Modeling micropollutant removal by nanofiltration and reverse osmosis membranes: considerations and challenges

S. Castaño Osorio [a,b], P.M. Biesheuvel [a], E. Spruijt [c], J.E. Dykstra [b], A. van der Wal [b,d,*]

[a] Wetsus, European Centre of Excellence for Sustainable Water Technology, Oostergoweg 9, Leeuwarden 8911 MA, the Netherlands
[b] Environmental Technology, Wageningen University & Research, P.O. Box 17, Wageningen 6700 AA, the Netherlands
[c] Institute for Molecules and Materials, Radboud University, Heyendaalseweg 135, Nijmegen 6525 AJ, the Netherlands
[d] Evides Water Company, P.O. Box 4472, Rotterdam 3006 AL, the Netherlands

ARTICLE INFO

ABSTRACT

Organic micropollutants (OMPs) in drinking water constitute a potential risk to human health; therefore, effective removal of these pollutants is required. Nanofiltration (NF) and reverse osmosis (RO) are promising membrane-based technologies to remove OMPs. In NF and RO, the rejection of OMPs depends on the properties and characteristics of the membrane, the solute, and the solution. In this review, we discuss how these properties can be included in models to study and predict the rejection of OMPs. Initially, an OMP classification is proposed to capture the relevant properties of 58 OMPs. Following the methodology described in this study, more and new OMPs can be easily included in this classification. The classification aims to increase the comprehension and mechanistic understanding of OMP removal. Based on the physicochemical principles used to classify the 58 OMPs, it is expected that other OMPs in the same groups will be similarly rejected. From this classification, we present an overview of the rejection mechanisms involved in the removal of specific OMP groups. For instance, we discuss the removal of OMPs classified as perfluoroalkyl substances (e.g., perfluorooctanoic acid, PFOA). These substances are highly relevant due to their human toxicity at extremely low concentration as well as their persistence and omnipresence in the environment. Finally, we discuss how the rejection of OMPs can be predicted by describing both the membrane-solution interface and calculating the transport of solutes inside the membrane. We illustrate the importance and impact of different rejection mechanisms and interfacial phenomena on OMP removal and propose an extended Nernst-Plank equation to calculate the transport of solutes across the membrane due to convection, diffusion, and electromigration. Finally, we show how the theory discussed in this review leads to improved predictions of OMP rejection by the membranes.

1. Introduction

Organic micropollutants (OMPs) are chemicals that occur in the environment due to human activities, e.g., agriculture, medicine consumption, and due to industrial activities. In general, the concentrations of these substances in aquatic environments remain at trace levels (i.e., ppb-level) (Stamm et al., 2016). Moreover, OMPs (e.g., carbamazepine, sotalol, PFOA, metronidazole, diuron) are increasingly found in water sources across the world, in Europe (Barbosa et al., 2016; Möller et al., 2010; Robles-Molina et al., 2014; Tröger et al., 2018), the USA (Mead et al., 2009; Oppenheimer et al., 2011; Wang et al., 2020b), and China (Ren et al., 2020; Yan et al., 2018). Therefore, concerns about drinking water safety and public health have been raised (Schwarzenbach et al.,

2006). Because of potential long-term effects of OMPs on human health, these compounds are often on national watch lists and defined as contaminants of emerging concern (Barbosa et al., 2016; Verliefde et al., 2007a). An example is the growing attention to perfluoroalkyl substances and the risk that they represent to human health. In Europe, contaminated drinking water with perfluorooctanoic acid (PFOA) and perfluorooctanesulfonic acid (PFOS) is one important contributor to the exposure to perfluoroalkyl substances (Schrenk et al., 2020). Another clear example is the concern about substances classified as nitrosamines, which can be carcinogenic, and which are not sufficiently removed by membranes.

Research on OMPs has focused on developing new analytical techniques and detection methods (Richardson and Ternes, 2011; Schmidt,

2018), evaluating environmental risks of different OMPs (Figuière et al., 2022; Gross and Osterle, 1968; Licona et al., 2018; Sanganyado et al., 2021; Yang et al., 2022), and developing technologies to remove OMPs in wastewater treatment (Luo et al., 2014; Ma et al., 2018b) and drinking water production (Piai et al., 2019; Plakas and Karabelas, 2012; Vergili, 2013). In this review, we will focus on OMP removal with membrane-based processes in drinking water production. Previous authors have thoroughly reviewed the theory behind removal of OMPs with membranes (Khanzada et al., 2020; Liu et al., 2009; Plakas and Karabelas, 2012; Schäfer et al., 2011; Teodosiu et al., 2018). In this review, we summarize this theory to support and explain the advantages of a properties-based classification and approaches and suggestions are given to improve existing models.

Conventional water treatment processes, such as coagulation-flocculation-sedimentation and sand filtration, do not effectively remove all OMPs, and advanced water treatment processes (AWT) are often considered to achieve higher removal in drinking water treatment plants (DWTPs). Several reviews discussed available technologies to remove OMPs in drinking water production (Benner et al., 2013; Teodosiu et al., 2018; ; Wang et al., 2020a; Yang et al., 2014). Of these technologies, adsorption on activated carbon or on other materials, advanced oxidation processes (AOPs), and membrane-based processes are the most promising in terms of removal efficiencies (Teodosiu et al., 2018). In adsorption processes, OMPs are adsorbed onto the adsorption materials, and are thereby removed from water (Piai et al., 2021). AOPs are based on the production of hydroxyl radicals to break down and remove OMPs from contaminated water. The downside of AOPs is the production of toxic by-products, which can be even more toxic than the original OMPs, during the oxidation process (Ates and Argun, 2021; von Gunten, 2018; Wang et al., 2019). Membrane-based processes, such as nanofiltration (NF) and reverse osmosis (RO), have become an attractive option to remove OMPs in DWTPs. The operational principle of these membrane-based processes is similar: a pressure gradient is the main driving force and a semi-permeable membrane acts as a barrier for contaminants. Compared to RO, NF employs membranes with bigger pores, resulting in a lower rejection of solutes, but NF has the advantage that it can be operated at lower pressure. The removal efficiency of most OMPs with RO and NF is higher than with other advanced water treatment processes, such as adsorption on activated carbon and advanced oxidation (Lee et al., 2012; Song et al., 2020; Sudhakaran et al., 2013), and toxic by-products are not produced (Mestankova et al., 2016; Schwarzenbach et al., 2006; Veloutsou et al., 2014).

Although NF and RO show high removal of most OMPs (Albergamo et al., 2020; Xu et al., 2020), the mechanisms of retention of these compounds remain poorly understood. Due to a lack of understanding, it has been challenging to determine the key factors that govern the rejection and that can be tailored to further improve the removal of OMPs. For instance, it is not well understood how different OMPs behave at the membrane-solution interface, or how membrane and OMP properties affect the transport of solutes inside the membrane. Therefore, there is a need for mechanistic models that are derived from physicochemical principles to accurately predict rejection efficiencies of OMPs and to improve the removal performance of membrane-based processes. Ideally, mechanistic models can quantify the effect of interfacial phenomena and of key molecular properties to predict the rejection of OMPs and optimize process design.

In this review, we will discuss several considerations in developing a theoretical approach to study and model OMP removal with NF and RO. This review covers the following topics: the classification of OMPs using molecular properties on a continuous scale, the rejection mechanisms involved in membrane-based processes, an overview of rejection rates with commercial membranes, and theory to account for phenomena at the membrane-solution interface and the transport of solutes inside the membrane.

Unlike previous studies, in this review, we critically analyze each of these topics to provide a clear view of important research areas that need

to be addressed, propose alternatives to overcome challenges in the field, and illustrate with model calculations the effect of physical and chemical phenomena on OMP removal. For instance, we show how our novel classification can facilitate the development of models to test the rejection of OMPs and enable selecting prototypical "model" OMPs that can be used for the validation of theoretical models. Besides, we explain and illustrate how the theory, considerations, and calculations in this review can be combined to improve the prediction of OMP removal with existing models.

A classification of OMPs based on molecular properties contributes to the identification of critical parameters that affect the removal in a complex mixture containing different micropollutants. OMPs are often complex organic molecules with a molecular weight up to 800 g/mol, a non-spherical shape, and a molecular structure that is composed of a combination of hydrophobic, hydrophilic, ionizable and ionic parts (Nam et al., 2014). The large number of compounds that are classified as OMPs, all with different molecular properties, is one of the difficulties to develop a model that can be applied to all OMPs. In this review, we stress the importance of a systematic, theory-driven approach to study the removal of OMPs in NF and RO. Therefore, to overcome the problem of the huge number of compounds that are considered as OMPs, a classification that is based on molecular properties is proposed. The molecular properties of OMPs together with the membrane characteristics, and the chemistry of the solution, are directly associated with the removal efficiency in NF and RO see Fig. 1 (Boussu et al., 2008; Zhu, 2015). With the classification proposed in this study, we can qualitatively indicate which rejection mechanisms (e.g., size exclusion, electrostatic repulsion, and specific solute-membrane interactions) and transport mechanisms are predominant in the rejection of OMPs with similar properties.

Furthermore, we discuss theory to describe the membrane-solution interface and to model OMP transport inside the membrane. We present approaches to account for size exclusion, charge repulsion/attraction, and solute affinity towards the membrane, which directly relate to the main rejection mechanisms (Section 3). In this review, we give an overview of the transport theories commonly used in NF and RO and summarize previous attempts to study the transport of OMPs. The extended Nernst-Plank (ENP) equation is used to calculate the transport of solutes due to diffusion, convection, and electromigration. We discuss how the ENP equation can be coupled to the description of the membrane-solution interface to include the effect of size-based exclusion, charge regulation, solute-membrane interaction, and molecule-molecule interaction on the rejection of OMPs, and therefore predict the removal performance of membrane-based processes.

In summary, this review focuses on the development of a theoretical approach to study and model OMP removal. Only a model that combines the physicochemical interactions and transport mechanisms involved in the rejection of OMPs will be able to predict the removal performance of NF and RO for the wide range of OMPs that are present in commonly used water sources, and support technology improvements, e.g., new membrane developments and process optimization and design.

2. Classification

Models that capture all relevant molecular properties of OMPs and their transport through membranes are essential to gain a fundamental understanding of the mechanisms involved in OMP removal and to help the design of more effective membranes. Key steps in the development of these models are the identification of the relevant physicochemical properties and the validation of the models with experimental data. For both, a systematic analysis of OMPs is required and a classification of OMPs into well-defined groups can help to achieve this. In this section, we propose a new apprach to classify micropollutants that has the potential to qualitative compare OMP removal data, identify problematic OMPs (insufficient removal with specific membranes), and facilitate model development and validation, thus greatly advancing the study of OMP removal.
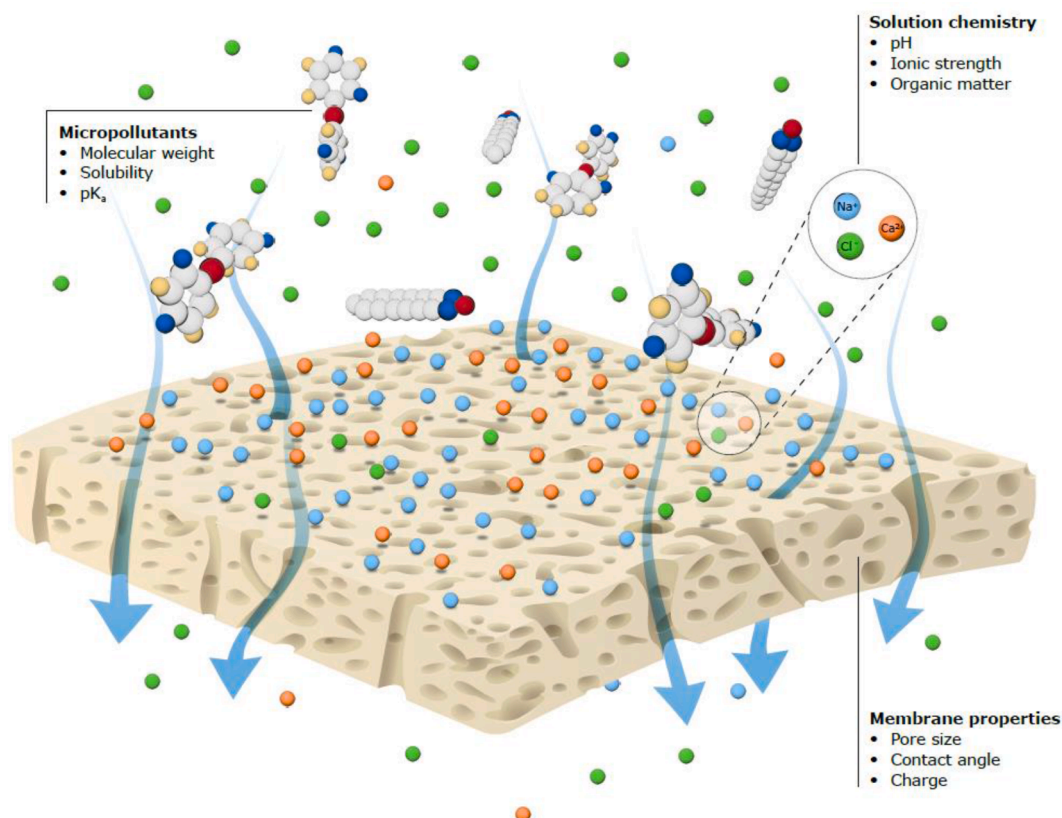
Fig. 1. The properties of the OMPs, the membrane, and the chemistry of the solution determine the removal efficiency of OMPs.

Micropollutants are traditionally classified based on their industrial provenance or usage (Lefebvre et al., 2010; Ren et al., 2020; Schwarzenbach et al., 2006), such as pharmaceuticals, pesticides, flame retardants, hormones, industrial chemicals, personal care products, and, more recently, perfluoroalkyl substances (PFAS). This classification is useful when evaluating and assessing the sources of contamination, but it does not provide much relevant information to study and understand OMP removal in membrane-based processes. To mitigate the limitations of provenance-based classification, many researchers list a collection of molecular properties in their studies (Kimura et al., 2004; Liu et al., 2009; Taheran et al., 2016). However, the OMP application area is usually kept as the main classification criterion.

A different approach that can be more adequate is to group the organic compounds based on molecular properties (Bellona et al., 2011; Verliefde et al., 2007a; Yangali Quintanilla, 2010), such as hydrophobicity, molecular weight, M_W, solubility, polarizability, etc. This approach holds great potential because the molecular properties of OMPs give more insight into the possible removal mechanisms that are involved and that affect rejection efficiency during membrane-based processes (Kiso et al., 2001b; Liu et al., 2009; Verliefde et al., 2007b). For instance, high hydrophobicity of OMPs might lead to lower retention by RO membranes due to adsorption and partitioning into the membrane (Boussu et al., 2008; Nghiem et al., 2004). In most cases, NF and RO membranes are hydrophobic; therefore, depending on the membrane characteristics, the diffusion of hydrophobic solutes inside the membrane is enhanced. Octanol-water partitioning coefficients, log K_{ow}, are frequently used to quantify the hydrophobicity of a molecule. Likewise, polarity, parametrized by the dipole moment, could be an indicator of both hydrophobicity and attractive interactions between organic molecules (Steed and Atwood, 2009); the latter may be relevant to consider when studying the aggregation or cluster formation of molecules at or near membranes. In addition to hydrophobicity and polarity, the classification of OMPs must consider the capacity of these

molecules to dissociate and carry a charge. Whether a molecule is ionic or neutral has been shown to significantly affect the retention of organic micropollutants (Albergamo et al., 2019; Yangali Quintanilla, 2010). The acid dissociation constant, pK_a, is often used to define the charge ability of molecules (e.g., weakly charged, uncharged) (Schäfer et al., 2011).

Several authors have started to explore the use of molecular properties to classify OMPs. For instance, Verliefde et al. (2007a) classified 22 compounds to qualitatively study the prediction of OMP rejection. They defined groups based on a binary division of each compound into hydrophobic/hydrophilic, charged/uncharged, and below/above the cutoff size of the membrane pores. These three binary choices yielded eight groups, which could be used to explain the behavior of the 22 OMPs reasonably well. Similarly, De Ridder et al. (2010) used the structure of the molecules (aromatic or aliphatic) and whether these are able to form hydrogen bonds, or not, to define binary classes of compounds. However, many of the molecular properties invoked in these studies are continuous variables. Hence, there is significant variation in the degree of hydrophobicity or net charge between OMPs that are classified as hydrophobic and charged in the binary choice models. For instance, using the aqueous solubility as a measure of hydrophobicity, micropollutants commonly found to be hydrophobic can differ in solubility by three orders of magnitude. Likewise, the K_a of these micropollutants, and thus their degree of (de)protonation, can vary by as much as seven orders of magnitude. Consequently, the properties of micropollutants within one binary group, and therefore their retention by membranes may differ significantly.

To account for these differences between the binary classified hydrophobic or charged OMPs, we suggest to take the classification of micropollutants one step further and propose here to identify groups of micropollutants based on their actual coordinates in the continuous 3D phase space defined by solubility in water, charge ability, γ, and molecular weight. Charge ability is defined as pK_a for acid OMPs and 14-

pK$_b$ for base OMPs, and it indicates whether an OMP will be charged at neutral pH, regardless of the sign. These properties are selected because they are good indicators/molecular descriptors to analyze three fundamental phenomena involved in OMP removal. Specifically, molecular weight relates with steric exclusion, γ with Donnan exclusion, and solubility with possible OMP-membrane interactions. Molecular weight is not a direct measure of molecular dimensions; however, it can still indicate the molecule size and it is an easily accessible and well-defined parameter (van der Bruggen and Vandecasteele, 2002). Solubility in water is used as an improved measure of hydrophobicity instead of the octanol-water partitioning coefficient because some of the OMPs we have included (notably PFAS) are also barely soluble in organic solvents, such as octanol, which could distort the interpretation of log K$_{ow}$'s. This approach uses the quantitative physicochemical properties of micropollutants and contains no implicit bias based on the usage or occurrence of compounds. Moreover, by using a continuous scale all the values of the molecular properties are considered; therefore, a more precise description of each group is possible.

In total, 58 of the most frequently detected and problematic micropollutants were classified. The selection was made based on previous studies and aims to include a broad number of compounds with various molecular properties and different usage (e.g., pharmaceuticals, pesticides, industrial chemicals) (De Grooth et al., 2014; Khanzada et al., 2020; Lai et al., 2016; Schoonenberg Kegel et al., 2010; Taheran et al., 2016; van Beelen, 2000; Verliefde et al., 2007a; Yangali-Quintanilla et al., 2010b, 2010a). The OMPs were then automatically allocated to separate groups using a cluster-finding algorithm in MATLAB, i.e., hierarchical clustering, and an F-test was used to determine the optimal number of groups. The optimal number of groups to classify the 58 OMPs based on their molecular weight, charge ability, γ, and solubility in water was found to be 8. In Fig. 2, the groups are presented in a 3D plot, the 2D views are given in the supplementary information (SI).

Classifying OMPs into groups like these can provide useful insight in the possible membrane-based removal mechanisms and it enables selecting prototypical "model" OMPs that can be used in the validation of theoretical models (Jin and Peldszus, 2012). For instance, in models using quantitative structure-activity relationship (QSAR) and quantitative structure-property relationships (QSPR), the classification of OMPs based on molecular properties is crucial (Agenson et al., 2003; Bellona et al., 2011; De Ridder et al., 2010; Libotean et al., 2008; Yangali-Quintanilla et al., 2010b). The ideal classification will not only facilitate the development of models to test the rejection of OMPs, but will also remain unchanged when different organic compounds are added to the growing list of micropollutants as they become known in the future. It is therefore important to continuously evaluate and revise the proposed classification.

We emphasize that the classification proposed here is not the only possible classification. It is based on three important molecular properties that we discuss in detail in section 3. It is possible to extend or modify the current classification with additional parameters, such as dipole moment or net charge. An extensive validation based on data obtained under comparable conditions is required to distinguish between different classifications, which is currently not possible because of the limited available experimental data, as we will discuss later in section 3. Nevertheless, this novel classification is an important step towards a new classification approach based on molecular properties on a continuous scale, which can be more helpful in understanding the removal of OMPs and replacing traditional provenance-based classifications. Moreover, this classification provides insight into the relevant mechanisms involved in the removal of OMPs with similar molecular properties. Further efforts are needed to validate and improve the classification proposed in this work.

It is interesting to take a closer look at the molecular and physicochemical differences between the groups identified by our classification. In Table 1, each group from Fig. 2 is described in qualitative terms. This table is a simplified way to understand and illustrate the general differences between groups. However, the classification used in this review is based on a continuous scale, and binary interpretation of the characteristics of each group should be avoided. Furthermore, the descriptive names given in this table are meant to facilitate referencing to each group during the analysis. To fully benefit from the classification presented in this study, one must look at the values of the three molecular descriptors used to define the 8 OMP groups.

The compounds in the iodide and perfluoroalkyl groups have high M_w (>500 g/mol). Despite the similar size, these two groups are different because of the high solubility in water of the iodide compounds, due to the presence of many polar groups, and the strong charge combined with a very low polarity of the perfluoroalkyl compounds. The
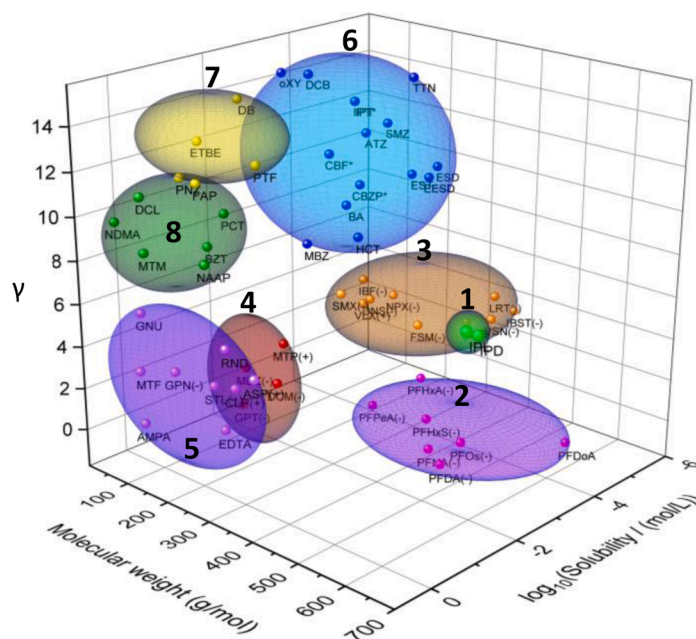

Fig. 2. 3D view of the groups that were defined in the classification of OMPs. The 3D phase space is defined by the M_w, the charge ability, γ, and the solubility of the OMPs in water. All values and 2D views of the plot are reported in the SI.

Table 1
Description of the 8 groups defined in the classification of OMPs (detailed information in SI).

Group	Descriptive name	Example compound	M_W	Charge	Solubility (water)
1	Iodide	Iopamidol	high	uncharged	high
2	Perfluorinated	Perfluorooctanoic acid (PFOA)	high/ intermediate	strong	poor
3	Cyclic-hydrophobic	Ibuprofen	intermediate	moderate	poor
4	Cyclic-charged	Metoprolol- glyphosate	intermediate/ low	strong	moderate
5	Nitrogen	Metformin	intermediate/ low	strong	high
6	Small-hydrophobic	Metribuzin	low	weak/ uncharged	poor
7	Small-neutral	Ethyl T-butyl ether (ETBE)	low	uncharged	moderate
8	Small-hydrophilic	Benzotriazole	low	weak	moderate

molecular structure of the perfluoroalkyl compounds can be divided into a polar part that gives a strong charge to the molecule and a large (perfluorinated) aliphatic or aromatic part that makes it poorly soluble; typical examples include PFOA. The removal of iodide compounds is governed mainly by steric exclusion, contrary to perfluoroalkyl compounds, where other phenomena, such as charge repulsion/attraction between the membrane and the OMPs, must also be considered. The smaller the OMP, the larger the importance of other molecular properties in the removal of OMPs.

Compounds in group 3 are labeled as "cyclic-hydrophobic". All the OMPs in this group have a backbone of aromatic or aliphatic rings and lack a significant amount of highly polar or strongly charged substituents. These molecules are thus poorly soluble, despite the few polar or weakly charged groups. For instance, ibuprofen, IBF, which is used as medication against pain and inflammation, contains one aromatic benzene ring. It has a single carboxylic acid functional group, which gives it an overall negative charge, but that is not sufficient to improve the solubility to the mM range.

The compounds in group 6 are the most diverse in structure, usage, and properties. We labeled them as "small-hydrophobic". Despite the difference in chemical structure, aromatic rings are also the core of the small-hydrophobic compounds. These compounds are slightly smaller than the cyclic compounds (group 3) and have about the same solubility, but the main difference is the fact that these molecules are uncharged or only very weakly charged. The presence of some polar and uncharged functional groups results in neutral compounds that are hardly soluble in water. For instance, in this group, we can find cholesterols, such as hormones, and phenolic compounds.

In contrast, cyclic-charged and nitrogen compounds (groups 4 and 5) are simpler and smaller and have at least one functional group that can be easily (de)protonated (e.g., metformin). Therefore, compounds in these groups have a strong ionic character and a minor hydrophobic part, which results in high solubility in water. The most soluble OMPs are the nitrogen rich compounds. They are not necessarily smaller than the cyclic-charged compounds, but they typically have much smaller hydrophobic elements (e.g., gabapentine) or no hydrophobic elements at all (e.g., aminomethylphosphonic acid, AMPA). Based on the description of the OMPs within these groups, the removal by membranes can be insufficient and special attention might be needed to these two groups. For instance, in the cases of metronidazole and metformin, the low molecular weight and positive charge of these compounds leads to a low rejection by NF membranes (Lipp et al., 2010; Yangali Quintanilla et al., 2011).

In groups 7 and 8, we classify the small-neutral and small-hydrophilic compounds respectively. The compounds in these two groups are interesting because of their very low molecular weight, high solubility, and neutral or partially charged character. Based on these characteristics, it is expected that membranes with large pores do not represent a proper barrier for these compounds. Besides, the distribution of these molecules in the bulk is not affected by the surface charge of the membrane; thus, repulsive energies do not contribute to rejection. For instance, removal of N-nitroso dimethylamine (NDMA), a compound classified as small-polar, has been reported to be lower than 20% in NF (Fujioka et al., 2014). Therefore, special attention must be given to OMPs that are in this group.

3. Removal of OMPs with membranes

Different mechanisms affect the removal of OMPs. In NF and RO, the mechanisms responsible for the rejection of specific solutes depend on the properties and characteristics of the membrane, the solute, and the aqueous media/solution, see Fig. 1 (Boussu et al., 2008; Libotean et al., 2008; Mänttäri et al., 2006; van der Bruggen et al., 1999; Zhang et al., 2004; Zhu, 2015). However, three key mechanisms can be identified: size exclusion, electrostatic repulsion, and solute-membrane interactions. In Fig. 3, these rejection mechanisms are illustrated. This section covers the principles on OMP rejection and provides a clear view on the phenomena that need to be considered in a mechanistic model. Moreover, the key rejection mechanisms are linked to the different groups of OMPs in Section 2.

Size exclusion is the most important rejection mechanism for many compounds, since the membrane is, in principle, a porous, physical barrier to solutes. An OMP will be sieved based on the ratio between its size and the pore size of the membrane. In a membrane, a pore is the structure of continuous and connected pathways for transport of water and ions. Water is the entity that 'explores', that 'finds', these pathways and fills them up. Ions move through these pathways. These connected pathways we refer to as pores. We note that membrane pores are sometimes depicted as straight channels, but this is not in agreement with the microscopic structure of most NF and RO membranes. In theory, the molecules that are larger than the membrane pores will just be rejected. Size exclusion is dependent on the properties of the membrane and the OMP, yet determining these properties might be a challenge. The pore dimensions of NF and RO membranes are different, and their size distribution can widely vary depending on the membrane used. Currently, the membrane's pore size can be estimated with transport models (Bowen and Mukhtar, 1996) or can be experimentally determined with techniques such as microscopy observation and thermoporometry (Otero et al., 2008; Zhao et al., 2000).

The molecular weight, M_W, is commonly used to relate the size of OMPs with their rejection. Therefore, the term molecular weight cut-off (MWCO) is often found in the specifications of commercial membranes and refers to the lowest M_W at which 90% of solutes is retained by the membrane (Singh, 2005). The M_W is a well-defined and easily accessible property of OMPs, and experimental studies have shown clear correlations between the M_W and OMP rejection, as expected based on the importance of size exclusion in the rejection of solutes (van der Bruggen et al., 1999). Nevertheless, the use of M_W is frequently debated because the rejection of some OMPs has been lower than expected, based on their M_W (Chen et al., 2004; Yangali-Quintanilla et al., 2010b). Ozaki and Li (2002) indicated that, in the case of dissociated OMPs, there is no linear relationship between rejection and M_W. We believe that the discrepancy found between M_W and rejection for some (classes of) OMPs originates from the contributions of other interactions between OMPs and the membrane. Therefore, we propose in this review that the other molecular aspects shown in Fig. 3 need to be incorporated in physicochemical models of OMP removal. In this work, M_W is used to describe the size of OMPs. Nevertheless, one must consider and evaluate whether, for a
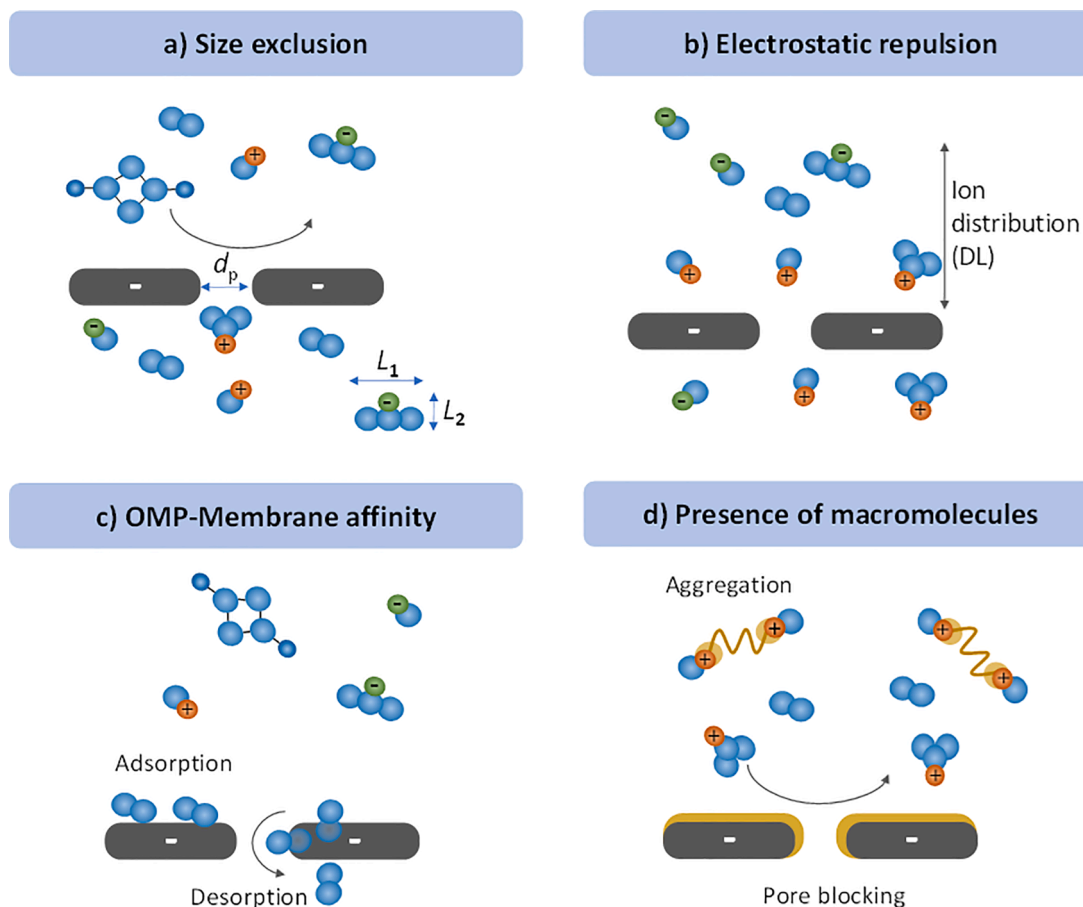
Fig. 3. Rejection mechanisms and interactions involved in the removal of OMPs. a) Particles larger than the pore diameter, d_p, are excluded based on size, e.g. molecular length, L_1, and molecular width, L_2. b) The membrane charge results in electrostatic repulsion/attraction of OMPs in the diffuse layer (DL). c) The affinity of some OMPs towards the membrane results in adsorption on the surface. d) The presence of macromolecules in solution can result in the formation of OMP-macromolecules aggregates and in pore blocking, which can improve the effect of size exclusion by reducing d_p and the increased size of the OMP-macromolecule aggregates.

specific case, M_W should be replaced with a more realistic descriptor of molecular volume or size.

Instead of using M_W, several authors have proposed using other molecular properties that describe the molecular geometry and size, such as length and width, to model OMPs (Agenson et al., 2003; Kiso et al., 2001b, 2001a). This is a promising approach that can indeed lead to improvements on the study of OMP rejection; however, there are practical challenges to be addressed before implementing this method. For instance, the definition of single size can be ambiguous, as a molecule has different dimensions, such as width, length, and height. Moreover, the estimation of these molecular dimensions relies on molecular studies that can be difficult and time demanding. Nevertheless, we have correlated M_W with a descriptor of molecular volume, the solvent excluded volume, for the OMPs used in the classification. The solvent excluded volume is the volume from which a solvent is excluded by the presence of a molecule (OMP). This volume corresponds to the van der Waals volume plus the interstitial volume (Connolly, 1983, 1985). It was calculated in Chemdraw-3D (Perkin Elmer) with the built-in property calculator. The molecular area and volume are based on a Connolly calculation with a probe (water) radius of 1.4 Å. The correlations between M_W and solvent excluded volume are given Fig. 4. The M_W correlates with the volume calculated. However, for compounds in group 2 (perfluorinated) a different correlation was found with slope $m \approx 0.50$, which means that M_W would overpredict the size of these compounds.

The repulsion of solutes due to charge offers an extra barrier, especially when size exclusion is insufficient (molecular size $\leq$ MWCO). The
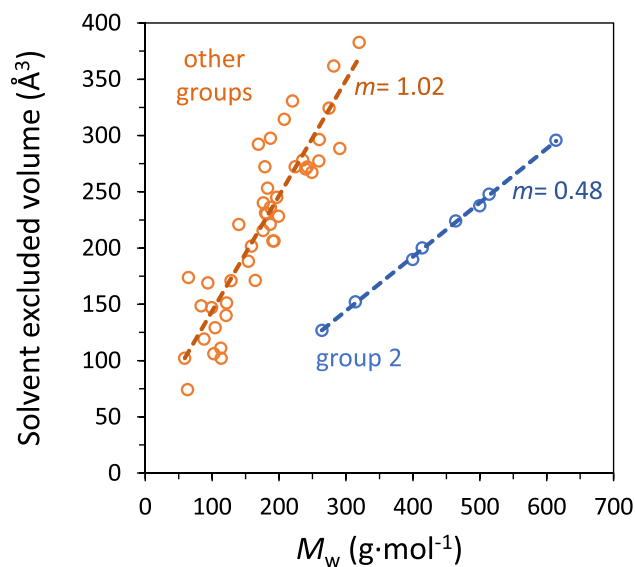

Fig. 4. The correlation between the solvent excluded volume and the M_w of different OMPs, m corresponds to the slope of the linearisation.

effect of electrostatic repulsion is dependent on the solution, membrane, and OMP properties. In general, the membrane and OMP charge will determine the distribution of solutes close to the membrane. OMPs of which the charge is of opposite sign to the membrane charge will have an increased concentration in the membrane (charge-based attraction), while OMPs with the same sign will have a decreased concentration (repulsion). However, the charge of OMPs and of the membrane surface often depend on pH and the presence of other charged compounds, because of chargeable functional groups. As a result, the precise contribution of charge repulsion or attraction to the rejection can be non-trivial and must be carefully considered based on the physicochemical characteristics of the membrane and the OMP.

The surface charge of NF and RO membranes results from the deprotonation (acid-base equilibria) of functional groups in the membrane. Therefore, the polymeric material of the membrane and the pH and composition of the solution determine the membrane charge (Hassan et al., 2007; Mänttäri et al., 2006; Mohammad et al., 2003). To study solute rejection due to electrostatic repulsion, a commonly used approach is the experimental determination of the membrane potential or zeta potential (Afonso et al., 2001; Elimelech et al., 1994; Jun et al., 2020). The zeta potential is strongly dependent on the pH and ionic strength of the solution (Afonso et al., 2001), and it is an indicator of the membrane charge; for instance, it has been used to demonstrate that the polyamide top layer of thin film composite (TFC) membranes, commercially mostly used, gives a strong negative charge to the membrane (Hurwitz et al., 2010).

Besides the membrane charge, the charge of the OMP needs to be defined. Whether an organic molecule is charged or not is determined by the solution pH and the acid or base dissociation constant of the molecule, pK_a or pK_b value (Luo and Wan, 2013), that can be inferred from the previously described classification. Furthermore, to model and calculate OMP rejection, the valence of the ionizable OMP is needed. At neutral pH, some OMPs will have multiple functional groups that can be charged, e.g., EDTA and glyphosate. In the SI, Fig. 2, we present the valence of all the micropollutants used in this study.

Finally, specific solute-membrane interactions can also significantly impact the removal of OMPs (Semião and Schäfer, 2013). Solute-membrane affinity results in adsorption at the surface. OMPs can have a particular affinity towards the membrane due to their hydrophobic character, or their hydrogen-bonding ability. In membrane characterization, the membrane's hydrophobicity is expressed by water contact angle (Hurwitz et al., 2010); the more hydrophobic a membrane is, the larger the water contact angle. For instance, Kiso et al. (2001b) discussed the effect of hydrophobicity on the rejection of pesticides and concluded that highly hydrophobic pesticides are prone to adsorb onto the membrane, which directly impacts the rejection efficiency. Moreover, Schäfer et al. (2011) recently reviewed the adsorption of estrogenic compounds, which are hydrophobic compounds and one of the most endocrine disrupting OMPs, onto polymeric membranes). They reported that adsorption of estrogens was dependent on the type of membrane polymer, the micropollutant characteristics, solution chemistry, operational conditions of the filtration process, and membrane morphology. Moreover, they concluded that the estimation of chemical interactions between polymers and micropollutants and the integration of adsorption phenomena into models are fundamental knowledge gaps.

Besides the physicochemical properties of OMPs and the membrane, the water matrix (chemistry) also plays a role in solute-membrane interactions. For instance, the presence and influence of macromolecules, such as natural organic matter (NOM) and other foulants, in the rejection of OMPs has been investigated. Yoon and Lueptow (2005) reported that competitive adsorption of NOM could outweight the effect of OMP adsorption. Schäfer et al. (2010) described that the presence of NOM or other organic substances can lead to hydrophilization of the membrane surface, which reduces the effect of hydrophobic solute-membrane interaction. Moreover, the presence of NOM has been reported to enhance the effect of size exclusion and electrostatic repulsion (Zhang

et al., 2004). Zhu (2015) reported that for membranes with a larger pore size the presence of foulants can increase the size exclusion effect of OMPs due to pore blocking. The foulant particles deposit on the membrane and can reduce the size of the pores.

The presence of macromolecules in solution not only affects solute-membrane interactions but can also induce solute-solute interactions (Azaïs et al., 2016; Kimura et al., 2009). The association of OMPs with different macromolecules can result in enhanced rejection. For instance, Xu et al. (2019) found that positively charged pharmaceuticals could be adsorbed onto humic acid (HA) molecules. Overall, the OMP-HA complex has a large number of hydrophilic groups, from the HA, which leads to enhanced rejection of the OMPs associated with the HA molecules.

The membrane and the OMP properties, sometimes dependent on the solution chemistry, can provide insight into which mechanism is predominant in the rejection of OMPs. For instance, the membrane properties can be compared with the characteristics of the groups reported in Section 2 to analyze OMP removal. For this purpose, we summarized experimental data on the rejection of OMPs using four NF membranes in Fig. 5. Although experimental studies have covered the use of RO membranes (Ebrahimzadeh et al., 2021; Zhang et al., 2020), we will limit this section to NF; mainly because there is more experimental data with NF on the 58 OMPs used in this study. In Table 2, we summarized the properties of four different thin film composite NF membranes. Pore size and MWCO are used to describe size exclusion, zeta potential for electrostatic repulsion or attraction, and water contact angle as an indicator of the hydrophobicity of the membrane. These membranes were selected because they have been the most used in experimental studies, and thus more data is available for the comparison.

Fig. 5 presents the passage values of several OMPs for different NF membranes. Passage, P_i, is the fraction of micropollutants that is not rejected by the membrane and ends up in the clean water stream. The passage relates to rejection, R_i, as $P_i = 1 - R_i$, and rejection is defined by Eq. (12). Each bar corresponds to the average passage of the groups defined in the classification; besides, the color used in Fig. 5 matches the color of the groups in Fig. 2.

The selection of the OMPs that are used for this figure is based on the available data in literature. Detailed information on the operational conditions and the micropollutant that each data point represents is given in the SI. Three different markers are used to represent different studies from literature (◊: Yangali Quintanilla et al., 2011,*: Lipp et al., 2010, ○: Fujioka et al., 2014). Direct comparison between the experimental data reported in these three studies is not possible because of differences in operating conditions. In literature, the lack of protocols with standardized conditions to test OMP removal represents a significant challenge to compare results and analyze the chemical properties and membrane characteristics that influence OMP rejection. Therefore, defining such standard conditions would be highly relevant. With a validated theoretical framework, experimental data collected under standardized conditions, can be extrapolated to determine the rejection of OMPs under other, environmentally relevant, conditions.

Below, we aim to compare and analyze the removal of OMPs based on the membrane properties and the OMP characteristics; for this purpose, we only compare experimental data from the same reference. Overall, the membranes with the smallest pore size (<0.4 nm), Desal HL and NF90, showed higher rejection than the other membranes, regardless of the charge and hydrophobicity of the membrane and the compounds, which indicates that size exclusion is a dominant parameter in the rejection of OMPs. Despite the importance of size exclusion, electrostatic repulsion and hydrophobic interactions still affect OMP removal and become more important in certain cases. For instance, the membrane Desal HL is less hydrophobic (lower water contact angle) than the membrane NF90. The difference in hydrophobicity of these two membranes could be the reason for the lower passage of cyclic-charged OMPs (group 4) with Desal HL. Compounds in this group are small (M_W [100–300] g/mol) and moderately charged; thus, the effects of size exclusion and electrostatic repulsion are less pronounced. In this
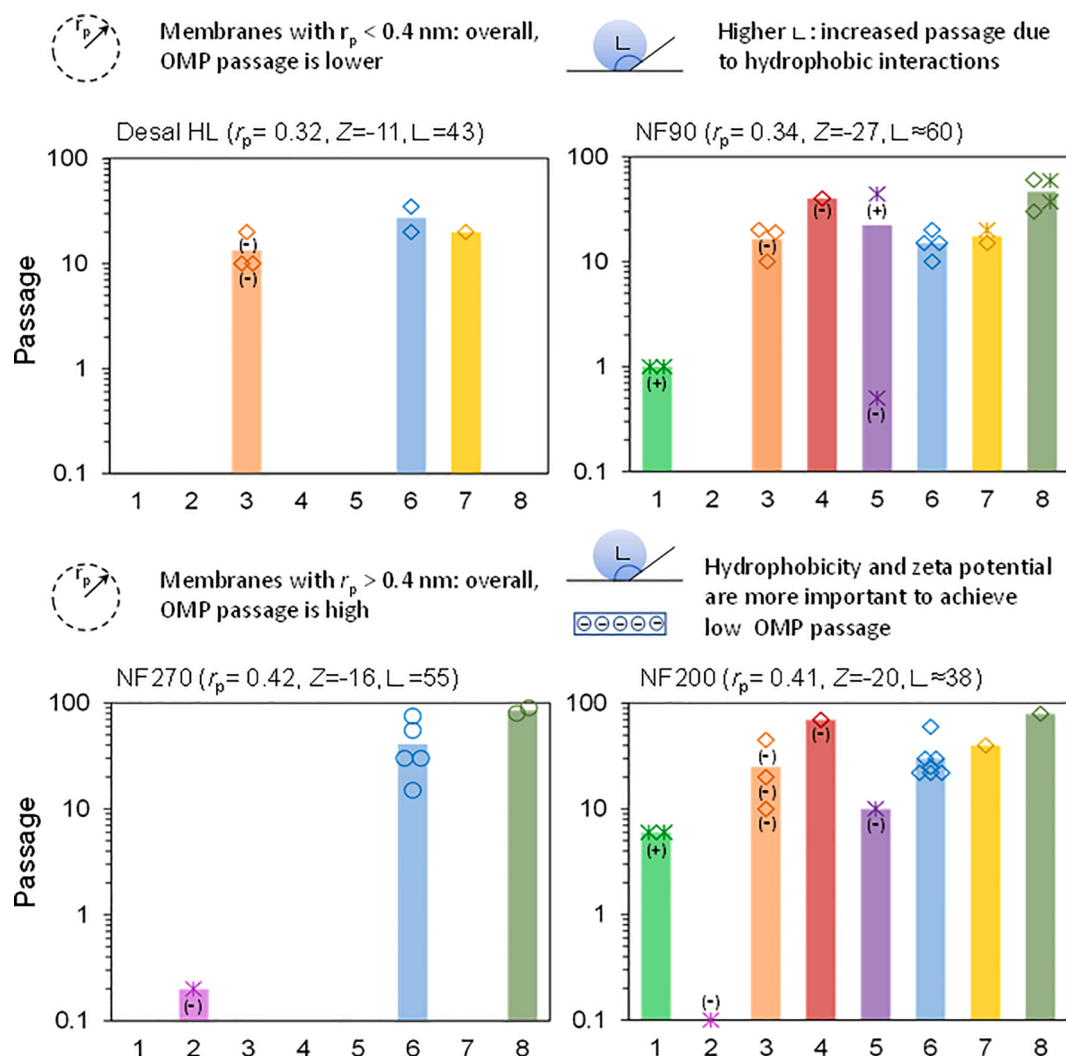
Fig. 5. Passage of OMPs with four different NF membranes, the color bars represent the average rejection of all compounds in a specific group. The symbol r_p refers to pore radius (nm), Z to zeta potential (mV), and ∟ to the water contact angle of the membrane (°). Three marker styles are used to represent different studies in literature. (◇: Yangali Quintanilla et al., 2011, *: Lipp et al., 2010, ○: Fujioka et al., 2014).

Table 2
Properties of four commercial NF membranes.

Membrane	MWCO (Da)	Pore radius (nm)	Zeta potential (mV)[1]	Water contact angle (°)
NF90	200 (Yangali Quintanilla et al., 2009)	0.34 (Schäfer et al., 2011)	−27 (Yangali Quintanilla et al., 2009)*	≈60 (Yangali Quintanilla et al., 2009)
NF200	300 (Yangali Quintanilla et al., 2009)	0.41 (Cuartas Uribe et al., 2007)	−20 (Yangali Quintanilla et al., 2009)*	≈38 (Yangali Quintanilla et al., 2009)
NF270	400 (Fujioka et al., 2014)	0.42 (Schäfer et al., 2011)	−16 (Mänttäri et al., 2004)**	55 (Nghiem, 2005)
Desal HL	150–300 (Yangali Quintanilla et al., 2009)	0.32 (Al-Amoudi et al., 2008)	−11 (Yangali Quintanilla et al., 2009)*	43 (Yangali Quintanilla et al., 2009)

[1] pH 7–8
* 10 mM KCl, 10 mM NaCl
** 10 mM KCl

scenario, hydrophobic interactions may become more relevant in the removal of OMPs. The higher hydrophobicity of the membrane NF90 could increase the concentration of partially soluble compounds in the membrane, such as the cyclic-charged, and enhance the transport through the membrane.

The membranes NF200 and NF270 are similar in pore size but have a substantially different membrane charge and hydrophobicity. The higher membrane charge and lower hydrophobicity of the membrane NF200 can be the reason for the lower passage of the perfluorinated compounds (group 2). The improved rejection of the membrane NF200 (compared to membrane NF270) is due to the fewer hydrophobic interactions between the highly hydrophobic compounds classified in group 2.

As expected from the classification, the small-polar compounds in group 8 were problematic to remove. Size exclusion and electrostatic repulsion offered by all membranes were insufficient to remove the compounds classified in this group. Interestingly, there is a large difference in passage of OMPs in group 5 with the membrane NF90. OMPs in this group are molecules with medium size and strongly charged, and therefore electrostatic repulsion becomes more important. The two compounds depicted are metformin (+) and EDTA (−). The charge of these OMPs and the negatively charged membrane explains the higher passage of metformin compared to EDTA. Therefore, determining whether an OMP is charged or not is not enough to calculate OMP rejection; instead, the valence of the ionizable OMP is needed. Considering to classify positively and negatively charged OMPs in different

groups could improve the classification of OMPs. However, in this work, with the few positively charged OMPs that are considered and the limited experimental data this step is not implemented.

The experimental data reported in previous studies cannot be used to accurately predict rejection of individual OMPs based on the membrane properties and the characteristics of the groups defined in our classification. Therefore, in future experiments, the analysis of the membrane and OMP properties should drive the selection of target compounds. Additionally, standardized conditions are needed to determine the key factors that affect the removal of OMPs with different membranes. Only in this way the validation of a theoretical framework based on OMP properties, as discussed in the next section, will be possible.

Despite the lack of experimental data to show the classification potential and fully validate the defined groups based on OMP removal data, this approach has an advantage over the traditional provenance-based classification, as it can provide a better idea of the relevant phenomena that must be included in a transport model to study a specific OMP. Nevertheless, we emphasize here that any type of classification has limitations. For instance, a narrow classification with only a few OMPs may capture the passage better, but does not allow one to draw general conclusions or to extend the conclusions to other molecules. Instead, in our classification, broad groups with multiple OMPs were identified. Therefore, the passage of some specific components may deviate from the average of its group.

4. Interfacial theory

To understand and even predict which micropollutants can be effectively removed by membrane filtration and to propose strategies to improve the rejection of certain micropollutants, an appropriate theoretical description of the membrane-based removal process is required. It is necessary to account for both the physicochemical diversity in micropollutants (Section 2) and the principal rejection mechanisms (Section 3). Rejection is an interfacial phenomenon that takes place at the boundary between solution and the membrane (Figura and Teixeira, 2007). In this section, we discuss the theoretical approaches used to study OMPs at the membrane-solution interface. Interestingly, OMPs can be roughly classified between ions and small colloids (Fig. 6), which allows us to apply approaches that are used to describe the behavior of ions and colloids at the interface. We take the main rejection mechanisms discussed in Section 3 to explain how each of these mechanisms can be considered, and we discuss possible corrections to account for micropollutant size, shape, charge, pH changes, hydrophobicity, and adsorption. Moreover, we present model calculations to illustrate the

effect of different phenomena on the concentration of OMPs inside the membrane.

To describe the concentration of species in the membrane at the boundary, the chemical potential across the membrane-solution interface is used. In equilibrium, the chemical potential μ of a solute i at both sides of the membrane interface – the solution side and the inside of the membrane – are related according to

$$\mu_{\text{ref},i} + \mu_{i,\infty}^{\text{exc}} + \mu_{i,\infty}^{\text{aff}} + \mu_{i,\infty}^{\text{mol}} + \ln(c_{i,\infty}) + z_i\phi_\infty = \mu_{\text{ref},i} + \mu_{\text{m},i}^{\text{exc}} + \mu_{\text{m},i}^{\text{aff}} + \mu_{\text{m},i}^{\text{mol}} + \ln(c_{\text{m},i}) + z_i\phi_{\text{m}} \quad (1)$$

where $\mu_{\text{ref},i}$ is a reference value of the chemical potential, μ_i^{exc} accounts for the volumetric exclusion of the solute (steric exclusion), μ_i^{aff} represents the affinity of the solute towards the membrane, μ_i^{mol} accounts for molecule-molecule interactions at the interface, z_i is the charge of the molecule, and ϕ is the electric potential to account for the electrostatic repulsion or attraction of charged solutes. In Eq. (1), the chemical potential, μ, and the electric potential, ϕ, are dimensionless. However, Eq. (1) can be multiplied by RT to arrive at unit J mol^{-1}. To calculate the concentration in the pores of the membrane, at the membrane-solution interface, we can rewrite Eq. (1) as

$$c_{i,\text{m}} = c_{i,\infty} \cdot \exp\left(-z_i\Delta\phi - \Delta\mu_i^{\text{exc}} - \Delta\mu_i^{\text{aff}} - \Delta\mu_i^{\text{mol}}\right) \quad (2)$$

where $c_{i,\text{m}}$ is the concentration inside the membrane and $c_{i,\infty}$ is the concentration of the solution. Concentrations inside the membrane are defined per unit total membrane volume. Additionally in the membrane, electro-neutrality must be considered.

$$\sum z_i c_{i,\text{m}} + X = 0 \quad (3)$$

where X is the membrane charge density. The potential terms, $\Delta\mu_i^{\text{exc}}$, $\Delta\mu_i^{\text{aff}}$, and $\Delta\mu_i^{\text{mol}}$, will be simply expressed as μ_i^{exc}, μ_i^{aff}, and μ_i^{mol}. The volumetric excess effect, μ_i^{exc}, can be defined as a steric partitioning coefficient $\Phi_{i,\text{exc}} = \exp(-\mu_i^{\text{exc}})$, which is dependent on the size of the molecules and the membrane pores.

An equation of state (EOS) can be implemented to include a realistic approximation of the porous medium, i.e., which is formed by connected and immobile beads, and to estimate μ_i^{exc} for OMPs. For instance, the Boublik-Mansoori-Carnahan-Starling-Leland (BMCSL) EOS can be used to calculate μ_i^{exc} of single spheres or multiple spheres that are connected to each other (Spruijt and Biesheuvel, 2014). With this approach, we can model a porous medium as a network of connected beads (Biesheuvel et al., 2020). To model the volumetric excess function of an OMP, modeled as a sphere, entering the porous medium, we assume tracer conditions, i.e., the volume fraction occupied by a solute i (spherical OMP) is minimal with respect to the beads that form the porous medium.
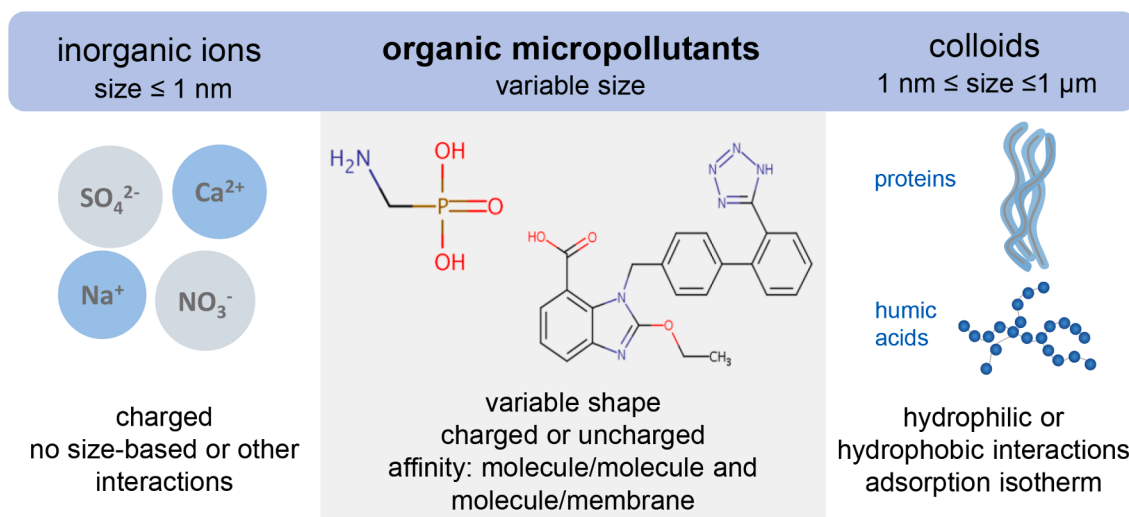

Fig. 6. Approaches used to study inorganic ions and colloids can be extended to study the interactions of OMPs at the membrane-solution interface.

Under this condition, the excess term for a spherical OMP is given by

$$\mu_i^{\text{exc}} = \frac{3\eta}{1-\eta}\alpha_i + 3\alpha_i^2\left(\ln(1-\eta) + \frac{\eta(2-\eta)}{(1-\eta)^2}\right)$$
$$- 2\alpha_i^3\left(\ln(1-\eta) + \frac{\eta(2\eta^2 - 4\eta + 1)}{(1-\eta)^3}\right) \tag{4}$$

where η is the packing degree of the porous medium, which relates to the membrane porosity, p, as $\eta = 1 - p$, and $\alpha_i = \sigma_i/\sigma_p$ represents the size ratio between the spherical OMPs and the beads of which we consider the porous medium to be formed. However, to model the porous medium as a large array of beads it is better to define the size ratio between the OMPs and the characteristic pore dimension of the porous medium, $\alpha_i' = \sigma_i/h_p$, where h_p is equal to pore volume over the area, or the inverse of the specific surface area, a_L. The characteristic pore dimension of the membrane is a much more accessible property of the membrane. This modified size ratio, α_i', relates to the size ratio in Eq. (4) as

$$\alpha_i' = \frac{6\eta}{1-\eta} \alpha. \tag{5}$$

Now, we extend the BMCSL theory to consider the shape of the OMPs. The molecular shape of OMPs can widely vary, especially for those compounds with high M_w. The molecular structure of OMPs can be represented as a number of subunits or touching beads, and this number may correspond to some of the molecule's functional groups, e.g., carboxyl, sulfonate, halogenate, benzene, etc. Therefore, in this approach, such an OMP can be envisioned as a complex of connected spheres, which we will call N-mers, e.g., dimers, trimer, or tetramers. For this situation, μ_i^{exc} of a monomer is calculated with Eq. (4); note that α_i represents the size of the monomer over the dimension of the beads of which the porous medium is formed. The chemistry and composition of each monomer are not considered.

For this approach, the number of monomers, N, or beads in an OMP needs to be defined. Approximating molecules as building blocks or beads linked together is not new (Bonomi and Camilloni, 2019). This is called mapping, and it has been used in the development of molecular dynamics simulations. For instance, in Martini coarse-grain (CG) simulations, which are normally used to study the free energy of biomolecular systems, the first step is to map the molecule to building blocks called beads. In Martini CG simulations, a single bead represents four

nonhydrogen atoms; also, some specific chemical groups such as carboxylates, esters, and aromatic and aliphatic rings are represented as a single bead (Marrink, 2007; Wassenaar, 2015). Although we do not cover molecular dynamics in this review paper, the methodology used to define the beads in CG simulations can potentially be applied to study and predict the rejection of large and complex OMPs.

In Fig. 7, we evaluate the effect of the number of monomers, N, and the packing degree of the porous media, η, on the total value of μ_i^{exc}. In Fig. 7a, μ_i^{exc} is given for molecules with identical volumes but different shape. One molecule is modeled as a sphere, $N = 1$, while the others are modeled as a dimer, a trimer, and a tetramer, $N = 2$, $N = 3$, and $N = 4$. The size of the molecule modeled as a sphere relates to the size of one monomer according to

$$d_{i,N>1} = d_o N^{-1/3} \tag{6}$$

where $d_{i,N>1}$ is the size of a monomer in the N-mer, d_o is the size of the OMP modeled as a single sphere, and N represents the number of monomers. In Fig. 7a, the results show that for OMPs with $\alpha_i'>0.5$ the value of the volumetric excess term increases with the number of monomers, i.e., a molecule that is modeled as a complex of connected monomers will be more excluded by the membrane than an OMP modeled as a single sphere ($\mu_{i,N=4}^{\text{exc}} > \mu_{i,N=3}^{\text{exc}} > \mu_{i,N=2}^{\text{exc}} > \mu_{i,N=1}^{\text{exc}}$). The size of each monomer of a complex OMP is smaller than the size of the OMP modelled as a single sphere; however, the total size of the complex OMP is larger by a factor $N^{1/3}$. Therefore, complex OMPs ($N>1$) are more excluded by the membrane.

For OMPs with $\alpha_i'<0.5$, μ_i^{exc} is similar in all the cases regardless of the number of monomers. In Fig. 7b, we evaluate the effect of η on μ_i^{exc} for dimers. Overall, the volumetric excess has small dependency on the packing degree of the membrane, and for molecules with $\alpha_i'\leq 1$ the volumetric excess is independent of η, i.e., μ_i^{exc} is the same for all the different values of η.

This novel method still needs to be validated. For instance, the model parameters that are needed in this method, i.e., η, h_p, and σ_i, should be related to membrane characteristics and molecular properties of OMPs. However, it can be a promising alternative to calculate the partitioning of OMPs, especially for large molecules. The approach presented in this work can improve estimates of the steric partitioning coefficient, because it offers a more realistic description of the porous medium, i.e., the porous medium is a dense packing of connected beads. Furthermore,
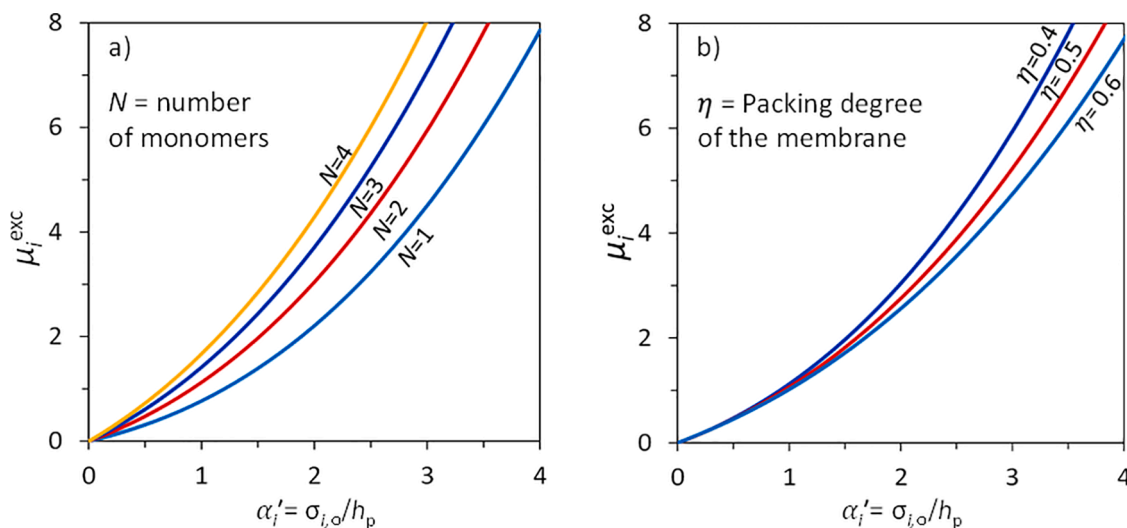

Fig. 7. The excess contribution to chemical potential calculated using the BMCSL-EOS (Eq. (4)) for molecules with N-mers. a) Molecules with the same volume but different numbers of monomers ($N = 1$, $N = 2$, $N = 3$, and $N = 4$) are evaluated with constant packing degree, $\eta=0.4$. The parameter $\sigma_{i,o}$ is the size of an OMP modeled as a single sphere and h_p is the characteristic pore dimension. b) Effect of packing degree of the membrane, η, on the excess contribution to chemical potential for dimers.

the calculation of the partitioning of OMPs with more complex structures can be improved.

In NF and RO, an appropriate model to describe the membrane-solution interface is the Donnan model (Epsztein et al., 2018; Seidel et al., 2001). With this model, the potential difference across the interface, $\phi_m - \phi_\infty$, is defined as the Donnan potential, $\Delta\phi_D$. In an ideal case where only electrostatic interactions are included and the contribution of affinity and size are neglected, this potential is only dependent on the concentration of all ionic species in solution and the membrane charge density, X. For a solution with only monovalent solutes, $z_i = \pm 1$, the Donnan potential is given by

$$\Delta\phi_D = \sinh^{-1}(\beta) \tag{7}$$

where $\beta = X/2c_\infty$. Although the pH of the solution is not implicitly included in Eq. (7), pH plays an important role in determining the Donnan potential and, hence, the electrostatic repulsion/attraction. The pH of the solution (hydronium concentration, $[H_3O^+] = 10^{-pH}$) is part of the equilibrium reactions that result in the dissociation of protons by the functional groups in the membrane, e.g., $[RCOOH] \rightleftharpoons [H_3O^+] + [RCOO^-]$. For instance, in polyamide thin film composite membranes, at low pH, the protonation of amide groups gives a positive surface charge to the membrane, while at high pH, the membrane is negatively charged due to the dissociation of carboxylic groups (see Fig. 8a).

Besides the equilibrium reaction of functional groups in the membrane, the pH affects the protonation or deprotonation of OMPs. Determining the charge of OMPs is crucial to accurately predict OMP rejection. Therefore, one should consider the acid-base equilibria to calculate the valence of charged OMPs (groups 2, 3, 4, and 5). Additionally, some OMPs, such as EDTA, have multiple ionizable groups and multiple pKa's, resulting in multivalent OMPs. For an OMP such as EDTA, we must estimate the deprotonation degree of each functional group to determine its valence and rejection. For an (acidic) ionizable group, the concentration ratio of deprotonated over protonated molecules, $[A^-/AH]$, is given by

$$\frac{[A^-]}{[AH]} = 10^{(pH - pK_a)}. \tag{8}$$

Small changes in pH can result in considerable changes of the dissociation degree of the molecules, especially for the OMPs with a pKa

value close to the bulk pH. Therefore, OMPs that would be neutrally charged in the bulk are partially charged at the interface and in the membrane, or vice versa. Changes in pH can result from the presence of amphoteric ions in solution and the potential difference across the interface. The pH difference across the membrane-solution interface is corrected by the Donnan potential

$$pH_m = pH_\infty + \frac{\Delta\phi_D}{\ln(10)}. \tag{9}$$

In Fig. 8b, the pH drop across the membrane-solution interface is presented together with the ratio of deprotonated over protonated molecules (Eq. (8)). On the x-axis, we have the distance from the membrane surface, where $d = 0$ represents the position at the membrane surface. These results were calculated for a solution with 50 mM NaCl, $3\cdot10^{-9}$ mM micropollutant, and membrane charge density $X = -100$ mM. The pH profile near the membrane is calculated with Eq. (9), evaluating the electrical potential across the interface $\phi(x)$, which was calculated with the classical Poisson-Boltzmann simplified for monovalent salts, Eq. (3.7) in Biesheuvel et al. (2020). The pKa of the OMPs determines the effect of the pH on the protonation degree. For OMPs with a pKa close to the bulk pH, a small change in pH ($\Delta pH \approx 0.2$) can strongly affect the amount of charged molecules, and therefore the effect of electrostatic repulsion. A predictive model that does not include the effect of pH on the charge of molecules would simply over (or under) predict the rejection of solutes. For instance, the change in local pH across the membrane has already proven to have an important effect on the selectivity, transport, and rejection of amphoteric ions (Biesheuvel et al., 2020).

The affinity, μ_i^{aff}, can be described as the preference of any OMP to be in the polymeric phase (membrane) rather than in the aqueous phase. A positive affinity would mean that the concentration of the OMP is higher in the membrane than in the bulk solution. Therefore, the affinity between specific solutes and the material of the membrane must be considered since it can affect the transport and rejection of solutes. The affinity term in Eq. (2) can be defined as model parameter and can be calculated by fitting transport models with experimental data. To illustrate the effect of affinity (independent variable) on the concentration of OMPs in the membrane, Eq. (2) is evaluated for a hypothetical case where only the Donnan potential and the affinity, $\Delta\phi_D$ and μ^{aff}, are
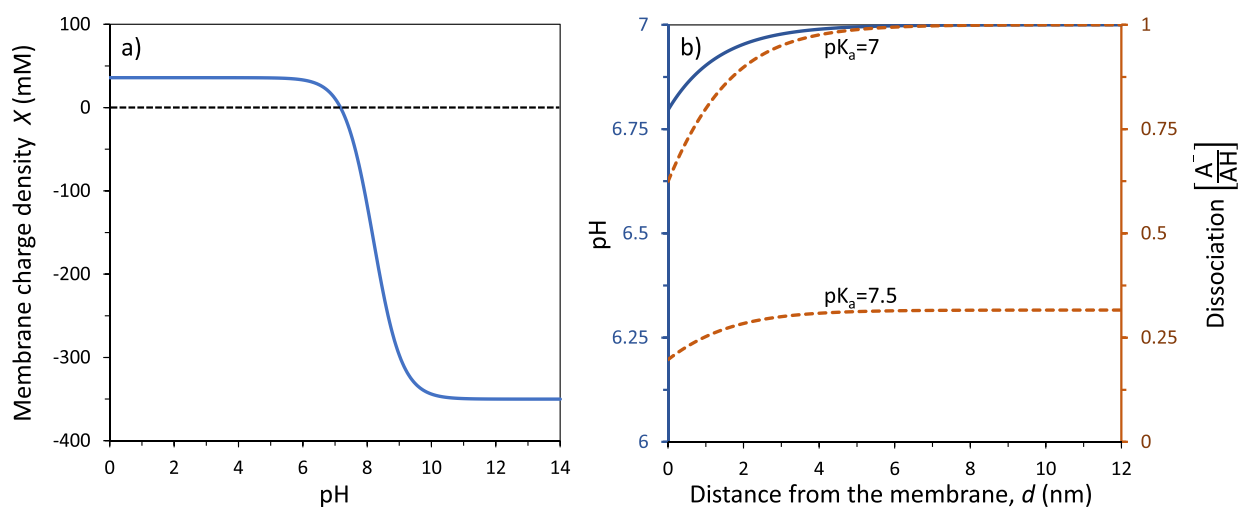

Fig. 8. a) Effect of pH on the membrane charge; pH determines the dissociation of functional groups and therefore the membrane charge. The concentration of charged functional groups in the TFC-membrane and the dissociation constants have been reported (Coronell et al., 2008); in this case we assumed that carboxylic groups have only one dissociation constant. b) The pH drop across the membrane-solution interface affects the protonation degree of OMPs. The potential across the interface is calculated for a solution with 50 mM NaCl, $3\cdot10^{-9}$ mM micropollutant, and membrane charge density $X = -100$ mM. The pH profile near the membrane is calculated with Eq. (9), evaluating the electrical potential across the interface, $\phi(x)$, which was calculated with the classical Poisson-Boltzmann simplified for monovalent salts, Eq. (3.7) in Biesheuvel et al. (2020).
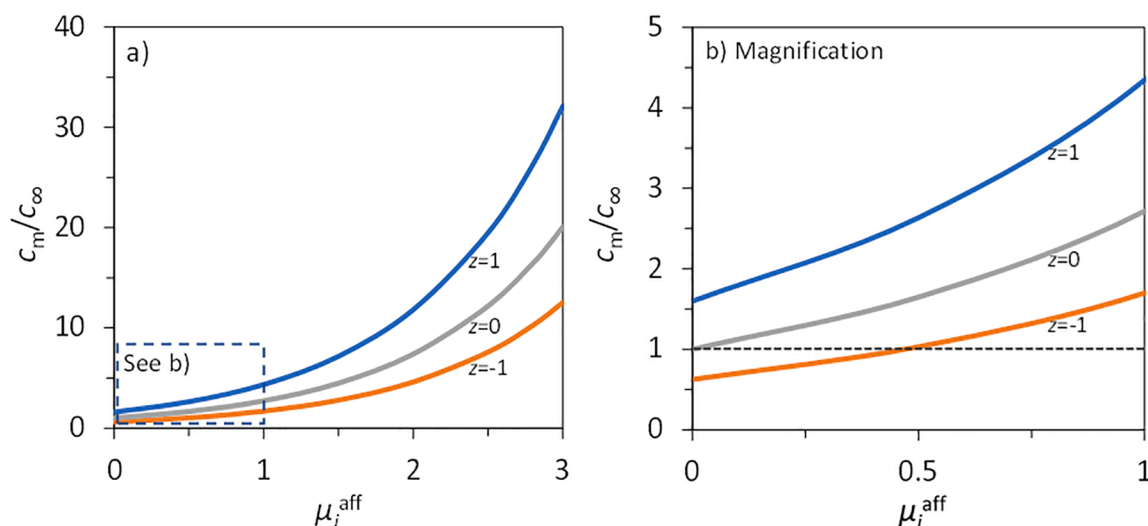
Fig. 9. Effect of OMP affinity on concentration in the membrane at the interface. A negatively charged membrane is used for the calculations. a) Ratio of the concentration in the membrane, c_m, over the concentration bulk solution, c_∞, as function of OMP affinity. b) Magnification of a) for low values of μ_i^{aff}.

considered. In Fig. 9 the increased concentration in the membrane at the interface for positive, negative, and neutral OMPs is given as function of μ_i^{aff}. For the calculation, a membrane charge of $X = -100$ mM was assumed.

In Fig. 9 the ratio between the concentration in the membrane, c_m, and the bulk, c_∞, is given as function of μ_i^{aff}. Compared with the bulk, neutrally and positively charged OMPs are always present in equal or higher concentrations in the membrane, which is not the case for negatively charged OMPs. At the surface of a negatively charged membrane, the concentration of negatively charged OMPs is lower in comparison with the bulk. Despite electrostatic repulsion, as illustrated in Fig. 9b, the concentration of negatively charged OMPs with a certain μ_i^{aff} value can increase at the surface. The affinity of co-charged OMPs can overcome the effect of electrostatic repulsion, resulting in enhanced transport through the membrane.

The Gibbs energy of interaction, ΔG_i, between the membrane and a specific solute can be used to account for the affinity of the solute towards the membrane. With ΔG_i, it is possible to calculate the partitioning coefficient, due to the affinity of OMPs, for the membrane. For instance, in a study by Semião and Schäfer (2013) the partitioning coefficient of estrogenic micropollutants is calculated by the ratio between the solute and the pore radius (steric) and a parameter $B = \frac{\Delta G_i}{kT}$ to account for interfacial interaction with the membrane. Although the authors included B as a parameter to fit the theory to experimental data, it can be experimentally determined. To calculate ΔG_i, we need to characterize the membrane and estimate the hydrophobic interactions by using contact angle experiments (Brant and Childress, 2002; Greiveldinger and Shanahan, 1999). In several studies, this experimental approach has already been used to estimate the influence of interfacial phenomena on the partitioning of solutes into the membrane (Ma et al., 2018a; Verliefde et al., 2009a).

Molecule–molecule interactions are the interactions between the micropollutants and other dissolved components, e.g., natural organic matter (NOM), other micropollutants, ions, etc. Such interactions can certainly affect the removal of OMPs. For instance, Neale and Schäfer (2012) used organic matter–water partition coefficients, K_{OM}, to study and quantify the removal of micropollutants due to OMP-NOM interaction, and they found that the removal of hormones was substantially improved by this type of interaction.

Alternatively, to account for molecule-molecule interaction between OMPs, the concept of free energy of mixing, ΔG_m, can be used which is given by the entropy and enthalpy of mixing (Young and Balsara, 2014).

At the trace concentration OMPs are present, the enthalpy of mixing can be neglected, and therefore interaction between OMPs is not likely. However, for the OMPs with extremely low solubility the molecule-molecule interactions will become more favorable, and the enthalpy term can be significant. The enthalpy of mixing is given by the concentration of OMPs and an attraction term K_{M-M}. Such an attraction term can be associated to the solubility of OMPs in water.

5. Transport principles in RO and NF

To completely describe the removal of OMPs in membrane-based processes, to quantify the fluxes of OMPs, and to estimate the concentration of OMPs in the permeate, we must consider the transport of OMPs through the membrane. In NF and RO, the transport of the solutes inside the membrane is due to diffusion, electromigration, and convection. Solutes diffuse across the membrane in response to the concentration gradients inside the membrane; it is important to mention that such a gradient is determined by the partitioning of solutes into the membrane (interfacial theory). Electromigration is the transport of charged molecules due to an electric potential difference across the membrane; convection is the transport of molecules associated to the velocity of the media (water) they are dissolved in (drag force). In this section, we provide a summary of the modeling approaches to study OMP transport in porous media and elaborate on the improvement of existing models.

Fig. 10 shows a schematic representation of the rejection and transport mechanisms involved in membrane-based processes. In this representation, 3 different mechanisms determine the partitioning of the solute inside the membrane. The different mechanisms are: (i) the steric exclusion that results in reduced concentration of big molecules (compared to the membrane pores) in the membrane; (ii) the Donnan exclusion (or attraction) of charged molecules; and (iii) the solute-membrane and molecule-molecule interactions that can lead to an increased or decreased concentration inside the membrane.

The transport models used in NF and RO mostly fall into two categories, irreversible thermodynamics (IT) and mechanistic models (Yaroshchuk et al., 2019). Former models are simpler since the membrane is seen as a "black box" and the membrane structure is not considered (Nikonenko et al., 2002). This simplified approach might be helpful to avoid complicated mathematical calculations. Among the IT models, we can find the solution-diffusion model and the Spiegler–Kedem model (Biesheuvel et al., 2022; Wang et al., 2021). In the study of OMP removal, IT models have already been considered to evaluate and
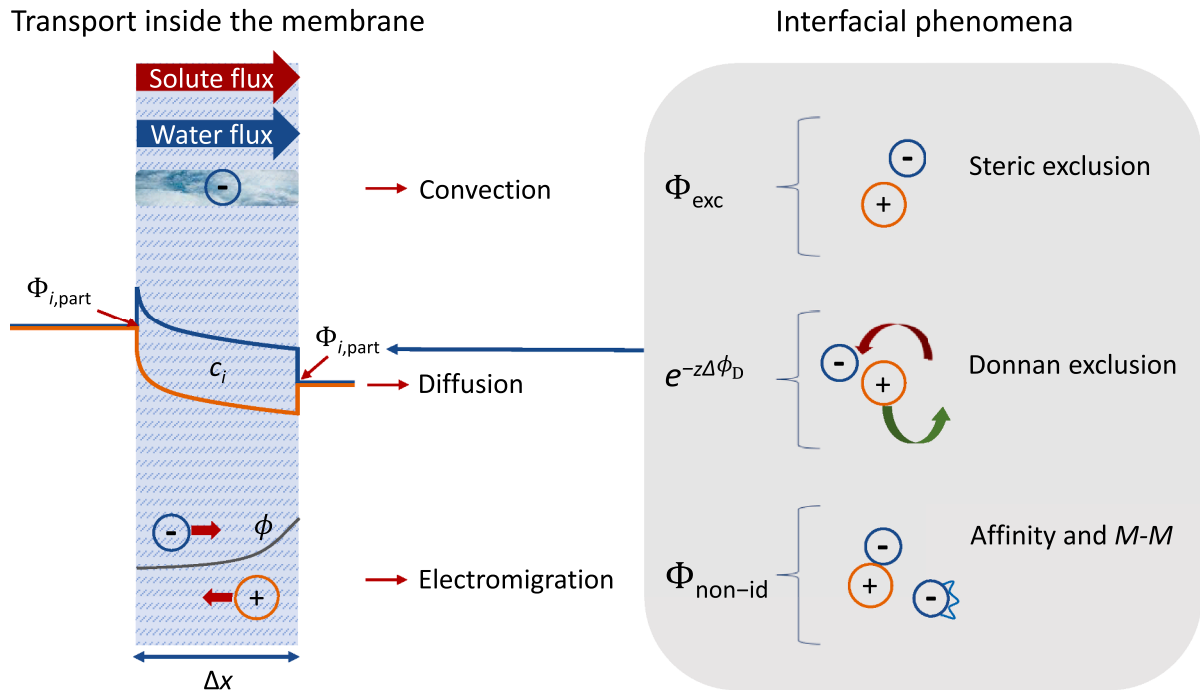
Transport inside the membrane

Interfacial phenomena

Fig. 10. Schematic representation of OMP removal with membrane-based processes. In the left part the membrane active layer (thickness Δx) is depicted with the transport mechanisms inside the membrane, i.e., convection, diffusion, and electromigration. In the right part, interfacial phenomena and rejection mechanisms at the interface are depicted, including (a) steric exclusion, (b) Donnan exclusion, and (c) other mechanisms that are related to non-idealities of OMPs. M-M stands for molecule-molecule interactions and the term affinity refers to the solute-membrane interactions.

compare the contribution of diffusion and convection in the total transport of OMPs inside the membrane (Kim et al., 2007) and to include solute-membrane interactions (Botton et al., 2012; Ma et al., 2018; Verliefde et al., 2009a, 2008). Contrary to IT models, mechanistic models do consider the inner structure and properties of the membrane allowing for a more fundamental understanding of the transport. Therefore, we will elaborate on these models.

In mechanistic models, membranes are commonly and conveniently considered as a thin layer with a specific charge and a finite nanoporous structure inside (Gross and Osterle, 1968; Jacazio et al., 1972). These porous structures can be approximated as cylindrical or slit channels with a specific diameter, and these channels exclude solutes based on size (Dechadilok and Deen, 2006a), or, as indicated in the previous section, the membrane can be seen as a network of interconnected voids (Dražević et al., 2014; Kłosowski et al., 2016; Yan et al., 2015).

To consider the membrane structure, mechanistic models can include a term to account for membrane porosity and tortuosity. This term allows to correct the fluxes and velocities per total cross-sectional area of the membrane and for the length of a tortuous non-straight pore (Oren and Biesheuvel, 2018). Another consideration in mechanistic models is that in liquid-filled pores of molecular dimensions, the transport of solutes is different from solution. Therefore, a friction factor is used to correct the transport inside the membrane. The friction factor is attributable to a combination of particle-wall and hydrodynamic interactions, and steric restrictions (Dechadilok and Deen, 2006a). In NF and RO membranes, the assumption is made that solute transport is hindered due to those steric restrictions. Therefore, solute transport is directly associated with the molecular weight and the size of the molecule.

As an example of a mechanistic model, we will discuss the extended Nernst-Planck equation (ENP). The ENP equation is derived from the Maxwell-Stefan equation and considers only the friction of solutes with the membrane and the fluid and it is extended to include hindered transport (Oren and Biesheuvel, 2018). The ENP equation describes the transport of solutes as the sum of electromigration, diffusion, and

convection. Moreover, the ENP equation accounts for the membrane characteristics by including a friction factor between the solute and the membrane, the membrane porosity, and the tortuosity. With the ENP equation, the flux J of a solute i across the membrane is given by

$$J_i = v_F K_{f,i} c_i - K_{f,i} \tau D_i \left(\frac{\partial c_i}{\partial x} + z_i c_i \frac{\partial \phi}{\partial x} \right). \tag{10}$$

The three terms on the right-hand side account for the transport due to convection, diffusion, and electric field gradient, respectively. The water velocity through the membrane is v_F, $K_{f,i}$ is a friction factor. This friction factor depends on the solute–membrane friction, and thus relates to porous medium properties and the size of the solutes. The term τ is a reduction factor dependent on membrane porosity and tortuosity, D_i is the diffusion coefficient in the bulk, and z_i represents the charge (valence) of the solute. In case the diffusion coefficient of a solute (OMP) is unknown, different correlations can be used. For instance, with the Hayduk and Laudie relation the diffusion coefficient of a solute in water can be calculated as a function of the water viscosity, ϑ_w, solute molecular weight, M_w, and density ρ (Kim et al., 2007), according to

$$D_i = \frac{\varepsilon}{(\vartheta_w)^{-1.14} \times (M_w/\rho)^{-0.589}} \tag{11}$$

where ε is a constant, $\varepsilon = 13.26 \cdot 10^{-5}$, ϑ_w is the viscosity of water (1.002 mPa·s) at 20 °C, M_w is the molecular weight of the solute (g/mol), and ρ is the density of the solute (g/cm

In previous studies, the friction factor, $K_{f,i}$, has been defined as two different hindrances factors for convection and diffusion, $K_{c,i}$ and $K_{d,i}$, which are a function of the ratio between ion size and pore diameter, λ_i, (Bandini and Vezzani, 2003; Bowen et al., 1997). With increasing ion size, $K_{d,i}$, which is always <1, goes down, while $K_{c,i}$ increases until it reaches a maximum value at certain λ_i. The calculation of the hindrance factors assumes that solutes have a sphere-like shape. However, as mentioned in previous sections, OMPs can have diverse shapes and structures; hence, the shape approximation to a sphere might be debatable. (Kiso et al., 2011) approximated OMPs as rectangular

parallelepipeds and calculated the partitioning coefficient as a function of the molecular width and length using molecular STERIMOL parameters (Harper et al., 2012), which was later used to correct the transport due to convection (Kiso et al., 2011). STERIMOL parameters are multidimensional and quantify steric demands along different principal axes of the molecule (Brethomé et al., 2019).

Coupling the ENP equation to the general Donnan equation to include solute partitioning at the interface between the membrane and the bulk results in the well-known Donnan steric pore model (DSPM) (Wang and Lin, 2021). With this model, it is possible to describe the mass transfer of charged and neutral solutes through porous media, calculate the concentration profiles inside the membrane, and calculate the concentration of solutes in the permeate side (rejection).

The DSPM model has been used to predict the rejection of OMPs by membranes. For instance, (Wang et al., 2015) used this model to predict OMP rejection in an NF process. However, they concluded that the applicability of the DSPM is limited to model the transport of those compounds that are hydrophilic and that have relatively low molecular weight. The main reason for this limitation is that the conventional DSPM model leaves out extra contributions (Castaño Osorio et al., 2022; Wang et al., 2015), such as solute-membrane affinity, to calculate the partitioning of solutes into the membrane. By including the interaction of solutes with the membrane, one can improve the accuracy of transport models to predict OMP rejection . For instance, (Verliefde et al., 2009b) compared the prediction of rejection from a model solely based on the steric exclusion and a model including the interaction of solutes with the membrane. They concluded that the model considering only steric exclusion overestimated the rejection of OMPs while including solute-membrane interactions improved the accuracy of the model. The effect of solute-membrane interactions on rejection was more pronounced for pesticides and for operating conditions employed to produce a higher permeate flux (> 6 μm·s^{-1}).

Bisphenol A (BA) is an interesting example of how model predictions of rejection can be improved with the considerations described in this review, e.g., including membrane affinity to estimate the partitioning of solutes. In experimental studies, the rejection of BA has been less than half of the value predicted by a model only based on steric exclusion (Nghiem et al., 2005). Therefore, we calculate the rejection of this OMP as function of water velocity, v_F. Rejection is defined by

$$R = 1 - \frac{c_{p,i}}{c_{f,i}} \qquad (12)$$

where $c_{p,i}$ is the concentration of a solute in the permeate (clean water), and $c_{f,i}$ the concentration in the feed. In this calculation, the model used is based on the ENP equation and the theory described in Section 4, Eqs. (2) and (10). A similar model was used in our previous work (Castaño Osorio et al., 2022). We assume the solution pH is neutral and the membrane properties correspond to the membrane NF270. At this pH the membrane is negatively charged, and BA is uncharged (pK$_a$=9.6, see S.I). Therefore, the contribution of electromigration in Eq. (10) is not considered. Moreover, the contribution of molecule-molecule interaction in Eq. (2) is not included in the calculation.

In Fig. 11, the results of BA rejection are presented. Different affinity values, μ_i^{aff}, were used to show the effect of solute-membrane affinity on the rejection of BA. The rejection progressively decreases from $\mu_i^{aff} = 0$ to $\mu_i^{aff} = 3$. Higher affinity results in an increased concentration of BA in the membrane (partitioning) and lower BA rejection. However, the affinity of a certain solute does not only impact its concentration in the membrane; in addition, the diffusion and convection can be hindered or promoted due to interaction with the membrane material. In the calculation performed for Fig. 11, the effect of membrane affinity on convection and diffusion is not yet accounted for. In further studies, the impact of affinity on the transport of solutes inside the membrane needs to be addressed. In Fig. 11, the gray star indicates the experimental value found for the rejection of BA (Nghiem et al., 2005). Including the affinity
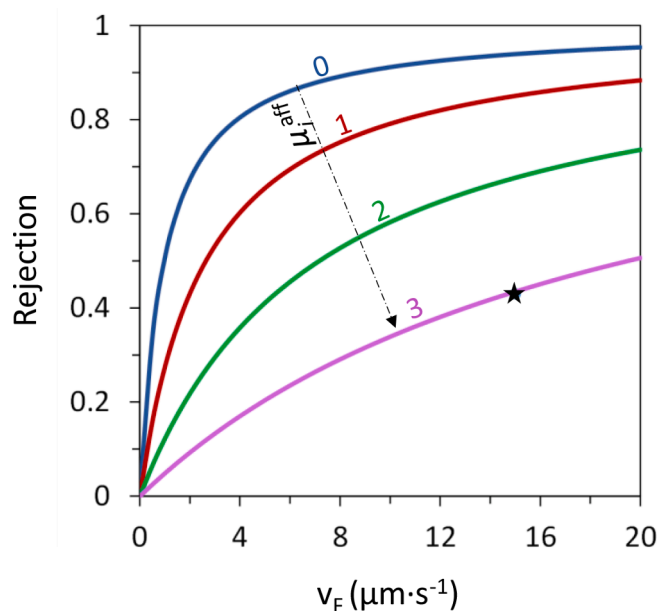

Fig. 11. Calculated rejection of bisphenol A (BA), using Eqs. (2) and (10), as a function of the water velocity, v_F, and the affinity, μ_i^{aff}. The gray star indicates the experimental value of BA rejection with $v_F = 15$ μm·s^{-1} (Nghiem et al., 2005). The DSPM model was used for these model calculations, Eqs. (1)–(6) in Castaño Osorio et al. (2022). Other model parameters used in the calculation are, $X=-100$ mM, $\sigma_{BA}=0.428$ nm, $\Phi_{BA}=3.63\cdot10^{-4}$, and $D_{BA} =5.08\cdot10^{-10}$ m^{2}s^{-1}.

contribution in the partitioning of BA into the membrane improves the prediction of rejection, compared to the experimentally determined rejection of BA.

Accurate models to predict OMP removal must consider the three main rejection mechanisms involved during NF and RO processes: size exclusion, electrostatic repulsion, and solute-membrane interactions (Azaïs et al., 2016; Kimura et al., 2009; Kiso et al., 2001b, 2001a; Schäfer et al., 2011; Semião et al., 2013; van der Bruggen et al., 1999; Xu et al., 2019; Yoon and Lueptow, 2005; Zhang et al., 2004; Zhu, 2015). Moreover, solute-solute interactions because of electrostatic interactions (pH-dependent), steric effects, and solute-solute affinity also play a role. Conventional models successfully account for the electrostatic repulsion of charged solutes; however, extra effort is required to improve the estimation of size exclusion of large OMPs with irregular shape and to integrate the solute-membrane interaction in the models. In Section 4, to estimate the partitioning of OMPs, we have elaborated on improved approaches to account for steric exclusion and to include the solute affinity, these approaches can be included in the transport theory to allow for more accurate predictions of OMP removal. For instance, in the DSPM model the partitioning at the membrane edges will not only include the size, but also the effect of solute-membrane interactions. Moreover, solute-membrane interactions can be included in the correction of transport due to convection (Kiso et al., 2011). In future research, the model parameters defined in the theoretical approach in Section 4 and 5 can be related to molecular properties of OMPs to determine any correlation and ease the study of OMP removal.

6. Conclusions

To address the problem of OMPs in drinking water production, there is a need for models to predict OMP removal in membrane-based processes. One of the main challenges in OMP removal is the vast number of compounds classified as OMPs, and their differences in molecular properties, e.g., size, charge, structure, and functional groups. However, a first step to ease this problem is by implementing a classification of

OMPs based on key molecular properties, and such a classification will allow us to identify different groups of OMPs.

Nonetheless, the classification of OMPs does not address modeling OMP removal in NF and RO. Although several authors have tried to address this problem, the lack of robust models based on physicochemical principles remains another knowledge gap. This review examined several possibilities to extend existing models and study the behavior and fate of OMPs in NF and RO.

From this review the following considerations for future studies and conclusions can be drawn:

- A classification based on molecular properties can be beneficial for the validation of theories like the ones that we discussed in this review. With this sort of classification, it is possible to define the main mechanisms involved in the rejection of OMPs in a specific group, which can provide a more fundamental understanding of the process and facilitate the development of new models. However, the limited experimental data to vindicate this classification is a major issue. Therefore, in future studies, it is important to consider the molecular properties of the OMPs in the selection of model compounds in experimental and theoretical studies. Only in this way a classification as the one proposed in this study can be validated.
- The classification does not provide a quantitative prediction of the rejection. However, it provides more relevant information, compared to provenance-based classifications, on the phenomena that affect OMP removal with certain membranes, and on the OMPs that represent a challenge for removal.
- One challenge for the validation of the given classification and for comparison of relevant experimental data was the lack of standardized operating conditions. It is important for the field to develop experimental protocols that provide well established conditions to test the rejection of OMPs with different membranes.
- To validate the relevance and applicability of the classification of OMPs, it is needed to evaluate the rejection of the compounds classified in the same group to determine whether their removal is similar.
- Steric effects are crucial to determine the removal of OMPs. In this work, the use of the BMCSL EOS is proposed to account for such effects. Although this theoretical approach is not new, it has not been used in the study of OMP removal yet. Therefore, future work must explore the potential of this approach for OMP removal.
- The membrane characteristics and the chemistry of the solution influence the rejection mechanisms and the interfacial phenomena in NF and RO. Therefore, predictive models need to be extended to consider the pH, interaction between the OMPs with macromolecules and different ions in solution, the properties of OMPs, and different membrane characteristics, such as pore size, and hydrophobicity.
- The estimation of solute-membrane affinity is crucial to model OMP removal. However, conducting experimental tests for all possible solute-membrane combinations is time demanding. New approaches must be used to determine solute-membrane affinity and relate affinity with the membrane and OMP properties. Besides, it is important to resolve whether the affinities of OMPs classified in a specific group are relatively similar.
- Transport models to study NF and RO can be extended to include various phenomena that affect the rejection of OMPs with specific characteristics. Based on physicochemical properties of the OMP, the membrane characteristics, and the solution composition one can decide whether specific mechanisms are important to be included in a transport model.

Declaration of Competing Interest

None.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.watres.2022.119130.

References

Afonso, M.D., Hagmeyer, G., Gimbel, R., 2001. Streaming potential measurements to assess the variation of nanofiltration membranes surface charge with the concentration of salt solutions. Sep. Purif. Technol. 22–23, 529–541. https://doi.org/10.1016/S1383-5866(00)00135-0.

Agenson, K.O., Oh, J.I., Urase, T., 2003. Retention of a wide variety of organic pollutants by different nanofiltration/reverse osmosis membranes: controlling parameters of process. J. Membr. Sci. 225, 91–103. https://doi.org/10.1016/j.memsci.2003.08.006.

Al-Amoudi, A., Williams, P., Al-Hobaib, A.S., Lovitt, R.W., 2008. Cleaning results of new and fouled nanofiltration membrane characterized by contact angle, updated DSPM, flux and salts rejection. Appl. Surf. Sci. 254, 3983–3992. https://doi.org/10.1016/j.apsusc.2007.12.052.

Albergamo, V., Blankert, B., Cornelissen, E.R., Hofs, B., Knibbe, W.J., van der Meer, W.G. J., de Voogt, P., 2019. Removal of polar organic micropollutants by pilot-scale reverse osmosis drinking water treatment. Water Res. 148, 535–545. https://doi.org/10.1016/j.watres.2018.09.029.

Albergamo, V., Blankert, B., van der Meer, W.G.J., de Voogt, P., Cornelissen, E.R., 2020. Removal of polar organic micropollutants by mixed-matrix reverse osmosis membranes. Desalination 479, 114337. https://doi.org/10.1016/j.desal.2020.114337.

Ates, H., Argun, M.E., 2021. Advanced oxidation of landfill leachate : removal of micropollutants and identification of by-products. J. Hazard Mater. 413, 125326. https://doi.org/10.1016/j.jhazmat.2021.125326.

Azaïs, A., Mendret, J., Petit, E., Brosillon, S., 2016. Evidence of solute-solute interactions and cake enhanced concentration polarization during removal of pharmaceuticals from urban wastewater by nanofiltration. Water Res. 104, 156–167. https://doi.org/10.1016/j.watres.2016.08.014.

Bandini, S., Vezzani, D., 2003. Nanofiltration modeling: the role of dielectric exclusion in membrane characterization. Chem. Eng. Sci. 58, 3303–3326. https://doi.org/10.1016/S0009-2509(03)00212-4.

Barbosa, M.O., Moreira, N.F.F., Ribeiro, A.R., Pereira, M.F.R., Silva, A.M.T., 2016. Occurrence and removal of organic micropollutants: an overview of the watch list of EU Decision 2015/495. Water Res. 94, 257–279. https://doi.org/10.1016/j.watres.2016.02.047.

Bellona, C., Budgell, K., Ball, D., Spangler, K., Drewes, J., Chellam, S., 2011. Models to predict organic contaminant removal by RO and NF membranes. IDA J. Desalin. Water Reuse 3, 40–44. https://doi.org/10.1179/ida.2011.3.2.40.

Benner, J., Helbling, D.E., Kohler, H.P.E., Wittebol, J., Kaiser, E., Prasse, C., Ternes, T.A., Albers, C.N., Aamand, J., Horemans, B., Springael, D., Walravens, E., Boon, N., 2013. Is biological treatment a viable alternative for micropollutant removal in drinking water treatment processes? Water Res. 47, 5955–5976. https://doi.org/10.1016/j.watres.2013.07.015.

Biesheuvel, P.M., Porada, S., Elimelech, M., Dykstra, J.E., 2022. Tutorial review of reverse osmosis and electrodialysis. J. Memb. Sci. 647, 120221 https://doi.org/10.1016/j.memsci.2021.120221.

Biesheuvel, P.M., Zhang, L., Gasquet, P., Blankert, B., Elimelech, M., van der Meer, W.G. J., 2020. Ion selectivity in brackish water desalination by reverse osmosis: theory, measurements, and implications. Environ. Sci. Technol. Lett. 7, 42–47. https://doi.org/10.1021/acs.estlett.9b00686.

Bonomi, M, Camilloni, C, 2019. Biomolecular Simulations : Methods and Protocols. Humana Press, New York.

Botton, S., Verliefde, A.R.D., Quach, N.T., Cornelissen, E.R., 2012. Influence of biofouling on pharmaceuticals rejection in NF membrane filtration. Water Res. 46, 5848–5860. https://doi.org/10.1016/j.watres.2012.07.010.

Boussu, K., Vandecasteele, C., van der Bruggen, B., 2008. Relation between membrane characteristics and performance in nanofiltration. J. Memb. Sci 310, 51–65. 10.1016/j.memsci.2007.10.030.

Bowen, W.R., Mohammad, A.W., Hilal, N., 1997. Characterisation of nanofiltration membranes for predictive purposes - use of salts, uncharged solutes and atomic force microscopy. J. Memb. Sci. 126, 91–105. https://doi.org/10.1016/S0376-7388(96)00276-1.

Bowen, W.R., Mukhtar, H., 1996. Characterisation and prediction of separation performance of nanofiltration membranes. J. Memb. Sci. 112, 263–274. https://doi.org/10.1016/0376-7388(95)00302-9.

Brant, J.A., Childress, A.E., 2002. Assessing short-range membrane-colloid interactions using surface energetics. J. Memb. Sci. 203, 257–273. https://doi.org/10.1016/S0376-7388(02)00014-5.

Brethomé, A.V., Fletcher, S.P., Paton, R.S., 2019. Conformational effects on physical-organic descriptors: the case of sterimol steric parameters. ACS Catal. 9, 2313–2323. https://doi.org/10.1021/acscatal.8b04043.

Castaño Osorio, S., Biesheuvel, P.M., Dykstra, J.E., Virga, E., 2022. Nanofiltration of complex mixtures: The effect of the adsorption of divalent ions on membrane retention. Desalination 527, 115552. https://doi.org/10.1016/j.desal.2022.115552.

Chen, S.S., Taylor, J.S., Mulford, L.A., Norris, C.D., 2004. Influences of molecular weight, molecular size, flux, and recovery for aromatic pesticide removal by nanofiltration membranes. Desalination 160, 103–111. https://doi.org/10.1016/S0011-9164(04)90000-8.

Connolly, M.L., 1983. Analytical Molecular Surface Calculation. J. App. Cryst 16, 548–558. https://doi.org/10.1107/S0021889883010985.

Connolly, M.L., 1985. Computation of Molecular Volume. J. Am. Chem. Soc. 107, 1118–1124. https://doi.org/10.1021/ja00291a006.

Coronell, O., Mariñas, B.J., Zhang, X., Cahill, D.G., 2008. Quantification of functional groups and modeling of their ionization behavior in the active layer of FT30 reverse osmosis membrane. Environ. Sci. Technol. 42, 5260–5266. https://doi.org/10.1021/es8002712.

Cuartas Uribe, B., Alcaina-Miranda, M.I., Soriano-Costa, E., Bes-Piá, A., 2007. Comparison of the behavior of two nanofiltration membranes for sweet whey demineralization. J. Dairy Sci. 90, 1094–1101. https://doi.org/10.3168/jds.S0022-0302(07)71596-5.

De Grooth, J., Reurink, D.M., Ploegmakers, J., de Vos, W.M., Nijmeijer, K., 2014. Charged micropollutant removal with hollow fiber nanofiltration membranes based on polycation/polyzwitterion/polyanion multilayers. ACS Appl. Mater. Interfaces 6, 17009–17017. https://doi.org/10.1021/am504630a.

De Ridder, D.J., Villacorte, L., Verliefde, A.R.D., Verberk, J.Q.J.C., Heijman, S.G.J., Amy, G.L., van Dijk, J.C., 2010. Modeling equilibrium adsorption of organic micropollutants onto activated carbon. Water Res. 44, 3077–3086. https://doi.org/10.1016/j.watres.2010.02.034.

Dechadilok, P., Deen, W.M., 2006a. Hindrance factors for diffusion and convection in pores. Ind. Eng. Chem. Res. 45, 6953–6959. https://doi.org/10.1021/ie051387n.

Dražević, E., Košutić, K., Kolev, V., Freger, V., 2014. Does hindered transport theory apply to desalination membranes? Environ. Sci. Technol. 48, 11471–11478. https://doi.org/10.1021/es502085p.

Ebrahimzadeh, S., Wols, B., Azzellino, A., Martijn, B.J., van der Hoek, J.P., 2021. Quantification and modelling of organic micropollutant removal by reverse osmosis (RO) drinking water treatment. J. Water Process Eng. 42, 102164 https://doi.org/10.1016/j.jwpe.2021.102164.

Elimelech, M., Chen, W.H., Waypa, J.J., 1994. Measuring the zeta (electrokinetic) potential of reverse osmosis membranes by a streaming potential analyzer. Desalination 95, 269–286. https://doi.org/10.1016/0011-9164(94)00064-6.

Epsztein, R., Shaulsky, E., Dizge, N., Warsinger, D.M., Elimelech, M., 2018. Role of ionic charge density in Donnan exclusion of monovalent anions by nanofiltration. Environ. Sci. Technol. 52, 4108–4116. https://doi.org/10.1021/acs.est.7b06400.

Figuière, R., Waara, S., Ahrens, L., Golovko, O., 2022. Risk-based screening for prioritisation of organic micropollutants in Swedish freshwater. J. Hazard. Mater. 429, 128302 https://doi.org/10.1016/j.jhazmat.2022.128302.

Figura, L, Teixeira, A, 2007. *Food physics: physical properties-measurement and applications*. Springer Science & Business Media.

Fujioka, T., Khan, S.J., McDonald, J.A., Nghiem, L.D., 2014. Nanofiltration of trace organic chemicals: a comparison between ceramic and polymeric membranes. Sep. Purif. Technol. 136, 258–264. https://doi.org/10.1016/j.seppur.2014.08.039.

Greiveldinger, M., Shanahan, M.E.R., 1999. A critique of the mathematical coherence of acid/base interfacial free energy theory. J. Colloid Interface Sci. 215, 170–178. https://doi.org/10.1006/jcis.1999.6259.

Gross, R.J., Osterle, J.F., 1968. Membrane transport characteristics of ultrafine capillaries. J. Chem. Phys. 49, 333–339. https://doi.org/10.1063/1.1669814.

Harper, K.C., Bess, E.N., Sigman, M.S., 2012. Multidimensional steric parameters in the analysis of asymmetric catalytic reactions. Nat. Chem. 4, 366–374. https://doi.org/10.1038/nchem.1297.

Hassan, A.R., Ali, N., Abdull, N., Ismail, A.F., 2007. A theoretical approach on membrane characterization: the deduction of fine structural details of asymmetric nanofiltration membranes. Desalination 206, 107–126. https://doi.org/10.1016/j.desal.2006.06.008.

Hurwitz, G., Guillen, G.R., Hoek, E.M.V., 2010. Probing polyamide membrane surface charge, zeta potential, wettability, and hydrophilicity with contact angle measurements. J. Memb. Sci. 349, 349–357. https://doi.org/10.1016/j.memsci.2009.11.063.

Jacazio, G., Probstein, R.F., Sonin, A.A., Yung, D., 1972. Electrokinetic salt rejection in hyperfiltration through porous materials. Theory and experiment. J. Phys. Chem. 76, 4015–4023. https://doi.org/10.1021/j100670a023.

Jin, X., Peldszus, S., 2012. Selection of representative emerging micropollutants for drinking water treatment studies : a systematic approach. Sci. Total Environ. 414, 653–663. https://doi.org/10.1016/j.scitotenv.2011.11.035.

Jun, B.M., Cho, J., Jang, A., Chon, K., Westerhoff, P., Yoon, Y., Rho, H., 2020. Charge characteristics (surface charge vs. zeta potential) of membrane surfaces to assess the salt rejection behavior of nanofiltration membranes. Sep. Purif. Technol. 247 https://doi.org/10.1016/j.seppur.2020.117026.

Khanzada, N.K., Farid, M.U., Kharraz, J.A., Choi, J., Tang, C.Y., Nghiem, L.D., Jang, A., An, A.K., 2020. Removal of organic micropollutants using advanced membrane-based water and wastewater treatment: a review. J. Memb. Sci. 598, 117672 https://doi.org/10.1016/j.memsci.2019.117672.

Kim, T.U., Drewes, J.E., Scott Summers, R., Amy, G.L., 2007. Solute transport model for trace organic neutral and charged compounds through nanofiltration and reverse osmosis membranes. Water Res. 41, 3977–3988. https://doi.org/10.1016/j.watres.2007.05.055.

Kimura, K., Iwase, T., Kita, S., Watanabe, Y., 2009. Influence of residual organic macromolecules produced in biological wastewater treatment processes on removal of pharmaceuticals by NF/RO membranes. Water Res. 43, 3751–3758. https://doi.org/10.1016/j.watres.2009.05.042.

Kimura, K., Toshima, S., Amy, G., Watanabe, Y., 2004. Rejection of neutral endocrine disrupting compounds (EDCs) and pharmaceutical active compounds (PhACs) by RO membranes. J. Memb. Sci. 245, 71–78. https://doi.org/10.1016/j.memsci.2004.07.018.

Kiso, Y., Kon, T., Kitao, T., Nishimura, K., 2001a. Rejection properties of alkyl phthalates with nanofiltration membranes. J. Memb. Sci. 182, 205–214. https://doi.org/10.1016/S0376-7388(00)00567-6.

Kiso, Y., Muroshige, K., Oguchi, T., Hirose, M., Ohara, T., Shintani, T., 2011. Pore radius estimation based on organic solute molecular shape and effects of pressure on pore radius for a reverse osmosis membrane. J. Memb. Sci. 369, 290–298. https://doi.org/10.1016/j.memsci.2010.12.005.

Kiso, Y., Sugiura, Y., Kitao, T., Nishimura, K., 2001b. Effects of hydrophobicity and molecular size on rejection of aromatic pesticides with nanofiltration membranes. J. Memb. Sci. 192, 1–10. https://doi.org/10.1016/S0376-7388(01)00411-2.

Kłosowski, M.M., McGilvery, C.M., Li, Y., Abellan, P., Ramasse, Q., Cabral, J.T., Livingston, A.G., Porter, A.E., 2016. Micro-to nano-scale characterisation of polyamide structures of the SW30HR RO membrane using advanced electron microscopy and stain tracers. J. Memb. Sci. 520, 465–476. https://doi.org/10.1016/j.memsci.2016.07.063.

Lai, W.W.P., Lin, Y.C., Tung, H.H., Lo, S.L., Lin, A.Y.C., 2016. Occurrence of pharmaceuticals and perfluorinated compounds and evaluation of the availability of reclaimed water in Kinmen. Emerg. Contam. 2, 135–144. https://doi.org/10.1016/j.emcon.2016.05.001.

Lee, C.O., Howe, K.J., Thomson, B.M., 2012. Ozone and biofiltration as an alternative to reverse osmosis for removing PPCPs and micropollutants from treated wastewater. Water Res. 46, 1005–1014. https://doi.org/10.1016/j.watres.2011.11.069.

Libotean, D., Giralt, J., Rallo, R., Cohen, Y., Giralt, F., Ridgway, H.F., Rodriguez, G., Phipps, D., 2008. Organic compounds passage through RO membranes. J. Membr. Sci. 313, 23–43. https://doi.org/10.1016/j.memsci.2007.11.052.

Licona, K.P.M., Geaquinto, L.R.D.O., Nicolini, J.V., Figueiredo, N.G., Chiapetta, S.C., Habert, A.C., Yokoyama, L., 2018. Assessing potential of nanofiltration and reverse osmosis for removal of toxic pharmaceuticals from water. J. Water Process Eng. 25, 195–204. https://doi.org/10.1016/j.jwpe.2018.08.002.

Lipp, P., Sacher, F., Baldauf, G., 2010. Removal of organic micro-pollutants during drinking water treatment by nanofiltration and reverse osmosis. Desalin. Water Treat. 13, 226–237. https://doi.org/10.5004/dwt.2010.1063.

Liu, Z., Kanjo, Y., Mizutani, S., 2009. Removal mechanisms for endocrine disrupting compounds (EDCs) in wastewater treatment - physical means, biodegradation, and chemical advanced oxidation: a review. Sci. Total Environ. 407, 731–748. https://doi.org/10.1016/j.scitotenv.2008.08.039.

Luo, J., Wan, Y., 2013. Effects of pH and salt on nanofiltration-a critical review. J. Memb. Sci. 438, 18–28. https://doi.org/10.1016/j.memsci.2013.03.029.

Luo, Y., Guo, W., Ngo, H.H., Nghiem, L.D., Hai, F.I., Zhang, J., Liang, S., Wang, X.C., 2014. A review on the occurrence of micropollutants in the aquatic environment and their fate and removal during wastewater treatment. Sci. Total Environ. 473, 619–641. https://doi.org/10.1016/j.scitotenv.2013.12.065.

Ma, L., Gutierrez, L., Vanoppen, M., Lorenz, D.N., Aubry, C., Verliefde, A.R.D., 2018a. Transport of uncharged organics in ion-exchange membranes: experimental validation of the solution-diffusion model. J. Memb. Sci. 564, 773–781. https://doi.org/10.1016/j.memsci.2018.07.029.

Ma, X.Y., Li, Q., Wang, X.C., Wang, Y., Wang, D., Ngo, H.H., 2018b. Micropollutants removal and health risk reduction in a water reclamation and ecological reuse system. Water Res. 138, 272–281. https://doi.org/10.1016/j.watres.2018.03.059.

Mänttäri, M., Pekuri, T., Nyström, M., 2004. NF270, a new membrane having promising characteristics and being suitable for treatment of dilute effluents from the paper industry. J. Membr. Sci. 242, 107–116. https://doi.org/10.1016/j.memsci.2003.08.032.

Mänttäri, M., Pihlajamäki, A., Nyström, M., 2006. Effect of pH on hydrophilicity and charge and their effect on the filtration efficiency of NF membranes at different pH. J. Membr. Sci. 280, 311–320. https://doi.org/10.1016/j.memsci.2006.01.034.

Marrink, S.J., et al., 2007. The MARTINI force field: coarse grained model for biomolecular simulations. J. Phys. Chem. B 111 (27), 7812–7824. https://doi.org/10.1021/jp071097f.

Mead, R.N., Morgan, J.B., Avery, G.B., Kieber, R.J., Kirk, A.M., Skrabal, S.A., Willey, J.D., 2009. Occurrence of the artificial sweetener sucralose in coastal and marine waters of the United States. Mar. Chem. 116, 13–17. https://doi.org/10.1016/j.marchem.2009.09.005.

Mestankova, H., Parker, A.M., Bramaz, N., Canonica, S., Schirmer, K., von Gunten, U., Linden, K.G., 2016. Transformation of Contaminant Candidate List (CCL3) compounds during ozonation and advanced oxidation processes in drinking water: assessment of biological effects. Water Res. 93, 110–120. https://doi.org/10.1016/j.watres.2015.12.048.

Mohammad, A.W., Hilal, N., Nizam Abu Seman, M., 2003. A study on producing composite nanofiltration membranes with optimized properties. Desalination 158, 73–78. https://doi.org/10.1016/S0011-9164(03)00435-1.

Möller, A., Ahrens, L., Surm, R., Westerveld, J., van der Wielen, F., Ebinghaus, R., de Voogt, P., 2010. Distribution and sources of polyfluoroalkyl substances (PFAS) in the River Rhine watershed. Environ. Pollut. 158, 3243–3250. https://doi.org/10.1016/j.envpol.2010.07.019.

Nam, S., Jo, B., Yoon, Y., Zoh, K., 2014. Occurrence and removal of selected micropollutants in a water treatment plant. Chemosphere 95, 156–165. https://doi.org/10.1016/j.chemosphere.2013.08.055.

Neale, P.A., Schäfer, A.I., 2012. Quantification of solute-solute interactions in steroidal hormone removal by ultrafiltration membranes. Sep. Purif. Technol. 90, 31–38. https://doi.org/10.1016/j.seppur.2012.02.011.

Nghiem, L.D., Schäfer, A.I., Elimelech, M., 2005. Nanofiltration of hormone mimicking trace organic contaminants. Sep. Sci. Technol. 40, 2633–2649. https://doi.org/10.1080/01496390500283340.

Nghiem, L.D., 2005. Removal of Emerging Trace Organic Contaminants By Nanofiltration and Reverse Osmosis e. University of Wollongong By Long Duc Nghiem Faculty of Engineering. University of Wollongong.

Nghiem, L.D., Schäfer, A.I., Elimelech, M., 2004. Removal of natural hormones by nanofiltration membranes: measurement, modeling and mechanisms. Environ. Sci. Technol. 38, 1888–1896. https://doi.org/10.1021/es034952r.

Nikonenko, V., Zabolotsky, V., Larchet, C., Auclair, B., Pourcelly, G., 2002. Mathematical description of ion transport in membrane systems. Desalination 147, 369–374. https://doi.org/10.1016/S0011-9164(02)00611-2.

Oppenheimer, J., Eaton, A., Badruzzaman, M., Haghani, A.W., Jacangelo, J.G., 2011. Occurrence and suitability of sucralose as an indicator compound of wastewater loading to surface waters in urbanized regions. Water Res. 45, 4019–4027. https://doi.org/10.1016/j.watres.2011.05.014.

Oren, Y.S., Biesheuvel, P.M., 2018. Theory of ion and water transport in reverse-osmosis membranes. Phys. Rev. Appl. 9, 24034. https://doi.org/10.1103/PhysRevApplied.9.024034.

Otero, J.A., Mazarrasa, O., Villasante, J., Silva, V., Prádanos, P., Calvo, J.I., Hernández, A., 2008. Three independent ways to obtain information on pore size distributions of nanofiltration membranes. J. Membr. Sci. 309, 17–27. https://doi.org/10.1016/j.memsci.2007.09.065.

Ozaki, H., Li, H., 2002. Rejection of organic compounds by ultra-low pressure reverse osmosis membrane. Water Res. 36, 123–130. https://doi.org/10.1016/S0043-1354(01)00197-X.

Piai, L., Dykstra, J.E., Adishakti, M.G., Blokland, M., Langenhoff, A.A.M., van der Wal, A., 2019. Diffusion of hydrophilic organic micropollutants in granular activated carbon with different pore sizes. Water Res. 162, 518–527. https://doi.org/10.1016/j.watres.2019.06.012.

Piai, L., Langenhoff, A., Jia, M., de Wilde, V., van der Wal, A., 2021. Prolonged lifetime of biological activated carbon filters through enhanced biodegradation of melamine. J. Hazard. Mater. 422, 126840 https://doi.org/10.1016/j.jhazmat.2021.126840.

Plakas, K.V., Karabelas, A.J., 2012. Removal of pesticides from water by NF and RO membranes - a review. Desalination 287, 255–265. https://doi.org/10.1016/j.desal.2011.08.003.

Ren, H., Tröger, R., Ahrens, L., Wiberg, K., Yin, D., 2020. Screening of organic micropollutants in raw and drinking water in the Yangtze River Delta. China. Environ. Sci. Eur. 32 https://doi.org/10.1186/s12302-020-00342-5.

Richardson, S.D., Ternes, T.A., 2011. Water analysis: emerging contaminants and current issues. Anal. Chem. 83, 4616–4648. https://doi.org/10.1021/ac200915r.

Robles-Molina, J., Gilbert-López, B., García-Reyes, J.F., Molina-Díaz, A., 2014. Monitoring of selected priority and emerging contaminants in the Guadalquivir River and other related surface waters in the province of Jaén. South East Spain. Sci. Total Environ. 479–480, 247–257. https://doi.org/10.1016/j.scitotenv.2014.01.121.

Sanganyado, E., Bi, R., Teta, C., Buruaem Moreira, L., Yu, X., Yajing, S., Dalu, T., Rajput, I.R., Liu, W., 2021. Toward an integrated framework for assessing micropollutants in marine mammals: challenges, progress, and opportunities. Crit. Rev. Environ. Sci. Technol. 51, 2824–2871. https://doi.org/10.1080/10643389.2020.1806663.

Schäfer, A.I., Akanyeti, I., Semião, A.J.C., 2011. Micropollutant sorption to membrane polymers: a review of mechanisms for estrogens. Adv. Colloid Interface Sci. 164, 100–117. https://doi.org/10.1016/j.cis.2010.09.006.

Schäfer, A.I., Nghiem, L.D., Meier, A., Neale, P.A., 2010. Impact of organic matrix compounds on the retention of steroid hormone estrone by a "loose" nanofiltration membrane. Sep. Purif. Technol. 73, 179–187. https://doi.org/10.1016/j.seppur.2010.03.023.

Schmidt, T.C., 2018. Recent trends in water analysis triggering future monitoring of organic micropollutants. Anal. Bioanal. Chem. 410, 3933–3941. https://doi.org/10.1007/s00216-018-1015-9.

Schoonenberg Kegel, F., Rietman, B.M., Verliefde, A.R.D., 2010. Reverse osmosis followed by activated carbon filtration for efficient removal of organic micropollutants from river bank filtrate. Water Sci. Technol. 61, 2603–2610. https://doi.org/10.2166/wst.2010.166.

Schrenk, D., Bignami, M., Bodin, L., Chipman, J.K., del Mazo, J., Grasl-Kraupp, B., Hogstrand, C., Hoogenboom, L., Leblanc, J.C., Nebbia, C.S., Nielsen, E., Ntzani, E., Petersen, A., Sand, S., Vleminckx, C., Wallace, H., Barregård, L., Ceccatelli, S.,

Cravedi, J.P., Halldorsson, T.I., Haug, L.S., Johansson, N., Knutsen, H.K., Rose, M., Roudot, A.C., van Loveren, H., Vollmer, G., Mackay, K., Riolo, F., Schwerdtle, T., 2020. Risk to human health related to the presence of perfluoroalkyl substances in food. EFSA J. 18 https://doi.org/10.2903/j.efsa.2020.6223.

Schwarzenbach, R.P., Escher, B.I., Fenner, K., Hofstetter, T.B., Johnson, C.A., von Gunten, U., Wehrli, B., 2006. The challenge of micropollutants in aquatic systems. Science 313, 1072–1077. https://doi.org/10.1126/science.1127291, 5790.

Seidel, A., Waypa, J.J., Elimelech, M., 2001. Role of charge (Donnan) exclusion in removal of arsenic from water by a negatively charged porous nanofiltration membrane. Environ. Eng. Sci. 18, 105–113. https://doi.org/10.1089/10928750151132311.

Semião, A.J.C., Foucher, M., Schäfer, A.I., 2013. Removal of adsorbing estrogenic micropollutants by nanofiltration membranes: part B - Model development. J. Membr. Sci. 431, 257–266. https://doi.org/10.1016/j.memsci.2012.11.079.

Semião, A.J.C., Schäfer, A.I., 2013. Removal of adsorbing estrogenic micropollutants by nanofiltration membranes. Part A - Experimental evidence. J. Membr. Sci. 431, 244–256. https://doi.org/10.1016/j.memsci.2012.11.080.

Singh, R., 2005. Introduction to membrane technology. In: Singh, R. (Ed.), Hybrid Membrane Systems For Water Purification. Elsevier Science, pp. 1–56.

Song, W., Lee, L.Y., Ng, H.Y., 2020. Nanofiltration and reverse osmosis processes for the removal of micro-pollutants. Current Developments in Biotechnology and Bioengineering. Elsevier B.V, pp. 527–552.

Spruijt, E, Biesheuvel, P.M., 2014. Sedimentation dynamics and equilibrium profiles in multicomponent mixtures of colloidal particles. J. Phys. Condens. Matter 26. https://doi.org/10.1088/0953-8984/26/7/075101.

Stamm, C., Räsänen, K., Burdon, F.J., Altermatt, F., Jokela, J., Joss, A., Ackermann, M., Eggen, R.I.L., 2016. Unravelling the impacts of micropollutants in aquatic ecosystems: interdisciplinary studies at the interface of large-scale ecology. Adv. Ecol. Res. 55, 183–223. https://doi.org/10.1016/bs.aecr.2016.07.002.

Steed, J.W., Atwood, J.L., 2009. Supramolecular Chemistry. Wiley & Sons. John Wiley & Sons, Ltd, Chichester, UK. https://doi.org/10.1002/9780470740880.

Sudhakaran, S., Lattemann, S., Amy, G.L., 2013. Appropriate drinking water treatment processes for organic micropollutants removal based on experimental and model studies - a multi-criteria analysis study. Sci. Total Environ. 442, 478–488. https://doi.org/10.1016/j.scitotenv.2012.09.076.

Taheran, M., Brar, S.K., Verma, M., Surampalli, R.Y., Zhang, T.C., Valero, J.R., 2016. Membrane processes for removal of pharmaceutically active compounds (PhACs) from water and wastewaters. Sci. Total Environ. 547, 60–77. https://doi.org/10.1016/j.scitotenv.2015.12.139.

Teodosiu, C., Gilca, A.F., Barjoveanu, G., Fiore, S., 2018. Emerging pollutants removal through advanced drinking water treatment: a review on processes and environmental performances assessment. J. Clean. Prod. 197, 1210–1221. https://doi.org/10.1016/j.jclepro.2018.06.247.

Tröger, R., Klöckner, P., Ahrens, L., Wiberg, K., 2018. Micropollutants in drinking water from source to tap - method development and application of a multiresidue screening method. Sci. Total Environ. 627, 1404–1432. https://doi.org/10.1016/j.scitotenv.2018.01.277.

van Beelen, P., 2000. The Risk Evaluation of Difficult Substances in USES 2.0 and EUSES. Rijksinstituut voor Volksgezondheid en Milieu RIVM, Bilthove.

van der Bruggen, B., Schaep, J., Wilms, D., Vandecasteele, C., 1999. Influence of molecular size, polarity and charge on the retention of organic molecules by nanofiltration. J. Memb. Sci. 156, 29–41. https://doi.org/10.1016/S0376-7388(98)00326-3.

van der Bruggen, B, Vandecasteele, C, 2002. Modelling of the retention of uncharged molecules with nanofiltration. Water Res. 36 (5), 1360–1368. https://doi.org/10.1016/S0043-1354(01)00318-9.

Veloutsou, S., Bizani, E., Fytianos, K., 2014. Photo-Fenton decomposition of β-blockers atenolol and metoprolol; study and optimization of system parameters and identification of intermediates. Chemosphere 107, 180–186. https://doi.org/10.1016/j.chemosphere.2013.12.031.

Vergili, I., 2013. Application of nanofiltration for the removal of carbamazepine, diclofenac and ibuprofen from drinking water sources. J. Environ. Manag. 127, 177–187. https://doi.org/10.1016/j.jenvman.2013.04.036.

Verliefde, A.R.D., Cornelissen, E., Amy, G., Van der Bruggen, B., van Dijk, H., 2007a. Priority organic micropollutants in water sources in Flanders and the Netherlands and assessment of removal possibilities with nanofiltration. Environ. Pollut. 146, 281–289. https://doi.org/10.1016/j.envpol.2006.01.051.

Verliefde, A.R.D., Cornelissen, E.R., Heijman, S.G.J., Hoek, E.M.V., Amy, G.L., Van Der Bruggen, B., Van Dijk, J.C., 2009a. Influence of solute-membrane affinity on rejection of uncharged organic solutes by nanofiltration membranes. Environ. Sci. Technol. 43, 2400–2406. https://doi.org/10.1021/es803146r.

Verliefde, A.R.D., Cornelissen, E.R., Heijman, S.G.J., Verberk, J.Q.J.C., Amy, G.L., Van der Bruggen, B., van Dijk, J.C., 2009b. Construction and validation of a full-scale model for rejection of organic micropollutants by NF membranes. J. Memb. Sci. 339, 10–20. https://doi.org/10.1016/j.memsci.2009.03.038.

Verliefde, A.R.D., Heijman, S.G.J., Cornelissen, E.R., Amy, G., Van der Bruggen, B., van Dijk, J.C., 2007b. Influence of electrostatic interactions on the rejection with NF and assessment of the removal efficiency during NF/GAC treatment of pharmaceutically active compounds in surface water. Water Res. 41, 3227–3240. https://doi.org/10.1016/j.watres.2007.05.022.

Verliefde, A.R.D., Heijman, S.G.J., Cornelissen, E.R., Amy, G.L., van der Bruggen, B., van Dijk, J.C., 2008. Rejection of trace organic pollutants with high pressure membranes (NF/RO). Environ. Prog. 27, 180–188. https://doi.org/10.1002/ep.10272.

von Gunten, U., 2018. Oxidation processes in water treatment: are we on track? Environ. Sci. Technol. 52, 5062–5075. https://doi.org/10.1021/acs.est.8b00586.

Wang, C., Moore, N., Bircher, K., Andrews, S., Hofmann, R., 2019. Full-scale comparison of UV/H₂O₂ and UV/Cl₂ advanced oxidation : the degradation of micropollutant surrogates and the formation of disinfection byproducts. Water Res. 161, 448–458. https://doi.org/10.1016/j.watres.2019.06.033.

Wang, J., de Ridder, D., van der Wal, A., Sutton, N.B., 2020a. Harnessing biodegradation potential of rapid sand filtration for organic micropollutant removal from drinking water: a review. Crit. Rev. Environ. Sci. Technol. 0, 1–33. https://doi.org/10.1080/10643389.2020.1771888.

Wang, L., Cao, T., Dykstra, J.E., Porada, S., Biesheuvel, P.M., Elimelech, M., 2021. Salt and water transport in reverse osmosis membranes: beyond the solution-diffusion model. Environ. Sci. Technol. 55, 16665–16675. https://doi.org/10.1021/acs.est.1c05649.

Wang, R., Lin, S., 2021. Pore model for nanofiltration: history, theoretical framework, key predictions, limitations, and prospects. J. Membr. Sci. 620, 118809 https://doi.org/10.1016/j.memsci.2020.118809.

Wang, S., Matt, M., Murphy, B.L., Perkins, M.G., Matthews, D.A., Moran, S.D., Zeng, T., 2020b. Organic micropollutants in New York lakes: a statewide citizen science occurrence study. Environ. Sci. Technol. 54, 13759–13770. https://doi.org/10.1021/acs.est.0c04775.

Wang, X., Mao, L., Zhang, B., Li, T., Yan, X., 2015. Performance of nanofiltration membrane in rejecting trace organic compounds: experiment and model prediction. Desalination 370, 7–16. https://doi.org/10.1016/j.desal.2015.05.010.

Wassenaar, T.A., et al., 2015. High-throughput simulations of dimer and trimer assembly of membrane proteins. The DAFT approach. J. Chem. Theory Comput. 11 (5), 2278–2291. https://doi.org/10.1021/ct5010092.

Xu, R., Qin, W., Tian, Z., He, Y., Wang, X., Wen, X., 2020. Enhanced micropollutants removal by nanofiltration and their environmental risks in wastewater reclamation: a pilot-scale study. Sci. Total Environ. 744, 140954 https://doi.org/10.1016/j.scitotenv.2020.140954.

Xu, R., Zhang, P., Wang, Q., Wang, X., Yu, K., Xue, T., Wen, X., 2019. Influences of multi influent matrices on the retention of PPCPs by nanofiltration membranes. Sep. Purif. Technol. 212, 299–306. https://doi.org/10.1016/j.seppur.2018.11.040.

Yan, H., Miao, X., Xu, J., Pan, G., Zhang, Y., Shi, Y., Guo, M., Liu, Y., 2015. The porous structure of the fully-aromatic polyamide film in reverse osmosis membranes. J. Membr. Sci. 475, 504–510. https://doi.org/10.1016/j.memsci.2014.10.052.

Yan, Z., Yang, H., Dong, H., Ma, B., Sun, H., Pan, T., Jiang, R., Zhou, R., Shen, J., Liu, J., Lu, G., 2018. Occurrence and ecological risk assessment of organic micropollutants in the lower reaches of the Yangtze River, China: a case study of water diversion. Environ. Pollut. 239, 223–232. https://doi.org/10.1016/j.envpol.2018.04.023.

Yang, W., Zhou, H., Cicek, N., 2014. Treatment of organic micropollutants in water and wastewater by UV-based processes: a literature review. Crit. Rev. Environ. Sci. Technol. 44, 1443–1476. https://doi.org/10.1080/10643389.2013.790745.

Yang, Y., Zhang, X., Jiang, J., Han, J., Li, W., Li, X., Yee Leung, K.M., Snyder, S.A., Alvarez, P.J.J., 2022. Which micropollutants in water environments deserve more attention globally? Environ. Sci. Technol. https://doi.org/10.1021/acs.est.1c04250.

Yangali Quintanilla, V., Maeng, S.K., Fujioka, T., Kennedy, M., Li, Z., Amy, G.L., 2011. Nanofiltration vs. reverse osmosis for the removal of emerging organic contaminants in water reuse. Desalin. Water Treat. 34, 50–56. https://doi.org/10.5004/dwt.2011.2860.

Yangali-Quintanilla, V., Verliefde, A.R.D., Kim, T.U., Sadmani, A., Kennedy, M., Amy, G.L., 2009. Artificial neural network models based on QSAR for predicting rejection of neutral organic compounds by polyamide nanofiltration and reverse osmosis membranes. J. Memb. Sci. 342, 251–262. https://doi.org/10.1016/j.memsci.2009.06.048.

Yangali-Quintanilla, V., Maeng, S.K., Fujioka, T., Kennedy, M., Amy, G.L., 2010a. Proposing nanofiltration as acceptable barrier for organic contaminants in water reuse. J. Memb. Sci. 362, 334–345. https://doi.org/10.1016/j.memsci.2010.06.058.

Yangali-Quintanilla, V., Sadmani, A., McConville, M., Kennedy, M., Amy, G.L., 2010b. A QSAR model for predicting rejection of emerging contaminants (pharmaceuticals, endocrine disruptors) by nanofiltration membranes. Water Res. 44, 373–384. https://doi.org/10.1016/j.watres.2009.06.054.

Lefebvre, O., Lee, L.Y., Ng, H.Y., 2010. Physico-chemical treatment of Micropollutants : coagulation and membrane processes.*Treatment of Micropollutants in Water and Wastewater. IWA Publishing, London* (2010): 205-237.

Yangali Quintanilla, V.A., 2010. Rejection of Emerging Organic Contaminants by Nanofiltration and Reverse Osmosis Membranes: Effects of Fouling, Modelling and Water Reuse, 1st ed. CRC Press https://doi-org.ezproxy.library.wur.nl/10.1201/b10832.

Yaroshchuk, A., Bruening, M.L., Zholkovskiy, E., 2019. Modelling nanofiltration of electrolyte solutions. Adv. Colloid Interface Sci. https://doi.org/10.1016/j.cis.2019.03.004.

Yoon, Y., Lueptow, R.M., 2005. Removal of organic contaminants by RO and NF membranes. J. Membr. Sci. 261, 76–86. https://doi.org/10.1016/j.memsci.2005.03.038.

Zhang, Z., Zhang, W., Lichtfouse, E., 2020. Membranes For Environmental Applications, Environmental Chemistry For a Sustainable World. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-030-33978-4.

Young, N.P., Balsara, N.P., 2014. Flory–Huggins Equation. In: Encyclopedia of Polymeric Nanomaterials.. Springer.

Zhang, Y., van der Bruggen, B., Chen, G.X., Braeken, L., Vandecasteele, C., 2004. Removal of pesticides by nanofiltration: effect of the water matrix. Sep. Purif. Technol. 38, 163–172. https://doi.org/10.1016/j.seppur.2003.11.003.

Zhao, C., Zhou, X., Yue, Y., 2000. Determination of pore size and pore size distribution on the surface of hollow-fiber filtration membranes: a review of methods. Desalination 129, 107–123. https://doi.org/10.1016/S0011-9164(00)00054-0.

Zhu, L., 2015. Rejection of organic micropollutants by clean and fouled nanofiltration membranes. J. Chem. https://doi.org/10.1155/2015/934318.