, and freshwater resources. The global warming impact is influenced by three main factors, as identified by the Recipe approach: (1) direct emissions from the biological treatment process, (2) power-related indirect emissions, and (3) chemical consumption-associated indirect emissions. The lowest direct greenhouse gas emissions were observed in scenario A1, attributed to reduced COD and nutrient removal due to the absence of SSR, leading to lower emissions of CH_4 and CO_2. Notably, methane emissions from the plant's anaerobic section were the primary contributors to exacerbating global warming. These findings align with a previous study by Hernández-Padilla *et al.* (2017), highlighting methane's significant role in climate change. However, in other Midpoint categories (MP5 to MP22), scenario A1 showed the highest impact related to indirect emissions due to increased electricity and chemical consumption in both the water and sludge lines.

To further investigate this source, an uncertainty analysis has been conducted for the ELCA to evaluate the reliability and completeness of the data. A semi-quantitative method was employed using the pedigree matrix approach from Ecoinvent to assess uncertainty across all flows. This evaluation considers five indicators: reliability, completeness, and temporal, geographical, and technological correlations with the target system (Yoshida *et al.*, 2014). The Ecoinvent database assumes a lognormal distribution for all uncertain values, with particular emphasis on the inventory data for chemicals and electricity, as discussed in this study and presented in Tables S5-S8.

A1	A2	A3	
75.00	1.07	1.20	A1
	80.00	1.13	A2
		90.00	A3

(a)

A1	A2	A3	
57.00	1.11	1.35	A1
	63.00	1.22	A2
		77.00	A3

(b)

A1	A2	A3	
98.00	1.00	1.00	A1
	98.00	1.00	A2
		98.00	A3

(c)

A1	A2	A3	
0.42	0.23	0.65	A1
	0.10	2.76	A2
		0.27	A3

(d)

A1	A2	A3	
11.00	1.09	0.91	A1
	12.00	0.83	A2
		10.00	A3

(e)

A1	A2	A3	
9.00	1.11	0.89	A1
	10.00	0.80	A2
		8.00	A3

(f)

A1	A2	A3	
12.00	1.17	1.17	A1
	14.00	1.00	A2
		14.00	A3

(g)

A1	A2	A3	
16.00	0.88	1.13	A1
	14.00	1.29	A2
		18.00	A3

(h)

A1	A2	A3	
10.00	1.40	1.40	A1
	14.00	1.00	A2
		14.00	A3

(i)

A1	A2	A3	
10.00	1.40	1.40	A1
	14.00	1.00	A2
		14.00	A3

(j)

A1	A2	A3	
179.00	0.74	0.89	A1
	133.00	1.20	A2
		159.00	A3

(k)

A1	A2	A3	
189.00	0.83	0.50	A1
	156.00	0.61	A2
		95.00	A3

(l)

A1	A2	A3	
2.10	0.24	0.67	A1
	0.50	2.80	A2
		1.40	A3

(m)

A1	A2	A3	
2.74	1.35	1.01	A1
	3.70	0.75	A2
		2.78	A3

(n)

A1	A2	A3	
6.88	1.44	1.11	A1
	9.94	0.77	A2
		7.65	A3

(o)

A1	A2	A3	
28.00	0.80	0.53	A1
	22.40	0.67	A2
		14.90	A3

(p)

A1	A2	A3	
9.00	0.78	0.78	A1
	7.00	1.00	A2
		7.00	A3

(q)

A1	A2	A3	
15.00	1.00	1.00	A1
	15.00	1.00	A2
		15.00	A3

(r)

A1	A2	A3	
14.00	1.29	1.14	A1
	18.00	0.89	A2
		16.00	A3

(s)

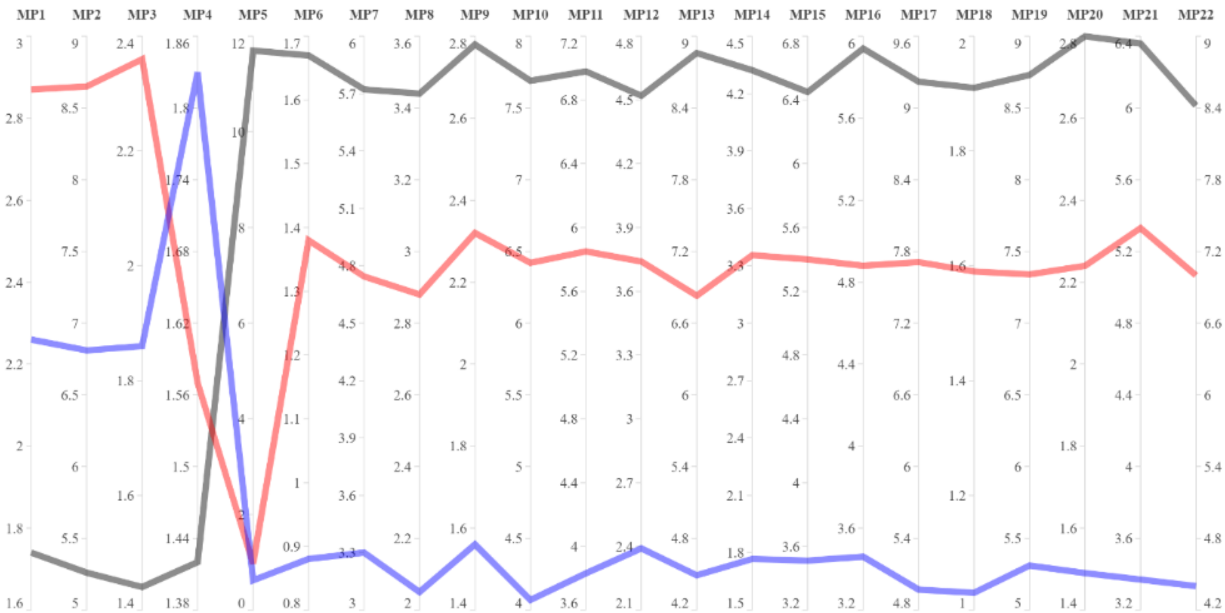
A1	A2	A3	
14.00	1.14	1.29	A1
	16.00	1.13	A2
		18.00	A3

(t)

Quantified value	Enhancement	Deficiency	No dieference

Figure 2. Relative scores of each alternative in each index: (a)TP removal (I1,%), (b) TN removal (I2,%), (c) COD removal (I3, %), (d) Sludge production (I4, Kg TSS/Kg COD removal), (e) Shock of wastewater quality (I5), (f) Shock of wastewater quantity (I6), (g) Operation and maintenance requirement (I7), (h) fouling tendency (total residence) (I8), (i) Complexity (I9), (j) Infrastructure replacement costs (I10,$/lifespan), (k) Chemicals (I11,$/g), (l) Electricity (I12,$/Wh), (m) Sludge and chemical transportation (I13,$/Kg.Km), (n) Human health (I14,10^6 DALY), (o) Resources (I15,10^6 Species.Y), (p) Ecosystem (I16,10^3 US$ 2013), (q) Odour pollution (I16), (r) Sanctions/Restrictions (I17), (s) Industrial use acceptance (I18), (t) Stakeholder collaboration (I19)

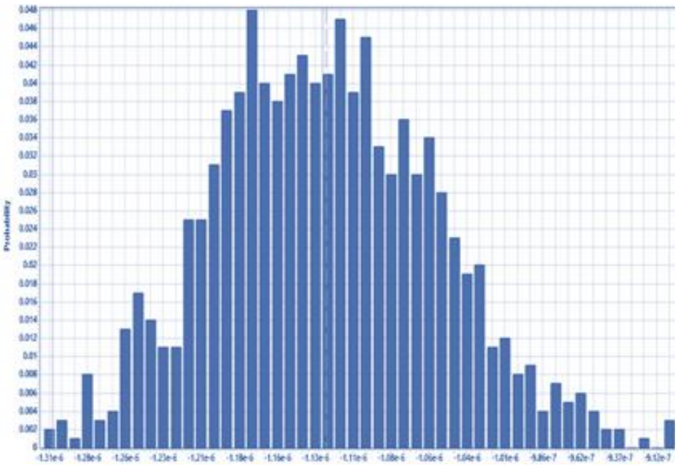
Here, the uncertainty analysis specifically focuses on the data related to chemicals and electricity, given their significant contribution to the life cycle impact categories and their calculation being performed within this study. See More details of setting up weights in Tables S6-9 in the Supplementary information. The results indicate, as shown in Figure 4a, marine eutrophication has a slight standard deviation and minimal variance. In contrast, the scarcity of fossil resources shows the most extraordinary dispersion, followed closely by global warming. The reduced reliability of results in the global warming category is primarily due to uncertainties related to data completeness and geographic correlation, as highlighted by the LCA analysis's meta-parameters (see MP1 to MP4 in Figure 4b-d). Hence, it seems that the following steps should be carefully considered for the transition from lab to industrial scale: (1) data must be verified through direct measurements; (2) all relevant market sites must provide data over a sufficient period to account for normal fluctuations; and (3) the data must originate from the specific area of study.

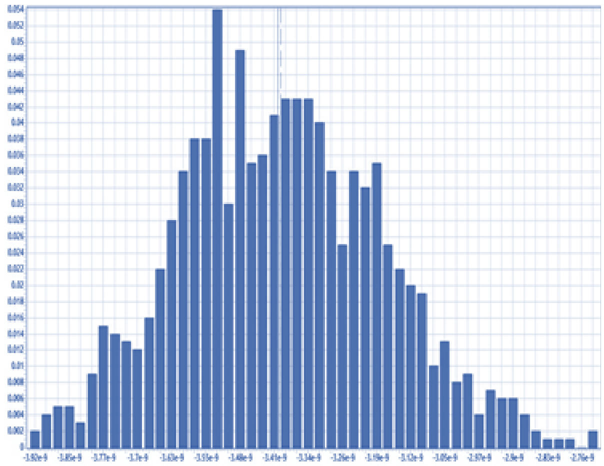


A1 A2 A3

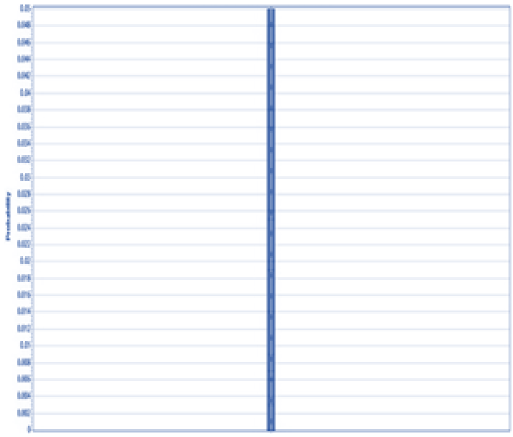
MP1: Global warming impact on health (10^6 DALY)
MP2: Global warming impact on terrestrial (10^9 Species.yr)
MP3: Global warming impact on freshwater (10^{13} Species.yr)
MP4: Stratospheric ozone depletion (10^9 DALY)
MP5: Ozone formation impact on health (10^9 DALY)
MP6: Ozone formation impact on terrestrial (10^{10} Species.yr)
MP7: Water consumption impact on human health (10^9 DALY)
MP8: Water consumption impact on Terrestrial (10^{11} Species.yr)
MP9: Water consumption impact on aquatic (10^{15} Species.yr)
MP10: Human carcinogenic toxicity (10^8 DALY)
MP11: Human non-carcinogenic toxicity (10^8 DALY)
MP12: Terrestrial acidification (10^{10} Species.yr)
MP13: Freshwater eutrophication (10^{10} Species.yr)
MP14: Marine eutrophication (10^{12} Species.yr)
MP15: Land use (10^{11} Species.yr)
MP16: Terrestrial ecotoxicity (10^{12} Species.yr)
MP17: Freshwater ecotoxicity (10^{12} Species.yr)
MP18: Marine ecotoxicity (10^{12} Species.yr)
MP19: Mineral resource scarcity (10^5 US\$2013)
MP20: Fossil resource scarcity (10^2 US\$2013)
MP21: Ionising radiation (10^{10} DALY)
MP22s: Fine particulate matter formation (10^7 DALY)

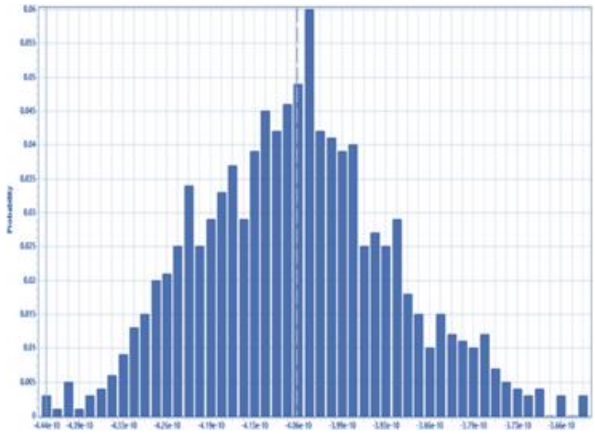
Figure 3. Meta-parameters (MPs) of RECIPE LCA Midpoint's analysis





(a) (b)





(c) (d)

Figure 4. Uncertainty analysis of (a) A1 VS A2 for Global warming impact on human health (MP1), (b) A1 VS A2 for Global warming impact on terrestrial (MP2), (c) A1 VS A2 for Global warming impact on freshwater (MP3), and (d) A1 VS A3 for Stratospheric ozone depletion (MP4)

4.3. Criteria analysis

Table 3 presents the scores of each alternative across various criteria. Both A2 and A3 demonstrate similar performance in ELCA and socio-political criteria. However, A2 and A3 show opposing results in the technical aspect, with A3 achieving the highest score for TN removal and the lowest for sludge production, at the same time, A2 performs inversely, with the best score for sludge production and the worst for TN removal. This contrast highlights the differing technical strengths and limitations of each alternative and how these factors influence their overall scores. The results indicate that A2 outperformed in the sludge reduction category based on technical criteria, while A3 excelled in nutrient removal. A3's superior nutrient removal performance is attributed to the strategic placement of the SRR within the wastewater treatment plant's waterline. Therefore, to fully scale these alternatives, it is crucial to address the deficiencies in A2's nutrient removal and A3's sludge reduction. The absence of SRR in the first option contributed to its better complexity score. However, A2's ASSR presents the highest potential for fouling, whereas A3's AMSR demonstrates improvements in fouling resistance and overall performance. Also, A2 and A3 are vulnerable to fluctuations in influent wastewater quantity. Transportation and chemical costs are significant components of the wastewater treatment plant's LCC. Due to its minimal sludge production, A2 achieved the highest LCC score, resulting in significantly lower chemical and transportation expenses. A3 followed, offering moderate sludge reduction and cost efficiency.

Alternatives A1 and A3 achieved the highest ELCA scores. The direct and indirect emissions from these plants significantly impact human health, making A1 the more environmentally friendly option due to its lower odour production and reduced direct emissions, primarily because it lacks the SRR setup. In contrast, the third scenario (A3) uses less electricity and chemicals, leading to lower indirect emissions, and it can remove the highest percentage of nutrients thanks to the AMSR design, which benefits the ecosystem and human health. However, the second alternative (A2) produced the highest direct emissions, primarily due to methane emissions from the ASSR configuration, resulting in the lowest LCA score. Additionally, sanctions and limitations, along with the acceptance of industrial use for both A2 and A3, are crucial socio-political factors influencing the decision-making process, particularly regarding industrial scaling, especially in developing regions like the Middle East.

Table 3. The weighted score of alternatives in each criterion and index*

Criterion/Index	Alternatives		
	A1	A2	A3
Technical (C1)	0.066	0.104	0.081
TP removal (I1)	0.069	0.073	0.082
TN removal (I2)	0.065	0.072	0.088
COD removal (I3)	0.086	0.086	0.086
Sludge production (I4)	0.043	0.184	0.066
Reliability (C2)	0.072	0.064	0.064
Shock of wastewater quality (I5)	0.054	0.059	0.049
Shock of wastewater quantity (I6)	0.043	0.048	0.038
O&M requirement (I7)	0.071	0.061	0.061
Total resistance (I8)	0.081	0.071	0.091
Complexity (I9)	0.113	0.081	0.081
LCC (C3)	0.057	0.114	0.078
Infrastructure replacement costs (I10)	0.039	0.039	0.039
Chemicals (I11)	0.087	0.117	0.098
Electricity (I12)	0.044	0.054	0.088
Sludge and chemical transportation (I13)	0.059	0.248	0.089
ELCA (C4)	0.087	0.071	0.092
Human health (I14)	0.120	0.089	0.118
Resources (I15)	0.105	0.073	0.095
Ecosystem (I16)	0.053	0.066	0.099
Odor pollution (I17)	0.071	0.055	0.055
Socio-Policy (C5)	0.082	0.090	0.089
Sanctions/Restrictions (I18)	0.133	0.133	0.133
Industrial use acceptance (I19)	0.064	0.082	0.073
Stakeholder collaboration (20)	0.048	0.055	0.061

*: The value of indices is independent on scenarios and is determined by the average of the quantified score of each alternative in each index times the weight of each index. The value of criteria is also independent on scenarios and is determined by the average of all indices in each criterion.

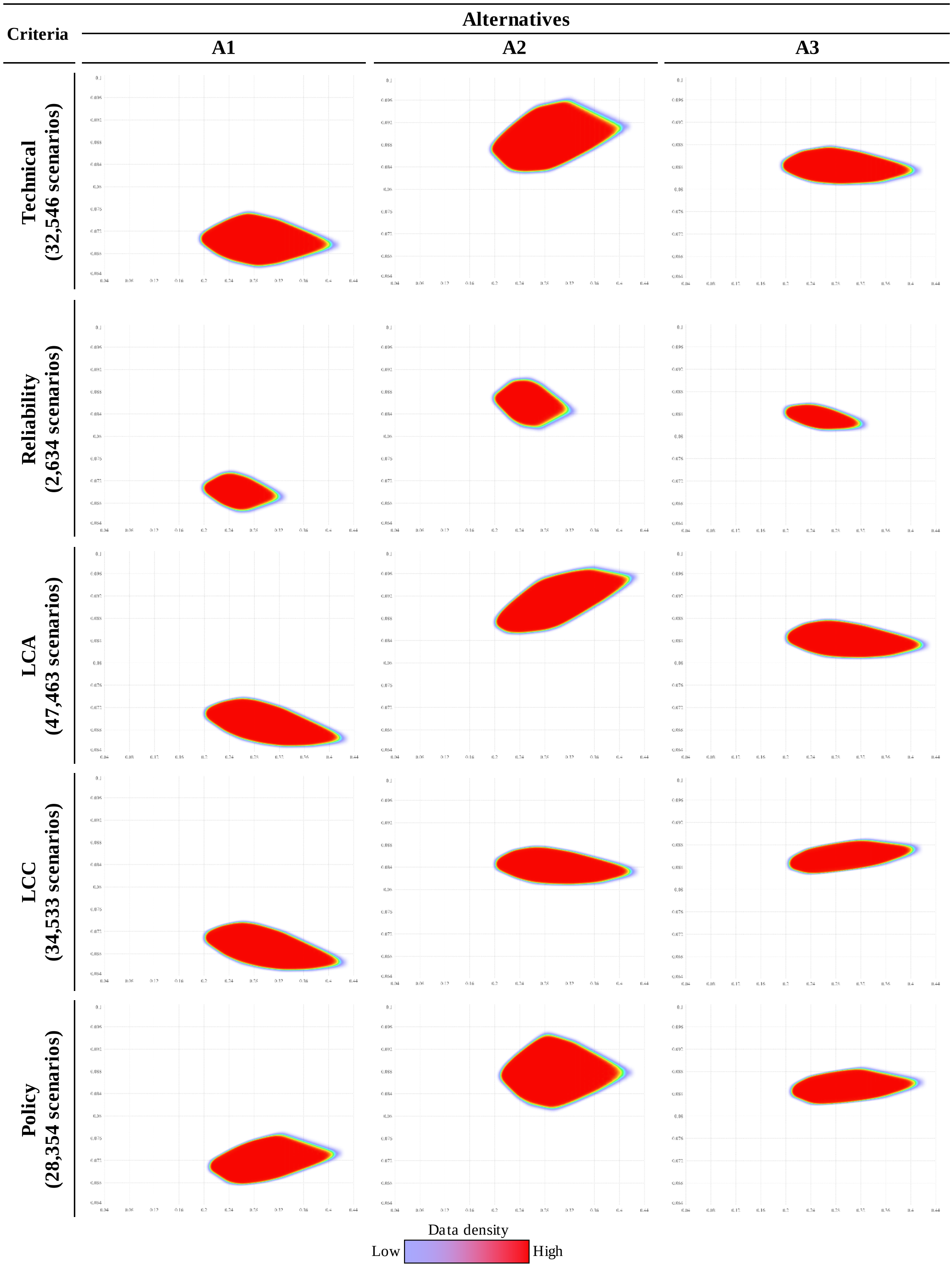
4.4. Optimal answer

The optimal solution was determined by evaluating the rank and score of each alternative across 145,530 scenarios. The results indicate that the second alternative, with a score of 0.088, was superior in nearly 86% of the scenarios, followed by the third alternative, which achieved a score of 0.085 and was superior in 13.82%. These findings demonstrate that both newly introduced alternatives outperformed the baseline. Although A2 proved superior in over 80% of the scenarios, a more in-depth discussion of its strengths and weaknesses is necessary to understand its potential and limitations fully.

In this case study, no extreme scenarios were identified. This suggests that stakeholders did not anticipate any single criterion to overwhelmingly surpass the others, indicating that all criteria were considered necessary and played a balanced role in the decision-making process. The performance of alternatives in core scenarios is illustrated in Figure 5. The number of scenarios in each class reflects the range of flexibility and uncertainty for the future (see Figure S2 in the Supplementary information).

As shown, core scenarios for LCA account for approximately 32% of the total scenarios (47,463 out of 145,630 scenarios). In contrast, only 1.8% of the total scenarios pertain to policy criteria, indicating that stakeholders foresee a more fixed and stable future for this aspect. This finding confirms that greater emphasis should be placed on the ELCA aspect for full scaling, aligning with previous analyses of index performance. Furthermore, the distribution of total scores for each alternative in core scenarios indicates that system reliability exhibits minimal variation across scenarios (as evidenced by the smaller area for all alternatives compared to other criteria). This suggests that system reliability is unlikely to change significantly in the future. In contrast, the distribution patterns for A2, particularly in technical and policy scenarios, indicate that this alternative may be sensitive to these two aspects.

The weights assigned to the criteria by experts are crucial in ranking the alternatives, and even a minor adjustment can significantly impact the results. In this study, the outcomes of the selected alternatives were evaluated based on varying criterion weights, as illustrated in Figure 5 (See more details in Figure S3 in the Supplementary information). For this analysis, the weight of the previously defined criterion was adjusted between 0 and 1, while the weights of the other criteria remained constant. Although A2 is presented as the best alternative, it cannot be considered the sole solution based on these results. For instance, the best alternative changes in indexes 1, 2, 3, 4, 10, 12, 13, 16, and 20 (refer to Table 1 for titles). Notably, electricity (index 12) is one of the indexes that most significantly influence the change in the best alternative. Therefore, to establish A2 as the optimal choice, it is essential to maintain the weights of electricity, TP, and TN removal within the ranges of 0-0.3, 0-0.6, and 0-0.5, respectively, for future planning and industrial scaling. Furthermore, as shown in Figure 6, the weights of indexes 4 and 13 must not be reduced. If managers or decision-makers at the wastewater treatment facility overlook the significance of sludge generation and transportation, the best alternative could change.



X and Y axis represent the total score of alternative and criteria weight, respectively.

Figure 5. Score density of each alternative for core scenarios, (in which each criterion has the larger weight in comparison to other criteria)

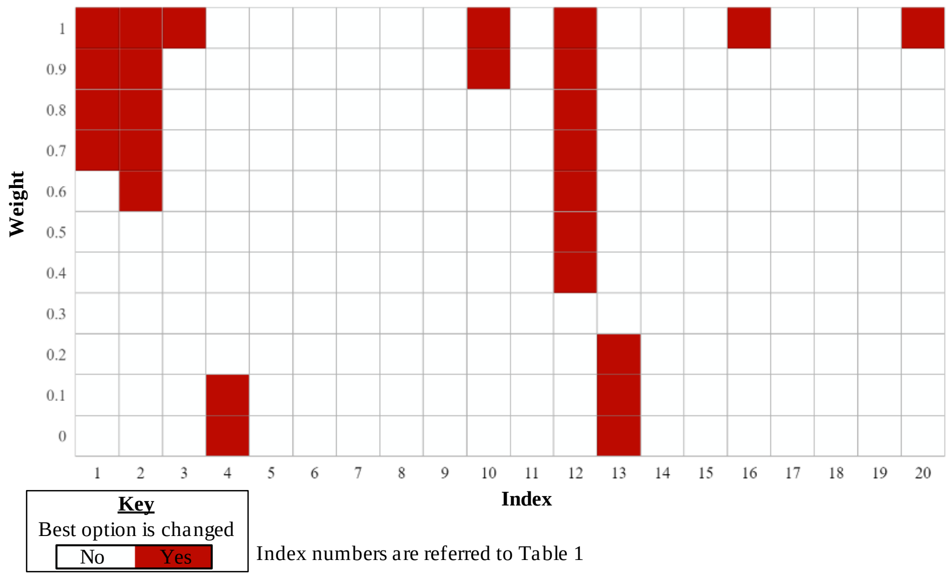


Figure 6: Sensitivity analysis on the role of indices weights in changing the best option

Finally, to investigate the role of experts and the impact of their differences in job position, educational level, and professional experience, proposed model and framework is applied within a systematic sensitivity analysis. This analysis allows to evaluate how variations in expert attributes influenced the outcomes and decision-making process, providing deeper insights into the robustness and adaptability of the framework. Table 4 presents the results of a sensitivity analysis examining how the influence of expert weight affects the optimal answer. The analysis reveals that among various factors such as education, job title, and service time, only service time significantly impacts the optimal response. This suggests that the duration of an expert's experience plays a crucial role in shaping the decision outcomes. In contrast, education and job title had minimal effects on altering the optimal response. However, it is noteworthy that while both education and job title were less influential, job title had a more pronounced impact compared to education. This implies that the specific role or position of an expert within an organisation can influence their perspective and, consequently, the evaluation outcomes more than their educational background alone. These findings underscore the importance of considering the practical experience and role of experts when assessing their influence on decision-making processes. It also highlights the need for careful consideration of these factors to ensure that the optimal solution is robust and reliable, irrespective of the variations in expert backgrounds.

Table 4. Sensitivity analysis on the role of the weight of experts on the best answer

Weighting part		Alternative		
		A1	**A2**	**A3**
Education	**Score**	0.073	0.087	0.083
	Presence (%)	0.00	80.79	19.11
Job title	**Score**	0.074	0.084	0.081
	Presence (%)	0.00	78.24	11.76
Service time	**Score**	0.068	0.078	0.079
	Presence (%)	0.00	49.87	50.13
All	**Score**	0.074	0.075	0.077
	Presence (%)	0.00	46.67	53.33

4.5. Novelty and advantages of proposed method compared to current practices

Table 5 shows the comparison between proposed method and previous well-explored expert-based scenario analysis methods. The results indicate that, among all scenario development methods, only the process-based approach produced similar outcomes to the proposed framework. This alignment is likely because the process-based approach considers the flow dynamics of different alternatives, which closely mirrors the full-scale application of current pilot studies. However, this approach may not always align with the broader adaptability of the proposed framework. In contrast, the single expert-driven approach favoured the baseline alternative as the most successful, suggesting that expert bias towards well-established practices can influence the assessment of emerging pilot alternatives. This demonstrates how an over-reliance on familiar practices can hinder the evaluation of innovative solutions, even when new criteria and indices expand the potential of advanced SRR methods. Finally, both condition-based and weight-quantification methods failed to capture the broader vision of future scenarios, identifying alternative A3 as the best option. This highlights the contrast between the proposed data-driven approach, which offers a more comprehensive and unbiased assessment of future possibilities, and conventional methods that may limit the exploration of emerging technologies.

Table 5. Comparison between scenario analysis of proposed method and conventional expert-based scenario analysis

Method	Best identified alternative		
	A1	**A2**	**A3**
Expert driven	✓		
Process driven		✓	
Condition driven			✓
Quantification driven			✓
Data driven - Proposed		✓	

However, this cannot be used as a verification method, as assessing the method's applicability would require practical operation of alternatives to determine which method demonstrates greater performance. However, this lies beyond the scope of this study, which focuses on identifying potentially effective alternatives without testing all at an industrial scale. Nonetheless, assumptions based on the development history of other processes, such as MBR alone, could serve as a potential verification approach.

The shortcomings of the LCSA Framework are data gaps and interpretation challenges. Both LCSA and LC^{3}SA (the LCSA framework that includes criticality and circularity evaluations) rely on data that may be lacking or inconsistent, especially in new systems and developing technologies (Curran *et al.*, 2020; Hackenhaar *et al.*, 2024). The IRSAF framework, which combines environmental, social, and economic factors into a single integrated model, can address these problems by overcoming traditional LCSA approaches that might favour one dimension over another. This is because integrating different impact categories can lead to misinterpretations because of data variability and modelling uncertainties (Hackenhaar *et al.*, 2024). Consistent evaluations across the sustainability spectrum are made possible by this comprehensive approach. In conclusion, the IRSAF may provide you with features that are excellent at managing future uncertainties and market changes, such as 1-Adaptability for Real-World Applications, 2-Reduced Interpretation Complexity, and Future Scenario Incorporation. This fills a gap that is commonly present in current approaches, when future scenarios are either underrepresented or subjectively imagined.

The proposed data-driven approach specifically addressed uncertainties and variability in scenarios through the following mechanisms: (1) dynamic scenario development: Instead of relying on fixed scenarios, the framework used MATLAB coding to generate huge number of unique scenarios by systematically varying input parameters and criteria weights. This ensured a comprehensive exploration of potential future conditions, capturing a wide range of uncertainties, (2) sensitivity analysis: The analysis evaluated the influence of dominant criteria by assigning them maximum weights, testing the system's robustness under extreme prioritisations as well as changes in weights for critical indices to understand how small adjustments affect outcomes, mitigating the impact of uncertainty in parameter importance; (3) uncertainty quantification in data: Data reliability, completeness, and relevance were assessed using pedigree matrix Approach, which quantifies the uncertainties in the life cycle inventory data, particularly for significant contributors like chemicals and energy usage; (4) Iterative consensus and stakeholder inputs: Expert inputs were normalised and integrated, with disagreements resolved systematically to reduce subjective biases. This approach balanced variability introduced by differing expert opinions, contributing to more consistent and reliable scenario evaluations

5. Conclusion

This study introduces the IRSAF to evaluate the scalability of pilot sludge reduction technologies, offering a comprehensive approach that spans technical, economic, reliability, environmental, and socio-political dimensions. Leveraging data-driven, scenario-based MCDM modelling, along with rigorous sensitivity and uncertainty analyses, the framework ensures robust evaluation of lab-based alternatives for industrial applications. Key findings from the comparative assessment of two lab-scale sludge reduction for MBR systems against a conventional baseline highlight following critical insights:

- The main challenges for industrial scaling of the evaluated technologies include ensuring system reliability under variable real-world conditions, minimizing operational and maintenance (O&M) costs, and reducing negative environmental impacts. The lower reliability scores of the new alternatives emphasize the need to improve their robustness against fluctuations in wastewater composition and volume before full-scale implementation. Evidence from the scenario analysis shows that technologies like ASSR-MBR, while promising, face challenges when scaling due to factors such as higher energy consumption and the intricacies of managing sludge generation and transportation in larger systems. ASSR-MBR as the top performer: The ASSR-MBR system emerged as the optimal solution in 86% of the 145,530 modelled scenarios. However, sensitivity analysis revealed that this ranking is highly dependent on the weights assigned to factors like electricity consumption and TP and TN removal. This suggests that if decision-makers undervalue key metrics such as sludge generation and transportation, the optimal choice may shift.

- Challenges with O&M costs and environmental impact: While both ASSR-MBR and AMSR-MBR systems outperformed conventional systems, they faced challenges with higher operational costs and global warming impacts, signalling the need for further innovation to enhance scalability.

- Expertise matters: The model showed greater sensitivity to experts' years of service rather than their education or job title, indicating that consulting industry veterans can significantly improve the accuracy of scaling predictions. Compared to other well-established methods, the significance of the newly proposed approach becomes evident, as only one method - the process-based approach - aligned with the research findings of this study

The insights gained from this study have practical implications for advancing the scalability of sludge reduction technologies. To successfully transition from lab-scale to full-scale applications, it is crucial to address key scalability challenges by focusing on enhancing system resilience, optimizing energy use, and reducing operational costs. Policymakers and industry practitioners should prioritise investments in pilot projects that simulate real-world operational variability, conduct LCC analyses, and explore energy-efficient measures to improve sustainability outcomes. Future research should aim to integrate data-driven methodologies to refine the weighting of indices and enhance statistical precision, thereby reducing the reliance on expert judgment. Incorporating larger and more diverse scenario datasets will enable a deeper understanding of the technologies' performance under varied conditions and improve the robustness of predictions. Additionally, ongoing challenges such as data reliability and accessibility must be addressed through collaborative industry-academic partnerships and improved data-sharing protocols. Future investigations should also explore the coupling of sludge reduction technologies with renewable energy and circular economy strategies to create synergies that maximise both sustainability and economic viability.

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