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An approach for modular environmental life cycle assessment of effluent treatment: Configuration of effluent treatment modules based on decision tree tailored to best available techniques

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ABSTRACT

An approach was developed to configure treatment scenarios for a given industrial effluent based on pollutant composition, intended end use, available technologies, as well as environmental impact assessments of the scenarios. To overcome the complexity of configuring the industrial effluent treatment chain due to the variety of contaminants and diverse available treatment technologies, a decision tree was developed based on the best available technology tailored to pollutant types. A parametric life cycle inventory was developed for the operation phase of fifteen conventional and advanced treatment technology modules to facilitate a comparative environmental impact assessment, including parametric sensitivity and uncertainty analysis. The comparative modular life cycle assessment revealed the hotspots and contributions of fifteen treatment modules to the environmental impacts of treating of $1 m^3$ effluent, with nanofiltration, reverse osmosis, and ion-exchange having the highest overall impacts, whereas cartilage, sand filtration, and UV have the lowest environmental impacts. Sensitivity analysis unveiled high sensitivity of midpoint and endpoint environmental impacts to energy, resin and chemical consumptions. This approach offers a foundational framework for further decision tree developments as a supporting tool for treatment configuration in the effluent treatment industry, as well as sustainability assessment of treatment scenarios derived from the decision trees. Modular treatment configuration integrated into a decision tree promises more flexibility in setting up fit-for-purpose treatment scenarios and conducting modular life cycle assessments for more sustainable effluent treatment.

1. Introduction

Industrial wastewater is a significant environmental concern due to the diverse pollutants and multifaceted potential impacts on the environment and public health (Mekuria et al., 2021; Singh et al., 2023). A change in point of view from focusing on industrial effluent as a challenge to a resource in the context of the circular economy may offer an opportunity rather than a threat (Soleimani et al., 2023a, 2023b). The incremental gap between water availability and demand due to the uneven distribution of water resources has extended wastewater treatment beyond the traditional paradigm of pollutant removal and effluent quality targets (treatment and disposal), towards the reuse of recycled wastewater and recovery of value-added products as a transition from a linear to a cradle-to-cradle context of circular economy (Guest et al., 2009; Corominas et al., 2020). In this context of resource recovery following the circular economy schemes of the European Union, industrial effluent would not be considered exclusively as a waste, but as a valuable resource stream (Ugrina and Milojković, 2024). Water stress, population growth, and climate change are the main drivers of this paradigm shift (Silva, 2023).

The efficient treatment of wastewater through wastewater treatment plants and reuse of treated wastewater would play an important role in the attenuation of water scarcity as well as the environmental impacts of urban and industrial wastewater. However, during their operation and the treatment process, they consume energy, chemicals, filter and membrane materials, which involves a large amount of local and global environmental impacts including greenhouse gas (GHG) emissions up to 3 % of total GHG global emissions (Bobby, 2016; Shao et al., 2021). In the area of wastewater management, there are two main treatment plant types of sewage treatment plants (STPs) for municipal sewage and

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effluent treatment plants (ETPs) for industrial effluent treatment. Industrial effluents could be highly different from sewage in terms of composition and discharge patterns (Islam et al., 2023). The presence of inhibitory substances in industrial wastewater such as heavy metals, refractory chemical oxygen demand (COD), sulphides, toxic compounds and overload of typical components, may inhibit the biological activity of microorganisms in the biological treatment process, as the common secondary treatment of sewage and urban wastewater (Tihomirova et al., 2020; Zhang et al., 2023; Degrémont, 2005). Accordingly, in case the concentrations of these substances exceed the inhibition thresholds, the yield of biological treatment would be low (Degrémont, 2005). The wastewater treatment process in STPs has fewer complex mechanisms dealing with organic waste, typically involves preliminary (removal of floating materials), primary (solid removal), secondary (bacterial decomposition) and tertiary (eliminating non-biodegradable pollutants) stages (Hung et al., 2017). On the other hand, ETPs are often tailored to the specific composition of the industrial effluent, usually containing a wide range of pollutants, including toxic chemicals, micro and nano-pollutants, heavy metals, nutrients, oils, pathogens, pharmaceuticals, etc. Industrial effluents are subjected to stricter regulatory requirements due to their potential environmental and health impacts (Babatunde et al., 2008).

The centralized conventional effluent treatment systems typically have extensive infrastructure configured based on a chain of treatment facilities to treat sequentially an effluent stream. In recent years, advances in modular technology for the integration of treatment processes, promise flexible, customizable, scalable and decentralized wastewater treatment solutions (Kumar et al., 2022). This paradigm shift of technology enhanced the modular approach as a trend in the emergence of new startups in the water treatment industry (StartUs Insights, 2024). The modular approach is more flexible to be integrated with artificial intelligence (AI) and the internet of things (IoT) to perform the decision tree for wastewater treatment by integrating the appropriate treatment processes based on the wastewater characteristics, as well as the real-time efficient monitoring, control, and maintenance (Wang et al., 2023).

The available technologies for the removal of pollutants from industrial effluents can be classified into three main categories 1) Conventional methods including coagulation/flocculation, precipitation, biodegradation, filtration (sand), adsorption (activated carbon), 2) Established recovery process including membrane separation, oxidation, electrochemical treatment, ion-exchange, and 3) Advanced (emerging) removal methods including nanofiltration, advanced adsorption and advanced oxidation (Crini and Lichtfouse, 2018).

Despite the growing complexity due to the increasing diversity of industrial effluent compositions and the multitude of available treatment techniques, there is still a critical demand for a comprehensive approach to effluent treatment configuration and environmental footprint assessment. This paper presents part of our solutions to the challenges encountered during an industrial pilot project involving the management of a modular effluent treatment plant. The modular design of this plant allows for bypassing individual treatment modules, facilitating a dynamic treatment configuration. This flexibility enables multiple treatment setups for industrial effluents, tailored to the effluent's characteristics and the desired water quality. The primary challenges addressed were: 1) identifying suitable treatment techniques for each type of pollutant, 2) determining the optimal arrangement of treatment modules to configure an effective process for specific effluents, and 3) determining the most sustainable treatment process among several feasible configurations for a given effluent composition. The objective of this study is to offer solutions for these challenges and develop an approach for environmental assessments of modular industrial effluent treatment, through the elaboration of the whole processes of: 1) developing the parametric model for a multitude of conventional, established and emerging treatment technologies in industrial effluent treatment; 2) developing a decision tree based on the best available techniques (BAT) for configuration of the appropriate treatment chain tailored to effluent pollutant composition; 3) developing a modular treatment chain for industrial effluent including three treatment stages of Pretreatment, Membrane treatment and Finishing treatment; 4) performing a comparative environmental life cycle assessment (LCA) for the treatment technology modules to provide insight into the difference in the order of magnitude of their environmental impacts. As a prerequisite for environmental assessments, parametric life cycle models were developed for fifteen effluent treatment modules based on an in-depth literature review to have versatility in the LCA of diverse treatment scenarios as well as flexibility in sensitivity and uncertainty analysis. This approach could be updated and customized for emerging treatment techniques and emerging contaminants for further LCAs in the effluent treatment industry.

2. Methods

2.1. Developing a decision tree to configure a fit-for-purpose treatment chain

The complexity of configuration for wastewater treatment chain arises from the diversity of pollutant types in a given industrial effluent as well as the availability of multiple treatment techniques for the same pollutant. In addition, some treatment modules such as RO and membrane technologies are effective to eliminate several pollutants at the same time, which minimize the treatment stages (Loiseau et al., 2010). Beyond the wastewater characteristic, regulatory limitations, treatment performance, and expected end use of treated water are important factors in the selection of techniques for wastewater treatment (Rajasulochana and Preethy, 2016; Adetunji and Olaniran, 2021). To overcome this complexity, decision trees have emerged as a powerful tool to provide a structured approach for decision-making in the wastewater treatment industry. A decision tree diagram is a hierarchical, flowchart-like structure which utilizes flowchart symbols to illustrate the process of decision-making by visually mapping out the associated potential outcomes of a sequence of decisions. As a prerequisite for the development of the decision trees, the reference documents (BREFs) provide essential detailed guidelines and standards for implementing best available techniques (BAT) in order to promote sustainable industrial practices across various industrial sectors, including wastewater treatment. These documents are developed by the European Integrated Pollution Prevention and Control Bureau (EIPPCB), which operates under the EU Joint Research Centre (JRC). (https://eippcb.jrc.ec.europa.eu/reference). The BREF for wastewater treatment (Brinkmann et al., 2016) detailed the best available techniques (BAT) for wastewater treatment based on the pollutant types present in a given industrial effluent, reliability and effectiveness, functional performance of the available technologies, regulatory limitation for the targeted end use of treated wastewater, and purification objectives. The BREF 2016 was applied to classify industrial wastewater pollutants into four main families of physical, chemical, biological, and emerging pollutants and the best available techniques were assigned to the appropriate pollutant subfamilies, all represented in Table 1.

The classified pollutant types and the appropriate BAT recommended by BREF (Table 1), alongside internal knowledge and experiences of domain experts were applied to develop a decision tree to configure the combination of treatment modules based on the pollutant types in a given industrial effluent. Biological treatments such as activated sludge process and MBR, which uses microorganisms to break down organic matter, are relatively slow processes, are not preferred to integrate into a dynamic modular effluent treatment plant. Additionally, biological treatment is not suitable for effluents containing high levels of toxic chemicals, heavy metals, or non-biodegradable substances. Accordingly, chemical, physic-chemical, and membrane-based modules were adopted. The graphical representation of the decision tree is depicted in Fig. 1.

This decision tree is developed by integration of classified pollutant

Table 1
Classification of industrial pollutants and assigning the best available technique (BAT) for wastewater treatment according to BREF guidelines (2016).

Pollutant Family		Pollutant	Best Available Technique (BAT)	Reference
Physical Pollutants		Total Suspended Solids (TSS): settleable solids (>100 μm), and non-settleable suspended solids (<100 μm)	Sedimentation, Filtration, Flotation, Sand filtration, Coagulation/flocculation, Electrocoagulation,	(Brinkmann et al., 2016)
Chemical Pollutants	Organic Chemicals	Biochemical (Biological) Oxygen Demand (BOD): Measure of the amount of oxygen microorganisms need to decompose organic material. Chemical Oxygen Demand (COD): Measure of the total quantity of oxygen required to oxidize both organic and inorganic substances.	Biological treatment, Chemical oxidation, Ozone and UV treatment (AOP), Nanofiltration Nanofiltration/Reverse Osmosis, Electrocoagulation, Wet oxidation (H_2O_2),	(Parsons, 2005), (Brinkmann et al., 2016)
		Refractory Organics: Organic compounds that resist conventional biological treatment methods, including persistent pesticides, phenols, complex hydrocarbons, and some surfactants.	Chemical precipitation, Chemical oxidation, Nanofiltration/Reverse Osmosis, Wet oxidation (H_2O_2), Adsorption	(Brinkmann et al., 2016)
		Oils and Greases: Fats, oils, waxes	Flotation, Oil-water separation, Adsorption Coagulation/flocculation, Microfiltration/Ultrafiltration,	(Brinkmann et al., 2016)
	Inorganic Chemicals	Heavy Metals: Elements like lead (Pb), mercury (Hg), cadmium (Cd), and arsenic (As)	Coagulation/flocculation, Microfiltration/Ultrafiltration, Electrocoagulation, Chemical precipitation, Adsorption Nanofiltration/Reverse Osmosis, Ion exchange, Biological removal	(Brinkmann et al., 2016)
		Nutrients: Nitrogen (N) and phosphorus (P) compounds	Membrane Bioreactors (MBRs), Advanced oxidation processes (AOPs), Adsorption, Ion exchange precipitation, Nanofiltration/Reverse Osmosis	(Ugwuanyi et al., 2024), (Brinkmann et al., 2016)
		Salts: Including sodium, chloride, and other mineral salts.	Nanofiltration/Reverse Osmosis, Ion exchange	(Brinkmann et al., 2016)
		Acids and Bases: Affecting the pH level of water	Neutralization	(Brinkmann et al., 2016)
		Ammonia and Cyanides: Specific inorganic compounds	Nanofiltration/Reverse Osmosis, Adsorption, Nitrification/denitrification, Aerobic treatment	(Brinkmann et al., 2016)
Biological Pollutants		Pathogens: Disease-causing bacteria, viruses	Chlorination, UV radiation, Ozonation, Photocatalytic Processes	(Gomes et al., 2019), (Shi et al., 2021), (González et al., 2023)
Emerging Pollutants		Pharmaceuticals and Personal Care Products (PPCPs): Drugs, cosmetics, and individually used chemicals	Adsorption, Microfiltration/Ultrafiltration, Nanofiltration/Reverse, Membrane Bioreactors (MBRs), Advanced oxidation processes (AOPs), Biological treatment, Combined Treatment	(Loganathan et al., 2023), (Osuoha et al., 2023)
		Endocrine Disrupting Chemicals (EDCs): Compounds that can interfere with hormonal systems.	Adsorption, Microfiltration/Ultrafiltration, Nanofiltration/Reverse Osmosis, Chlorination, Advanced oxidation processes (AOPs), Biological treatment,	(Azizi et al., 2022)
		Microplastics: Small plastic particles that originate from a variety of sources.	Advanced oxidation processes (AOPs), Coagulation/flocculation, Electrocoagulation, Algal masses, Bioinspired molecules, Metal organic framework (MOF)-based foams, Photocatalytic micromotors, Integrated carbocatalytic oxidation and hydrothermal hydrolysis	(Singh et al., 2021), (Nasir et al., 2024)

types and the best available technologies to configure the combination of treatment modules based on the types of pollutants present in industrial effluent. The decision tree for configuring the combination of treatment modules in industrial effluent treatment begins by identifying the presence of oils/fats in the effluent. If oils/fats are present, the effluent is directed towards MF followed by dissolved air flotation. If oils/fats are not present, the next decision point involves determining the presence of total suspended solids (TSS). When TSS is present, the decision tree differentiates between settleable and non-settling TSS. For non-settling TSS, the recommended treatment includes flocculation followed by a lamellar decanter, then continuing with the same processes used for settleable TSS, which include sand filtration, cartridge filtration, and bag filtration. If advanced TSS removal is necessary, the decision tree directs towards MF.

If heavy metals are present in the effluent, the decision tree directs towards treatments like precipitation or membrane filtration. If specific elements like arsenic (As) and molybdenum (Mo) are present, GEH may be used. In the presence of mineral salts, NF, RO, or ion-exchange are preferred. The presence of refractory chemical oxygen demand leads to a choice between NF, ozonation, or activated carbon treatments. For effluents containing nitrogen, such as ammonium, the decision tree recommends NF, RO, or ion-exchange. If disinfection is necessary to meet the expected end-use quality, MF (for bacteria), UF (for viruses), UV treatment, and ozonation are the best available techniques.

Proper development and implementation of decision trees, provides a systematic approach to decision-making, enhances flexibility, scalability and effectiveness of treatment processes towards sustainable wastewater management. Decision tree facilitates to identify the most appropriate treatment techniques based on the characteristics of the effluent. To configure a treatment chain for a given effluent, four essential prerequisites are: 1) the characteristics of the effluent composition, 2) the target quality of treated water, 3) a decision tree as a decision support tool, and 4) a modular treatment chain.

2.2. Modular effluent treatment chain

For a modular treatment chain, based on the internal knowledge and expertise from domain specialists, we have developed a modular treatment chain for industrial effluent including three treatment stages of Pretreatment, Membrane treatment and Finishing treatment, illustrated in Fig. 2.

The process begins with the pretreatment stage, crucial for removing large particles and other contaminants to ensure that the effluent is in a suitable condition for more advanced treatment processes. This stage

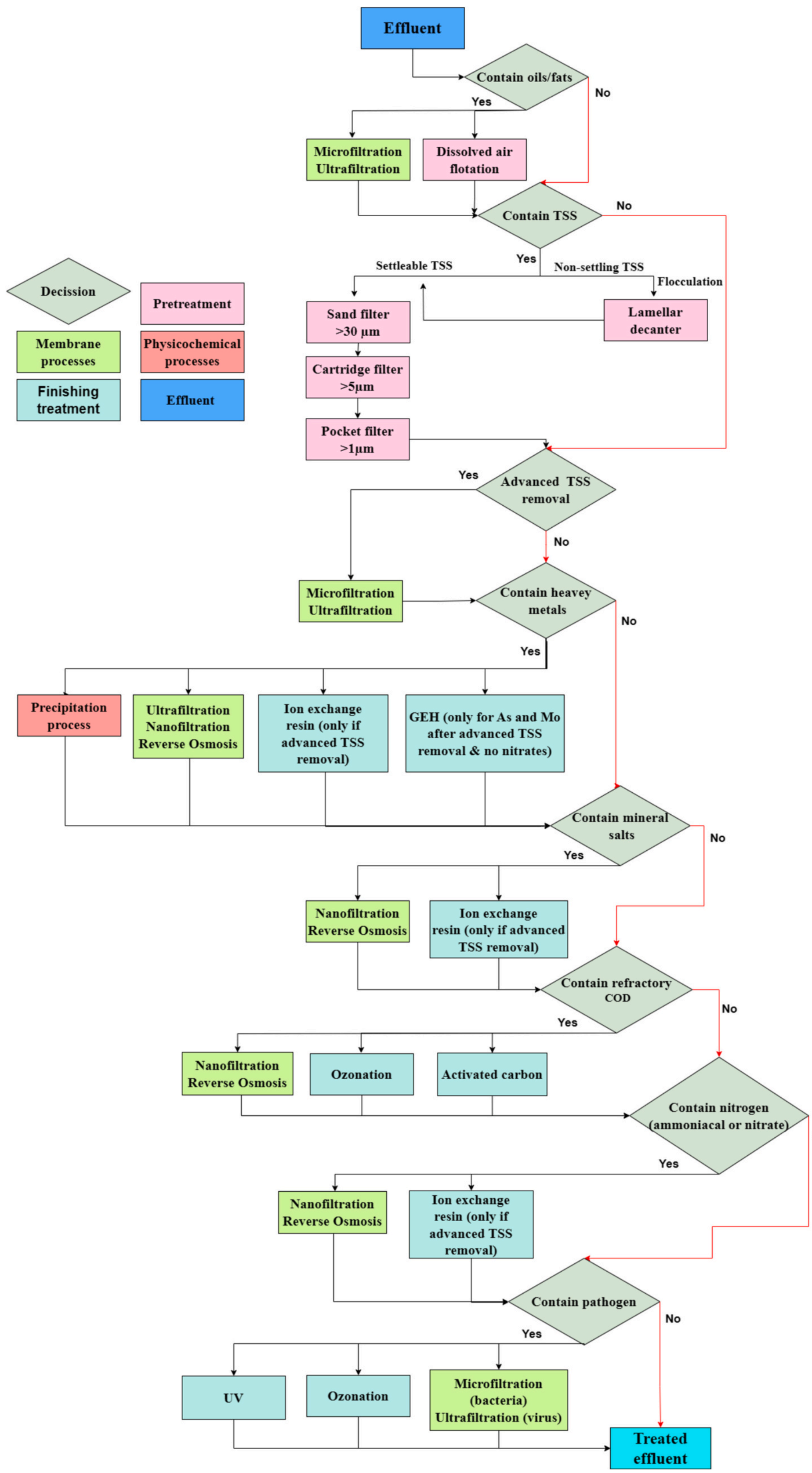

Fig. 1. Graphical representation of the decision tree developed to configure the combination of treatment modules according to the pollutant types present in a given industrial effluent. TSS: total suspended solids; COD: chemical oxygen demand.

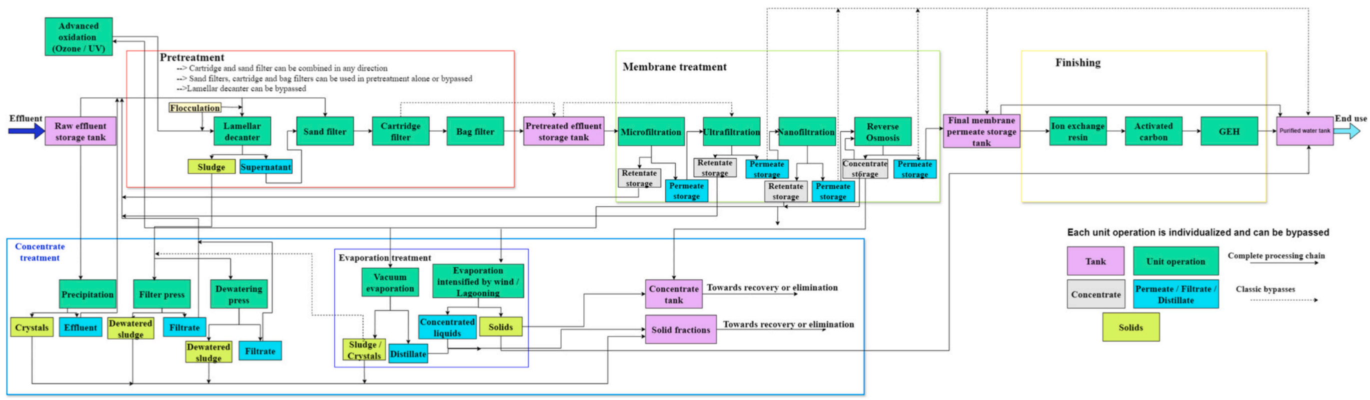

Fig. 2. Schematic of a modular treatment chain of industrial effluent in three treatment stages of pretreatment, membrane treatment and finishing to configure treatment scenarios according to decision tree.

includes various processes for grit removal and primary sedimentation, such as flocculation, lamellar decanter, sand filtration, cartridge filtration, and bag filtration.

Following pretreatment, the effluent undergoes membrane treatment, designed to remove dissolved solids and other microscopic contaminants. It typically includes techniques such as MF, UF, NF, and RO using different membrane pore sizes to target specific types of contaminants, ensuring a high level of purification. The final stage is finishing treatment to ensure that the treated water meets the required quality standards for its intended use. This stage may involve disinfection processes, like UV treatment or ozonation, to eliminate any remaining pathogens, activated carbon filters to remove residual organic compounds, or ion-exchange processes can be employed to target specific ions left in the water. Each of these stages is designed to address specific types of pollutants effectively, making the entire treatment process adaptable to different kinds of industrial effluent characteristics through a modular treatment chain concept. A modular effluent treatment chain involves a series of interconnected and bypassable treatment modules in which each module is designed to perform a specific treatment process. The effluent characteristics and the intended final quality of water determine the incorporation of modules in the treatment process. This modular configuration allows for targeted treatment of specific pollutants easy modification and expansion of the treatment system, tailored to the effluent composition. The modular design facilitates easier maintenance and replacement of individual treatment modules without disrupting the entire system and the integration of advanced and emerging treatment technologies, offering a robust and cost-effective solution for industrial effluent treatments.

Furthermore, the modular approach offers flexibility for integrating AI and IoT into a modular effluent treatment chain, could offer environmental sustainability through real-time proactive decision-making for optimal performance, precise control, continuous monitoring and automation of the treatment chain (Wang et al., 2023).

2.3. Environmental assessment

2.3.1. Life cycle assessment

Life cycle assessment (LCA) is the most universal framework for a comprehensive assessment of the environmental impacts of the life cycle of a product or process to unveil the hotspots with the highest contribution to the environmental impacts (Soleimani et al., 2023a, 2023b). An attributional life cycle assessment was carried out under the scope of ISO 14040, 2006 and ISO 14044, 2006 in the standard phases of goal and scope definition, inventory analysis, impact assessment, and interpretation. The parametric life cycle inventories (LCIs) of the effluent treatment modules were developed in openLCA 2.1.1, based on Table S1, using inventories from the database ecoinvent v.3.9.1 with allocation at the point of substitution (APOS).

2.3.2. Goal, scope and functional unit of the LCA

The objective of this LCA study is the comparative environmental impact assessment of fifteen effluent treatment techniques and to quantify their environmental impacts at local, regional, and global levels. The quantified environmental impacts are generally assigned to a reference unit called the functional unit to ensure comparability between LCA studies and reliable interpretations. Among the most commonly used functional units applied in LCA studies of wastewater treatment volume (m^3), population equivalent (PE/year) and mass of sludge (Corominas et al., 2020); the functional unit of $1m^3$ of treated wastewater as the most utilized functional unit (Bhatt et al., 2022) retained for all treatment modules. The system boundary determines which processes have been included in the LCA study. The environmental impacts of the construction phase are insignificant compared to the operation phase (Morera et al., 2020; Hijrah et al., 2023). According to Morera et al., 2017, between 82.5 % and 99.9 % of impacts belong to operation except metal depletion which is mainly for civil work and equipment (63.3 %). Gomez et al., 2023, demonstrated that the contribution of the operation phase of a wastewater treatment plant is higher than 90 % for 15 environmental impact indicators out of sixteen. The environmental impacts of the construction phase have an inverse relation with the designed lifetime of the plant, and considering the end-of-life and demolition phase do not have a significant influence on the environmental impacts of wastewater treatment plants (Moussavi et al., 2021). The infrastructure and end-of-life often have been excluded from system boundaries in the LCA studies of literature (Mehmeti and Canaj, 2022). Accordingly, only the operation phase of the treatment modules is included in the system boundary, and the construction phase, the end-of-life, effluent delivery, concentrates treatment and sludge disposal are purposely excluded in this study because of the uncertainty in site-specific factors and materials, the variability in effluent characteristics and lack of reliable data. As a cut-off approach, the industrial effluent was considered with zero environmental impacts, allocating all the environmental impacts to the treatment process. To ensure the reliability of the comparative assessments, consistency was sustained in the model, inventories, assessment method, system boundary, and functional unit.

2.3.3. System boundary

The system boundaries are generally defined based on the scope of the study and its objective (Pryshlakivsky and Searcy, 2013; Bhatt et al., 2022). All the processes and incoming flows into the system boundary including energy, transport, water, and raw materials, as well as all outgoing emissions from the system boundary into air, soil and water, were considered, as illustrated in Fig. 3.

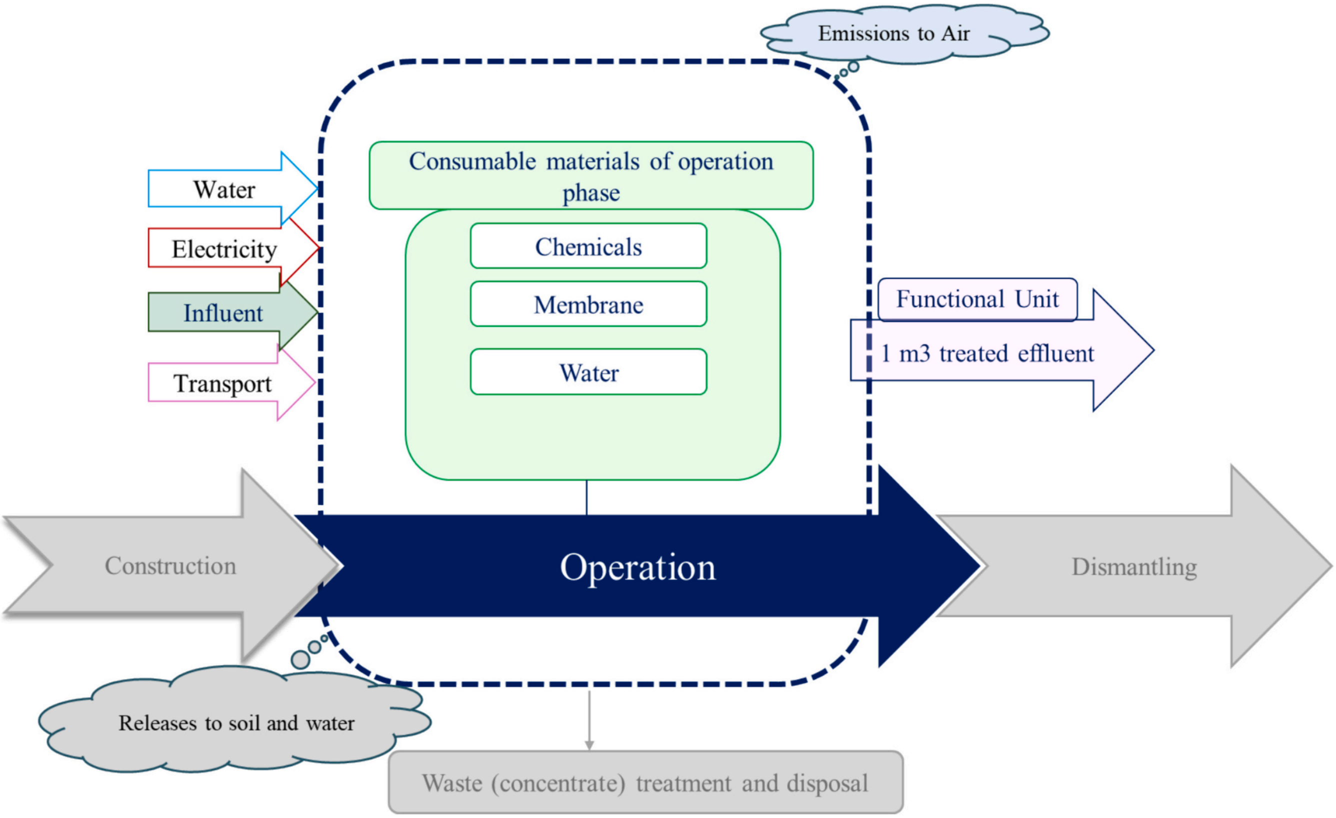

Fig. 3. Scheme of the system boundary including the operation phase of effluent treatment module, input energy and raw materials, consumable materials and transport of materials to the treatment plant.

2.3.4. Life cycle inventory assessment method

Among the appropriate methodologies for life cycle inventory assessment (LCIA) to quantify the potential environmental impacts of wastewater treatments, ReCiPe is the most commonly employed LCIA model in recent literature (Mehmeti and Canaj, 2022). Accordingly, the ReCiPe midpoint (H) method with the eighteen impact categories and the ReCiPe endpoint (H, A) method were used to estimate the environmental impacts at both midpoint and endpoint levels. At the endpoint level, the eighteen midpoint impacts are normalized to dimensionless scores (points) and accumulated in three main damages on human health, resource, and ecosystem diversity, as well as a total single score, perfect for comparison of the overall impacts of the effluent treatment modules. The endpoint damage categories and the total single score are illustrated in a graph to provide comparative insight into the difference in the order of magnitude between the impacts of the effluent treatment modules.

2.3.5. Data

For the inventory data, the mean values of processes, chemicals, raw materials, and energy flows within the system boundary were adopted from an in-depth literature review, background data and internal data (Table S1). Ecoinvent v3.9.1 databases have been used as the background data. To ensure consistency across all inventories, European average data has been used in most of the inventories from European (RER) databases. For electricity, a mixed grid of electricity generation data from French databases was employed. The transport distance for raw materials between origin and destination was estimated using Google Maps. It was assumed that raw materials were transported by truck from the port of Marseille to the city of Lyon in France, covering a distance of 309 km.

2.4. Developing parametric life cycle inventory models for treatment modules

To develop LCI models for the treatment modules adopted in this study, flexible for adapting and extending to emerging treatment techniques, we have developed parametric LCIs for fifteen conventional, established and advanced treatment modules,

The overall life cycle environmental impacts of effluent treatment by an effluent treatment plant (ETP) could be obtained from the impacts of construction, operation, concentrate treatment and valorization and final disposal phases:

Impacts $_{\text{ETP}}$ = [impacts of construction of platform and effluent treatment modules] + [impacts of operation and maintenance of effluent treatment modules] + [impacts of construction of concentrate treatment modules] + [impacts of operation and maintenance of concentrate treatment modules] + [impacts of valorization of residue] - [impacts of avoided products (substitution of valorized products) (Offsets)] + [disposal impacts] (1).

These overall life cycle environmental impacts of a modular treatment plant could be transformed into a general parametric model elaborated in the following equation:

$$\boldsymbol{Impacts}(\boldsymbol{FU})_{\boldsymbol{ETP}} = \sum_{i=1}^{n}\mathbf{ImpactConst}_i + \sum_{i}^{n}\left(\boldsymbol{Inf} - \sum_{j=2}^{i}\boldsymbol{C}_j\right)^{*}\boldsymbol{impact}_i + \sum_{j=1}^{m}\mathbf{ImpactConst}_j + \sum_{j=1}^{m}\left(\boldsymbol{C}_j{}^{*}\boldsymbol{impact}_j\right) + \sum_{k=1}^{p}\mathbf{ImpactVal}_k - \sum_{k=1}^{p}\mathbf{ImpactAvoid}_k + \sum_{r=1}^{q}\mathbf{ImpactDisp}_r \tag{2}$$

In which ***FU*** is the Functional Unit, defined as 1 cubic meter (m^3) of treated water, ***Inf*** is the industrial effluent volume (m^3), ***C*** is the concentrate volume (m^3), ***i*** is the i^{th} effluent treatment module, ***j*** is the j^{th} concentrate treatment module, ***k*** is the k^{th} valorizable product, ***r*** is the r^{th} disposal material, ***n*** represents the number of effluent treatment modules, ***m*** represents the number of concentrate treatment modules, ***p*** represents the number of valorizable products in residue, ***q*** represents the number of disposal materials in residue, $impact_i$ is the impact of operation and maintenance of the i^{th} effluent treatment module per cubic meter of effluent, $impact_j$ is the impact of operation and maintenance of the j^{th} concentrate treatment module per cubic meter of concentrate, $ImpactConst_i$ is the impact of construction of the i^{th} effluent treatment module, $ImpactConst_j$ is the impact of construction of the j^{th} concentrate treatment module, $ImpactVal_k$ is the valorization impact of the k^{th} valorizable product, $ImpactAvoid_k$ is the avoided impacts of the k^{th} valorized product, and $ImpactDisp_r$ is the impact of the r^{th} disposal material.

The impacts of construction phase of the effluent treatment modules depends on the construction technology, site-specific conditions, geological location, treatment capacity, operational lifetime, etc. As far as the construction inventories of many treatment modules were not available in the literature and actual databases like Ecoinvent, based on the reasoning in the introduction, we have excluded the construction phase in this study. Accordingly, the general parametric LCA model was tailored exclusively to the operation phase of fifteen conventional, established, and advanced treatment modules, considering consumable materials in the operation phase, including water, energy, and raw materials (Table S1). These fifteen treatment modules are elaborated in supplementary S2 along with their parametric LCIs through eqs. 1 to 15.

2.5. Sensitivity analysis

Sensitivity analysis determines the relative importance of the input parameters in the model outputs and unveils how sensitive the output of a model is to the variations of the input parameters (Soleimani and Gilbert, 2020). As a prerequisite for sensitivity analysis, parametric life cycle inventories (LCIs) were developed based on Eq.1 to Eq.15 (S2) in openLCA for 'one-at-a-time' sensitivity analysis of the environmental impacts. In this sensitivity analysis, the relative variation in the environmental impacts due to ±10 % change in an incorporated parameter in the model, holding all other parameters constant, was calculated.

2.6. Uncertainty analysis

Uncertainty arises in various forms throughout all steps of an LCA, from the uncertainty in input data, assumptions, model parameters, process parameters, etc. (Pintilie et al., 2016). In the uncertainty analysis, uncertainties in impact categories due to uncertainties in the process parameters were estimated using Monte Carlo simulation in a 90 % confidence interval. A Monte Carlo (MC) simulation is an efficient tool to illustrate the probability distribution for each environmental impact category due to uncertainties in the model parameters. Monte Carlo simulations were performed in openLCA, and the 90 % confidence interval (between the 5th percentile and the 95th percentile) of the endpoint environmental impact categories, as the outcome of 1000 MC simulations, have been illustrated as the upper and lower error bars in the graphs of environmental impacts.

3. Results

The results presented in this study offer a comprehensive comparison of the environmental impacts of fifteen different effluent treatment modules. Using the ReCiPe midpoint and endpoint methods, along with literature data, the study provides detailed insights into the specific and overall environmental impacts of each treatment module. This combined analysis, supplemented by sensitivity and uncertainty assessments, establishes a robust framework for evaluating and comparing the environmental impacts of various effluent treatment modules. This structured approach not only identifies the most impactful treatment processes and modules but also highlights potential areas for improving environmental performance. The results of midpoint and endpoint assessments are visually illustrated, along with the appropriate results of uncertainty and sensitivity analysis, in order to provide an at-a-glance comparative overview of the environmental impacts of treatment modules for decision makers.

3.1. Comparative environmental impacts of treatment modules - midpoint impacts

The midpoint environmental impacts of the operational phase of fifteen treatment modules for the functional unit of $1m^3$ treated effluent, obtained from LCIA in openLCA by ReCiPe midpoint (H) method based on the literature-derived operating parameters, are elaborated in Table 2 in eighteen impact categories.

The results indicate significant variations in the environmental impacts across different treatment modules. For instance, the impact on climate change ranges from as low as 2.80E-02 kg CO_2-Eq for cartridge filtration to as high as 1.90E+00 kg CO_2-Eq for ion-exchange, highlighting ion-exchange as the most significant contributor to climate change. Similarly, fossil depletion impacts are lowest for cartridge filtration (6.44E-03 kg oil-Eq) and highest for ion-exchange (6.37E-01 kg oil-Eq), demonstrating the substantial resource consumption associated with this module. Human toxicity impacts follow a similar trend, with cartridge filtration having the least impact (5.07E-03 kg 14-DCB-Eq) and ion-exchange the most (9.26E-01 kg 14-DCB-Eq), further emphasizing the environmental burden of ion-exchange.

Modules such as RO and NF also show high impacts in several categories, including climate change, fossil depletion, and human toxicity. Reverse osmosis (RO), for example, has significant impacts on climate change (1.56E+00 kg CO_2-Eq) and fossil depletion (3.63E-01 kg oil-Eq), indicating its intensive resource and energy requirements. Conversely, treatment modules like sand filtration and UV treatment exhibit relatively lower impacts across most categories, making them more environmentally favorable options. To provide insight into the difference in the order of magnitude between the impacts of effluent treatment modules, the midpoint environmental impacts are visually illustrated on a relative percentage basis in Fig. 4. for 18 impact categories of ReCiPe midpoint (H).

This visual representation enabling to understand at a glance the proportional contribution of each treatment module to various impact categories, reveals substantial differences in the environmental burdens posed by each module. For instance, ion-exchange consistently exhibits the highest impacts (100 %) across multiple categories such as climate change, fossil depletion, and human toxicity, signifying its dominant contribution to greenhouse gas emissions and fossil fuel consumption compared to other modules. Nanofiltration (NF) and RO also show considerable impacts across various categories, such as climate change (86 % and 82 %) and freshwater eutrophication (93 % and 89 %), illustrating the resource-intensive nature of these processes, particularly their high energy consumption and potential for eutrophication. Modules like sand filtration and UV treatment exhibit lower impacts across most categories, such as climate change and freshwater eutrophication (1 % to 2 %), suggesting these are more environmental friendly options.

3.1.1. Sensitivity analysis of environmental impacts of $1m^3$ effluent treatment

Parametric LCI models developed in openLCA enabled sensitivity analysis on intended parameters derived from literature, as incorporated into the models based on eqs. 1 to 15 (S2). Due to the numerous treatment modules, the diversity of incorporated parameters across the models, and the multitude of impact categories, the sensitivity analysis

Table 2
The midpoint environmental impacts of the operational phase of the fifteen treatment modules estimated by ReCiPe midpoint (H) method based on the literature-derived operating parameters.

Impact Category	Unit	Activated Carbon Filtration	Bag Filtration	Cartridge Filtration	Granular Ferric Hydroxide (GEH)	Ion Exchange Resin	Lamellar Decanter	Micro Filtration	Nano Filtration	Ozonation	Coagulation Flocculation	Reverse Osmosis	Sand Filtration	Solar Photo Fenton	Ultra Filtration	UV
Agricultural land occupation	m^2a	1.09E-03	4.44E-04	4.40E-04	8.44E-03	2.85E-02	2.17E-03	9.69E-03	2.54E-02	2.53E-03	6.95E-02	2.46E-02	7.96E-04	2.08E-02	9.69E-03	1.37E-03
Climate change	kg CO2-Eq	7.12E-02	2.81E-02	2.80E-02	2.58E-01	1.90E+00	1.40E-01	6.05E-01	1.63E+00	1.62E-01	6.19E-01	1.56E+00	4.53E-02	9.56E-01	6.05E-01	8.80E-02
Fossil depletion	kg oil-Eq	1.84E-02	6.47E-03	6.44E-03	6.73E-02	6.37E-01	3.21E-02	1.39E-01	3.75E-01	3.73E-02	2.90E-01	3.63E-01	1.07E-02	3.19E-01	1.39E-01	2.02E-02
Freshwater ecotoxicity	kg 1,4-DCB-Eq	4.29E-04	1.41E-04	1.36E-04	8.31E-03	3.24E-02	6.57E-04	3.04E-03	7.69E-03	7.66E-04	1.70E-02	7.72E-03	2.27E-04	2.11E-02	3.04E-03	4.14E-04
Freshwater eutrophication	kg P-Eq	2.12E-05	5.52E-06	5.46E-06	7.71E-05	3.39E-04	2.71E-05	1.19E-04	3.17E-04	3.15E-05	2.00E-04	3.04E-04	8.58E-06	2.22E-04	1.19E-04	1.71E-05
Human toxicity	kg 1,4-DCB-Eq	1.79E-02	5.14E-03	5.07E-03	9.73E-02	9.26E-01	2.50E-02	1.10E-01	2.92E-01	2.90E-02	2.40E-01	2.81E-01	8.43E-03	2.97E-01	1.10E-01	1.62E-02
Ionising radiation	kg U235-Eq	1.40E-03	5.98E-04	5.88E-04	1.22E-02	5.68E-02	2.89E-03	1.41E-02	3.38E-02	3.38E-03	2.92E-02	3.37E-02	9.32E-04	5.38E-02	1.41E-02	1.82E-03
Marine ecotoxicity	kg 1,4-DCB-Eq	4.13E-04	1.33E-04	1.29E-04	7.61E-03	2.31E-02	6.22E-04	2.86E-03	7.28E-03	7.26E-04	1.44E-02	7.29E-03	2.20E-04	1.82E-02	2.86E-03	3.93E-04
Marine eutrophication	kg N-Eq	7.80E-05	3.37E-05	3.35E-05	3.46E-04	1.85E-03	1.67E-04	7.23E-04	1.95E-03	1.94E-04	1.03E-03	1.90E-03	5.57E-05	2.26E-03	7.22E-04	1.05E-04
Metal depletion	kg Fe-Eq	5.48E-06	2.44E-06	2.40E-06	6.38E-05	3.28E-04	1.18E-05	5.74E-05	1.38E-04	1.38E-05	2.37E-03	1.39E-04	3.90E-06	2.78E-04	5.74E-05	7.48E-06
Natural land transformation	m^2	5.57E-06	1.41E-06	1.39E-06	4.36E-05	3.32E-04	6.82E-06	3.03E-05	7.98E-05	7.97E-06	2.64E-04	7.90E-05	4.35E-06	1.55E-04	3.02E-05	4.30E-06
Ozone depletion	kg CFC-11-Eq	1.54E-10	1.02E-10	7.33E-11	1.58E-09	6.55E-05	2.23E-10	4.74E-09	2.65E-09	2.64E-10	1.69E-08	5.79E-09	1.16E-10	6.26E-08	4.74E-09	1.41E-10
Particulate matter formation	kg PM10-Eq	1.53E-04	6.23E-05	6.17E-05	6.34E-04	2.77E-03	3.06E-04	1.32E-03	3.58E-03	3.56E-04	1.33E-03	3.40E-03	9.88E-05	1.72E-03	1.32E-03	1.93E-04
Photochemical oxidant formation	kg NMVOC	2.27E-04	9.31E-05	9.26E-05	1.05E-03	5.52E-03	4.61E-04	2.00E-03	5.39E-03	5.35E-04	2.90E-03	5.14E-03	1.59E-04	3.09E-03	1.99E-03	2.90E-04
Terrestrial acidification	kg SO2-Eq	3.37E-04	1.14E-04	1.13E-04	1.16E-03	5.54E-03	5.54E-04	2.40E-03	6.48E-03	6.44E-04	3.23E-03	6.20E-03	1.81E-04	3.68E-03	2.40E-03	3.49E-04
Terrestrial ecotoxicity	kg 1,4-DCB-Eq	3.06E-06	1.10E-06	1.08E-06	2.87E-05	2.90E-04	5.30E-06	2.35E-05	6.20E-05	6.17E-06	6.83E-04	5.99E-05	2.71E-06	4.29E-04	2.33E-05	3.44E-06
Urban land occupation	m^2a	7.73E-04	3.06E-04	3.04E-04	5.16E-03	1.47E-02	1.51E-03	6.56E-03	1.77E-02	1.75E-03	1.00E-02	1.68E-02	7.67E-04	9.49E-03	6.54E-03	9.51E-04
Water depletion	m^3	2.62E-04	1.03E-04	1.03E-04	9.52E-04	6.71E-03	5.16E-04	2.24E-03	5.98E-03	1.09E-03	1.21E-02	5.70E-03	3.46E-04	4.35E-03	2.24E-03	3.22E-04

Fig. 4. Comparative environmental impacts of effluent treatment modules, in 18 impact categories of ReCiPe midpoint (H), on a relative percentage basis.

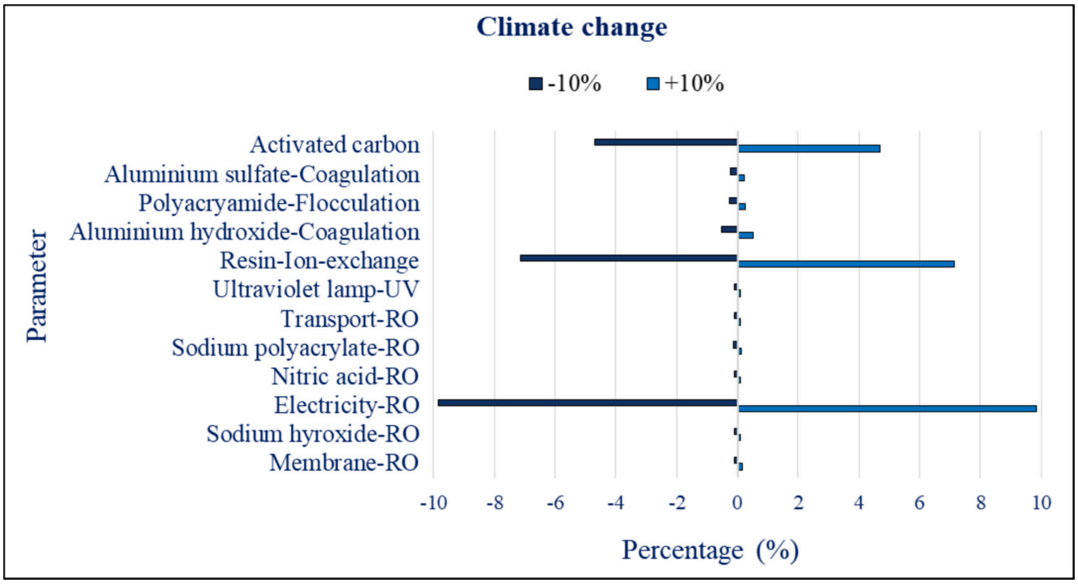

Fig. 5. Variation percentages in the midpoint global impact category of climate change, due to ±10 % one-at-time change of the intended input parameters.

was performed on selected parameters specifically for the climate change category. The variation percentage in the global midpoint environmental impact of climate change, due to a ± 10 % one-at-a-time change in parameters like granular activated carbon (GAC), aluminum sulphate, etc. is illustrated in Fig. 5.

The sensitivity analysis graph in Fig. 5. reveals that climate change has the highest sensitivity to electricity consumption, which is common across many treatment modules including membrane treatments (MF, UF, NF, RO), ion-exchange, ozonation, UV treatment, etc. The sensitivity analysis shows that a ± 10 % change in electricity consumption for RO leads to a substantial impact variation of ±9.85 % in the climate change category. This underscores the critical role of energy efficiency in the environmental footprint of membrane-based treatment technologies. The impact category of climate change is also sensitive to resin consumption (±7.15 %) in ion-exchange treatment and relatively sensitive to GAC consumption (±4.7 %) in activated carbon treatment, highlighting the importance of optimizing chemical use to reduce environmental impacts. Aluminum sulfate, consumed in coagulation processes, shows a small variation of ±0.21 %, still indicates a meaningful impact on the climate change footprint. The sensitivity analysis provides valuable insights into which parameters are most critical for improving the sustainability of effluent treatment technologies.

3.2. Comparative damage impacts on ecosystem quality, resources and human health of treatment modules – endpoint impacts

To have an overview of the ultimate impacts on ecosystem quality, resources and human health, the endpoint impacts of treatment modules were obtained in a dimensionless score of point (Pt) from the ReCiPe endpoint method. These endpoint impacts are visually compared in Fig. 6. for three impact categories of ecosystem quality, resources, and human health to provide comparative insight into the difference between the impacts of treatment modules at the endpoint level.

In the ecosystem quality category, ion-exchange shows the highest impact with a mean value of 0.042 Pt, indicating significant adverse effects on ecosystems. This is followed by NF (0.032 Pt) and RO (0.031 Pt). These high scores suggest that these modules have substantial ecological impacts, likely due to their high energy consumption and chemical use. Solar photo-Fenton, UF and MF follow in significance within this impact category. In contrast, modules like bag Filtration (0.00057 Pt) and Cartridge Filtration (0.00055 Pt) exhibit much lower impacts on Ecosystem Quality.

For resource depletion, ion-exchange resin again stands out with the highest impact at 0.087 Pt, reflecting significant resource usage. This is closely followed by NF, RO, and solar photo-Fenton with impacts of 0.045 Pt, 0.044 Pt, and 0.039 Pt respectively. RO also shows a considerable impact of 0.044 Pt. These high values underscore the intensive material and energy requirements of these processes. On the lower end, bag and cartridge filtration, sand filtration and UV treatment exhibit lower resource impacts, making them more resource-efficient options.

In the human health category, NF has the highest impact at 0.141 Pt, followed closely by RO at 0.095 Pt and ion-exchange at 0.089 Pt. These high scores indicate significant potential for adverse health effects. In contrast, modules like cartridge and sand filtration have much lower impacts on human health. Overall, the integrated analysis of these endpoint categories reveals that ion-exchange, NF, and RO are the dominant contributors to the three endpoint impact categories of ecosystem quality, resources, and human health. Solar photo-Fenton, UF and MF follow in significance within these three impact categories.

3.2.1. Overall environmental damage impacts - endpoint total impacts

The dimensionless scores (Pt) of the three endpoint impact categories were integrated to a single total score to provide a holistic view of the total environmental burden associated with each treatment module, visually are compared in Fig. 7. The uncertainties in these impacts obtained from 1000 Monte Carlo simulation runs, are shown as upper and lower error bands representing a 90 % confidence interval.

The analysis reveals that ion-exchange has the highest overall endpoint impact with a mean score of 0.2191 Pt. This significant score underscores the substantial environmental burden of ion-exchange, driven by its high impacts across all three categories. Nanofiltration (NF) follows closely with an overall impact score of 0.2188 Pt, indicating that it is also an environmentally intensive process, particularly due to its high energy consumption and associated emissions.

In terms of overall endpoint environmental impacts, ion-exchange, NF, and RO have the highest overall endpoint impact scores, followed by solar photo-Fenton, MF, UF, GEH and Coagulation/Flocculation.

3.2.2. Uncertainty analysis for environmental impacts of treatment modules

The uncertainties in endpoint environmental impacts, obtained from 1000 Monte Carlo simulation runs, are illustrated as upper and lower error bands in Fig. 6 and Fig. 7, representing a 90 % confidence interval in each impact category.

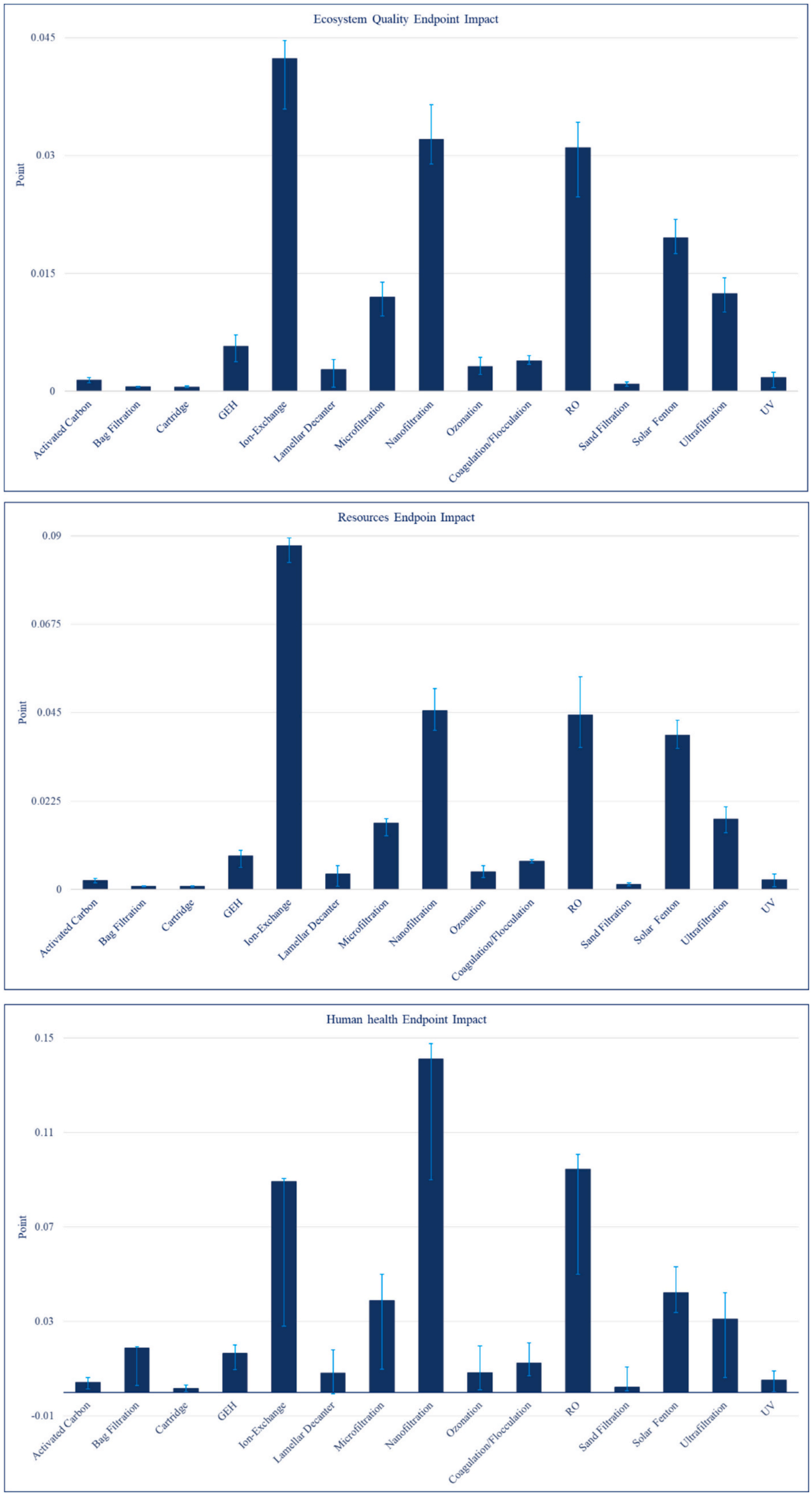

Fig. 6. Comparison of endpoint environmental impacts of effluent treatment modules in three categories of ecosystem quality, resources and human health, along with error bars representing a 90 % confidence interval between 5th and 95th percentiles in each impact category.

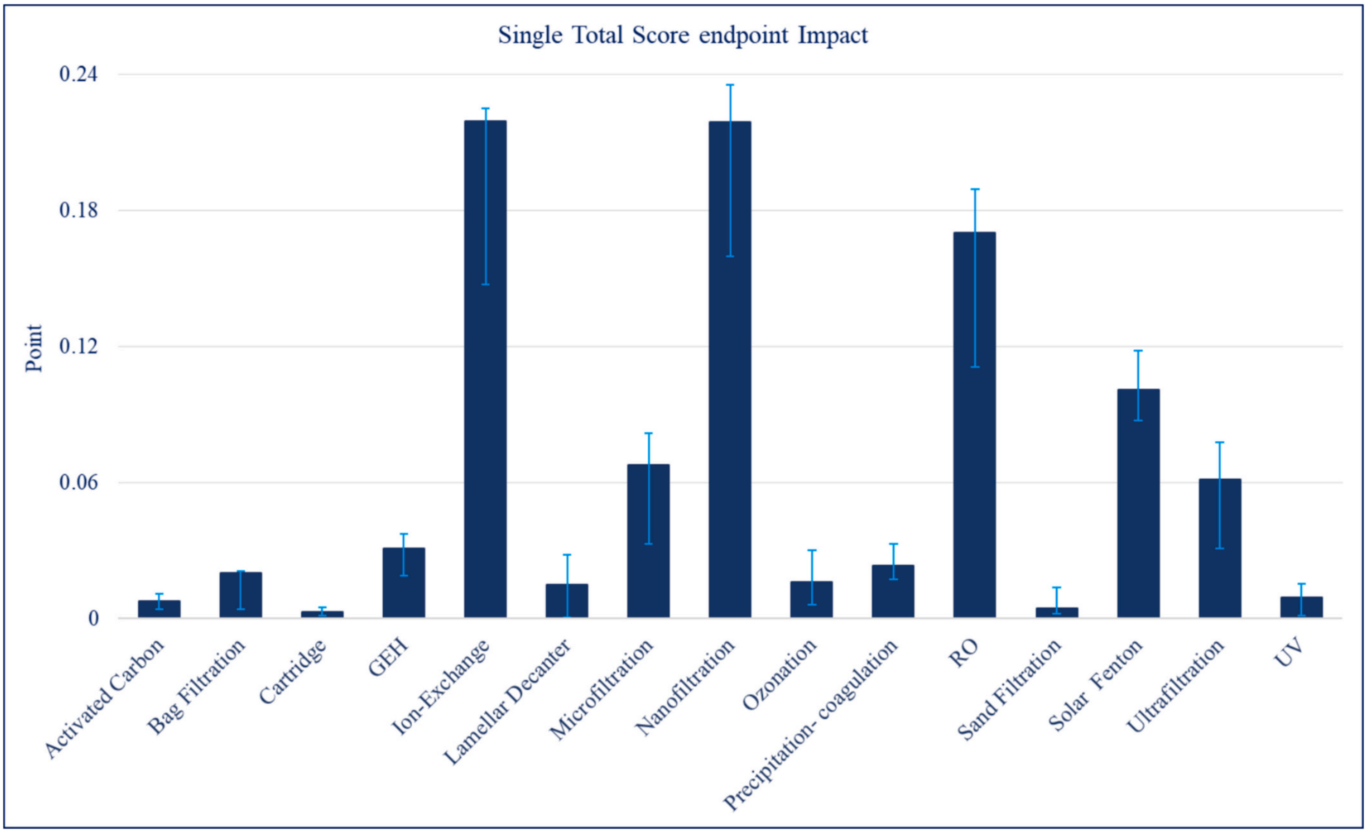

Fig. 7. Comparison of endpoint singles score environmental impacts of effluent treatment modules, along with error bars representing a 90 % confidence interval between the 5th and 95th percentiles.

4. Discussion

Understanding the environmental impacts is crucial for decision making on sustainable wastewater management practices, particularly to satisfy the gradually stricter regulatory requirements. This study offers an overall insight into the environmental impacts of the operation phase of different effluent treatment processes based on the internal data and secondary data in the literature. The comparative evaluation of fifteen effluent treatment modules reveals significant insights for decision makers into the environmental trade-offs associated with each treatment module. The high variability in impacts across different modules, as presented in Table 2, highlights the importance of considering multiple environmental factors when configuring and implementing effluent treatment processes. This detailed comparison serves as a critical tool for identifying the most sustainable treatment options and inspiring future improvements in effluent management practices.

Through this comparative approach, it was revealed that ion-exchange, NF, and RO have the highest overall endpoint environmental impacts, mainly due to their substantial contributions to damage on ecosystem quality, resources, and human health. This dominance at the midpoint level is primarily due to their substantial contributions to categories like climate change, fossil depletion, terrestrial acidification, particulate matter formation, photochemical oxidant formation, urban land occupation and freshwater eutrophication. The dominance of NF and RO could be attributed to relatively high energy consumption of 1.17 kWh/m^3 (NF) and 1.1 kWh/m^3 (RO) for treatment of 1m^3 effluent (Table S1), highly dependent to the electricity origin. UF and MF follow in significance, offering lower but still considerable environmental impacts. Unlike the membrane treatment modules, the significance of ion-exchange and solar photo-Fenton could be mainly attributed to the consumption of specific chemicals such as 0.385 kg/m^3 resin and 1.1 kg/m^3 EDDS as well as moderate energy consumption of 0.38 kWh/m^3 and 0.28 kWh/m3 for treatment of 1m^3 effluent (Table S1), respectively. However, ion-exchange is a reversible process and the resins could be regenerated to alleviate the environmental impacts of the process. Treatment modules like sand filtration, bag and cartridge filtration and UV treatment generally exhibit lower relative impacts across most categories, making them more environmentally favorable options. Integrating such lower-impact modules, where feasible, could enhance the overall sustainability of wastewater treatment processes. Although the coagulation/flocculation technique has relatively low overall impact, it is still dominant in categories like terrestrial ecotoxicity, water depletion, agricultural land occupation and metal depletion, mainly due to chemical coagulants and flocculants listed in Table S1. Identifying the dominant modules in each impact category facilitates to the development of targeted strategies in order to mitigate the environmental impacts of treatment modules.

The sensitivity analysis apparently revealed the importance of energy consumption in the environmental impact of the operation phase of these treatment modules. Electricity consumption was found to be the most significant influencing factor on climate change impact across the treatment processes, highlighting the importance of optimizing energy efficiency and utilizing renewable energy sources to mitigate the environmental impacts of wastewater treatment. Inferred from the comprehensive analysis of the results, to enhance the environmental sustainability of wastewater treatment processes, strategies should be developed to avoid energy-intensive treatment techniques, reduce energy consumption, improve the efficiency and reusability of chemicals, and integrate renewable energy sources.

Beyond implementing the environmental impact assessment for fifteen effluent treatment modules, we developed a versatile approach for decision-making on treatment configuration scenarios based on a decision tree, and estimating the local and global environmental impacts of the configured treatment scenarios, all based on the literature data, methods and the results presented in this study. In other words, by understanding the composition of effluent and knowing the intended end use of the treated water, we can follow the decision tree to configure a fit-for-purpose treatment scenario relying on the best available techniques and roughly estimate the overall impacts by integrating the impacts of the incorporated treatment modules. It is essential to select and optimize treatment modules not only for their technical efficacy but also with careful consideration of their environmental impacts. From a holistic perspective, evaluating a process requires assessing and considering technical efficacy, environmental sustainability, and economic viability together (Soleimani et al., 2022; Soleimani et al., 2023a, 2023b). In this study, we offered a framework to configure a technically efficient treatment process for a given effluent using best available techniques incorporated in a decision tree, and assess environmental sustainability through life cycle inventories. However, from a holistic perspective, the economic assessment to evaluate the economic viability of the configured treatment scenarios is missing in this study. Consequently, a further comprehensive life cycle economic assessment of effluent treatment modules could be expected as a complementary future work.

5. Conclusion

An all-in-one integrated framework was developed for: 1) identifying the best available techniques (BAT) tailored to the contaminant types, 2) developing a decision tree based on BATs, pollutant types, and intended water quality 3) configuring a fit-for-purpose treatment scenario proportional to the effluent composition using the decision tree and modular treatment chain, 4) developing parametric life cycle inventory (LCI) for the treatment processes, and ultimately 5) performing LCA for the treatment modules along with sensitivity and uncertainty analysis.

Since components of this approach, such as the decision tree and parametric LCIs, are developed to be flexible and easily updated for both conventional and emerging treatment techniques and contaminants, it offers an adaptable foundation for ongoing advancements in effluent treatment configuration and sustainability assessment of various scenarios. From the comprehensive modular environmental assessments along with sensitivity and uncertainty analysis, the following implications could be inferred:

- Comparative LCA revealed that nanofiltration and reverse osmosis have high overall environmental impacts mainly due to high energy consumption and ion-exchange has the highest overall impacts due to high chemical resin consumption.
- Decision tree, effluent characteristics, expected treatment quality, and modular treatment chain are the prerequisites for configuration of a fit-for-purpose treatment scenario for an effluent.
- Modular life cycle assessment of effluent treatment could reveal the environmental hotspots of a treatment chain, in terms of local, regional and global impacts.
- More sustainable effluent treatment involves strategies for avoiding energy-intensive and chemical-intensive techniques, improving energy efficiency or integrating renewable energy sources, improving chemical efficiency and reusability through regeneration and reactivation of consumed chemicals and low impact modules incorporation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eiar.2024.107782.

Data availability

Data will be made available on request.

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