

Review

Solar-Driven Photothermal Membrane Distillation: A Holistic Review of Transport Phenomena, Fouling Dynamics, and Advanced Simulation Paradigms

Hesam Bazargan Harandi ^{1,2,*}, Anahita Asadi ^{1,2} and José Luis Cortina Pallás ^{1,2,3,*}

¹ Group of R2EM, Chemical Engineering Department, Universitat Politècnica de Catalunya—BarcelonaTech (UPC), Av. Eduard Maristany, 16, 08019 Barcelona, Spain

² Barcelona Research Centre in Multiscale Science and Engineering, Universitat Politècnica de Catalunya—BarcelonaTech (UPC), Av. Eduard Maristany, 16, 08019 Barcelona, Spain

³ CETaqua, Carretera d'Esplugues, 75, 08940 Cornellà de Llobregat, Spain

* Correspondence: hesam.bazargan@upc.edu (H.B.H.); jose.luis.cortina@upc.edu (J.L.C.P.)

Abstract

Solar-Driven Photothermal Membrane Distillation (SPMD) integrates solar energy using photothermal coatings on the hydrophobic membranes, such as carbon black nanoparticles coated on PVDF membranes, to achieve localized heating at the liquid–vapor interface. This approach enhances energy efficiency by mitigating temperature polarization and reducing thermal energy demands compared to conventional membrane distillation (MD). However, the challenges of fouling and scaling, which can significantly impair membrane performance, continue to be a serious concern, similar to other MD configurations. This comprehensive review establishes a unified framework connecting core transmembrane mass and heat transfer mechanisms with the thermodynamic pathways of surface fouling and scaling. We critically evaluate various strategies for mitigating scaling and fouling, including the development of omniphobic membranes, the introduction of nano/micro bubbles, the addition of anti-scalants and surfactants, and the implementation of chemical and mechanical pretreatments. Subsequently, the impact of photothermal coatings, applied to the feed–membrane interface in SPMD to absorb solar radiation, on scaling and fouling resistance is also discussed. Finally, we provide a comprehensive review of advanced computational paradigms, for both coupled radiative-thermal and dynamic fouling models—contrasting deterministic, physics-based multi-phase Computational Fluid Dynamics (CFD) with empirical Response Surface Methodology (RSM) and predictive Artificial Intelligence (AI) data-driven models. Beyond this survey, we identify and directly address a critical, previously unquantified gap in the field of SPMD: the absence of an explicit thermodynamic link between transmembrane heat/mass transfer and the nucleation and adhesion processes that govern scaling and fouling, and we further highlight the practical barriers—photothermal coating durability, economic feasibility, and technology readiness—that currently separate laboratory-scale SPMD from field deployment. This holistic synthesis charts future engineering strategies for scalable, fouling-resistant, and optimized solar-driven desalination infrastructure.

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Keywords: SPMD; transmembrane mass transfer models; heat transfer models; fouling/scaling; fouling/scaling mitigation strategies; numerical modeling approaches

1. Introduction

As global concerns regarding water and energy shortages continue to grow, there has been a notable shift toward the development and adoption of novel desalination technologies [1,2]. Among these, membrane distillation (MD) has gained significant attention due to its advantages not only in desalination and wastewater treatment but also in applications across industries such as pharmaceutical, food, and medical sectors, as well as industrial recycling [3–5]. A promising innovation in membrane distillation is the integration of solar energy, achieved through the in situ heating of the feed solution directly at the membrane surface using photothermal coatings [6,7]. This Solar-Driven Photothermal Membrane Distillation (SPMD) approach incorporates solar energy by exploiting the self-heating properties of the membrane. Photothermal materials, such as carbon black (CB) nanoparticles (NPs), are applied to the membrane surface to absorb sunlight and generate localized heat at the liquid–vapor interface. This localized heating significantly mitigates temperature polarization effects, reducing the energy requirements in comparison to traditional MD methods, which typically involve heating the entire feed water. By concentrating the heat at the membrane surface, SPMD enhances energy efficiency relative to conventional MD configurations [8,9]. While SPMD is a relatively recent innovation, MD itself, along with its various configurations, such as Direct Contact Membrane Distillation (DCMD), Air Gap Membrane Distillation (AGMD), Vacuum Membrane Distillation (VMD), and Osmotic Membrane Distillation (OMD), has a much longer history. The first patent for MD systems was filed by Bodell in 1963 [10], followed by a second MD patent in the United States by Weyl in 1967 [11]. Weyl's patent proposed an improved method for freshwater extraction from saline water using DCMD, incorporating both stationary and moving water with the membrane, in a single or multi-stage process. Weyl used polytetrafluoroethylene (PTFE) membranes with a porosity of 42%, a thickness of 3175 μm , and an average pore size of 9 μm . In the same year, Findley conducted experiments with the DCMD configuration, evaluating the performance of various membrane materials, such as paper, nylon, diatomaceous earth mat, and aluminum foil [12]. He also investigated silicone and Teflon coatings to achieve the necessary hydrophobicity for the membranes and analyzed which membrane characteristics were most suitable for MD. Building on these developments, Bodell introduced a novel system in 1968 that used a parallel array of tubular silicone membranes for converting non-potable water into potable water [13]. Over time, researchers continued to introduce and refine different MD configurations, yet interest in the process declined during the 1970s and 1980s, partly due to the lower flux rates observed in MD compared to reverse osmosis (RO). However, MD experienced a resurgence in academic interest in the 1980s when new membranes with improved characteristics became available [14,15]. Membranes made from materials like PTFE, PP, and PVDF showed notable improvements, including reduced thickness and porosities as high as 90%. As research into membrane modifications continues, MD remains a promising and moderately energy-intensive desalination technology based on membrane principles. Recent literature indicates that MD typically requires an average energy input of 1.25 kWh (electrical equivalent) per cubic meter for large-scale desalination operations, which includes both thermal and electrical energy demands [16–18]. This contrasts with RO, which relies primarily on electrical energy. It is important to note that approximately 90% of the energy consumption in MD is attributed to the thermal energy required for the process. In this context, SPMD offers a promising solution, as it can effectively supply the necessary thermal energy for operation. By leveraging solar energy to directly heat the membrane surface, SPMD reduces the overall energy demand, enhancing the system's energy efficiency. In fact, sweeping-gas MD (SGMD) was first introduced by Summers and Lienhard, who demonstrated that directly delivering heat to the evaporation source could enhance vapor flux. They also provided a theoretical framework for

understanding heat loss in the module's unit volume [19]. Building on this concept of solar-assisted photothermal membrane distillation, Dongare et al. proposed a SPMD by incorporating CB nanoparticles into a PVDF membrane, enabling the membrane to absorb solar energy for direct contact distillation [20]. Following this, Said et al. developed and tested a pilot-scale SPMD system under varying solar irradiances [8]. More recently, they evaluated a low-cost, stand-alone SPMD configuration with a sweeping gas mechanism for desalinating hypersaline water, eliminating the need for an external heat exchanger [7,9,21]. Furthermore, this promising technology has been identified as a cost-effective solution for treating oil-produced water [22].

Despite its advantages, SPMD faces challenges similar to conventional MD processes when treating hypersaline wastewater with complex compositions [17]. The most important challenge is membrane fouling or scaling, where foulants or scalants adhere to the hydrophobic membrane surface, obstruct the pores, and significantly diminish water vapor flux [23]. For instance, organic compounds such as proteins from food and beverage wastewater or oil particles from oil and gas production are notable foulants, particularly for hydrophobic membranes. In the case of hypersaline brine treatment, mineral scaling presents an additional issue, involving the formation or accumulation of salt crystals on the membrane surface, leading to substantial flux reduction [24]. Fouling refers to the accumulation of organic, biological, or particulate matter, whereas scaling specifically involves the precipitation of dissolved salts, such as gypsum and other inorganic salts. Visually, scaling manifests as crystalline deposits on the membrane surface, while fouling appears as slimy, particulate, or heterogeneous layers. The second critical issue contributing to MD operational failure is membrane wetting, where liquid penetrates the membrane pores, compromising its hydrophobic nature and hindering effective separation. This phenomenon has been extensively studied in our prior research, focusing on different wetting states, including the Wenzel state, the transition state, and the Cassie-Baxter state [25,26].

Although the photothermal layer on the membrane surface in SPMD can influence scaling and fouling resistance, these issues remain a concern. As a result, scaling and fouling mitigation strategies must be incorporated into SPMD designs [27,28].

This article begins by comparing MD and SPMD systems and elaborating on the effect of employing solar-driving photothermal membranes on the enhancement of system efficiency. It then elucidates the theories of transmembrane mass transfer in SPMD and explores the various heat transfer mechanisms, including the absorption of solar radiation by the photothermal layer on the membrane surface, transmembrane heat transfer, heat transfer to the bulk, and heat losses, within SPMD modules. Then, this study explores the core mechanisms behind mineral scaling and fouling, along with strategies to mitigate these issues. It emphasizes the most effective approaches for minimizing scaling and fouling that must be incorporated into SPMD and other MD configurations. Subsequently, it evaluates the impact of photothermal coatings on scaling and fouling resistance, offering insights into their potential to enhance SPMD performance. This study concludes by presenting and reviewing several computational strategies—such as computational fluid dynamics (CFD), response surface methodology (RSM), artificial neural networks (ANN), and machine/deep learning (ML and DL)—that are employed to predict fouling and scaling on membrane surfaces and to simulate transient behavior in membrane-based water treatment systems. These simulations, either physics-based and data-based, demand a thorough examination of the interplay among multiple physical processes, including fluid dynamics, solute and solvent transport through membranes, energy transfer within modules, and the accumulation of foulants or scalants on membrane surfaces. Relative to previous reviews of MD and SPMD, which have generally treated transport modeling, fouling/scaling science, and computational simulation as separate bodies of literature, the

specific contribution of this review is to establish an explicit, quantitative connection between these domains—linking transmembrane heat and mass transfer variables directly to the thermodynamic drivers of nucleation and adhesion—and to provide a comparative, rather than purely descriptive, treatment of the CFD, RSM, and AI/ML paradigms used to simulate fouling and scaling behavior in SPMD systems.

2. Comparison of SPMD and Conventional MD Systems

Conventional membrane distillation (CMD) is a thermally driven desalination process in which a hydrophobic microporous membrane separates a heated saline feed from a cooler permeate (distillate) stream, as illustrated in Figure 1A. A temperature gradient between the two bulk streams results in a vapor pressure difference across the membrane. Under these conditions, water molecules at the interface of feed channel–membrane evaporate, diffuse through the pores of membrane, and subsequently condense at the interface of permeate channel–membrane. The latent heat released during condensation is transferred to the permeate channel, producing purified water. However, in this configuration, a considerable portion of the supplied thermal energy is lost through bulk feed heating and conductive heat transfer, leading to lower the system’s overall thermal efficiency.

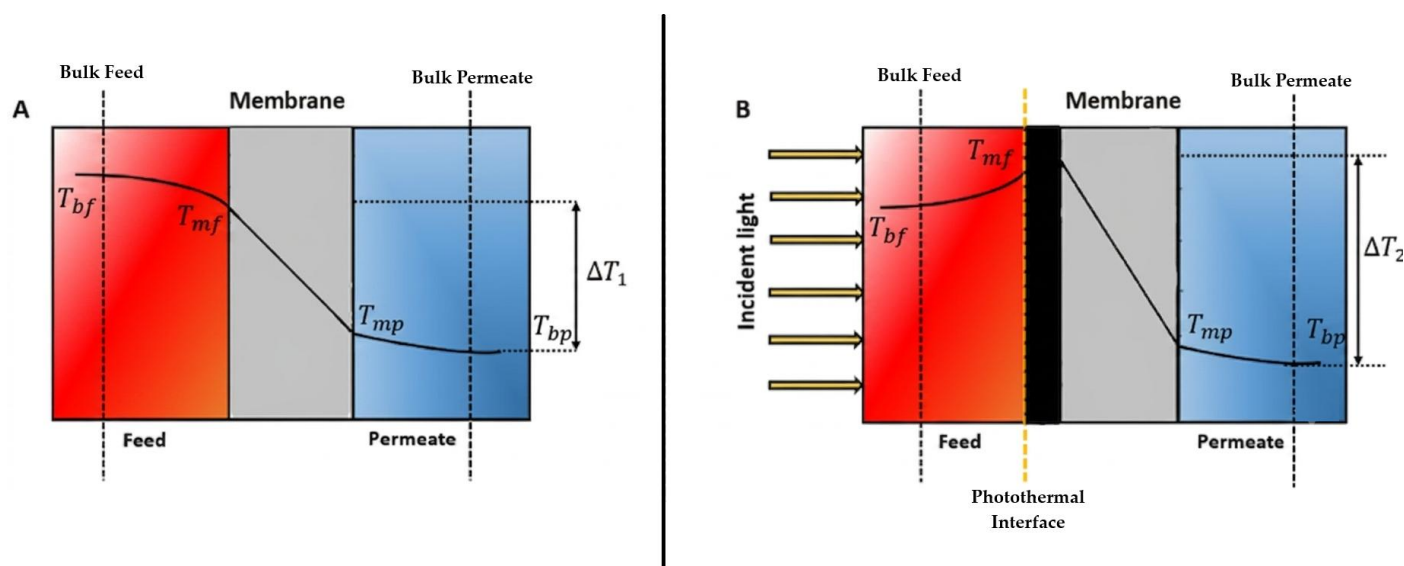


Figure 1. Configurations of (A) CMD and (B) SPMD.

In contrast, SPMD represents an advanced configuration of MD by inserting photo-thermal materials, such as CB, graphene oxide, or plasmonic nanoparticles, onto or within the membrane surface (Figure 1B). These materials directly absorb solar radiation and convert it into heat at the membrane surface, where evaporation occurs. By generating heat exactly at the evaporation interface rather than throughout the entire feed volume, SPMD substantially reduces heat loss and enhances the overall energy utilization. Reported solar-to-vapor conversion efficiencies for SPMD systems are ranged typically between 50% and 70%, whereas the thermal energy efficiency of conventional MD systems is often below 10%, depending on operating conditions and system design [29].

The low thermal efficiency of CMD systems is primarily caused by temperature polarization (TP). TP refers to the decrease in the effective temperature difference across the membrane due to heat and mass transfer resistances at the membrane interfaces. In conventional MD, the feed-side membrane surface temperature (T_{mf}) is lower than the bulk feed temperature (T_{bf}) because a portion of the supplied heat is consumed for vaporization at the interface. Likewise, on the permeate side, the distillate-side membrane surface temperature (T_{mp}) is higher than the bulk distillate temperature (T_{bp}) owing to the release of

latent heat during condensation. Therefore, the actual driving force for vapor transport, i.e., the vapor pressure difference between the two membrane surfaces, is smaller than the theoretical temperature difference between T_{bf} and T_{bp} .

In contrast, SPMD employs a photothermal layer that concentrates solar energy directly at the membrane surface, resulting in $T_{mf} > T_{bf}$. This phenomenon significantly minimizes temperature polarization, increases the transmembrane vapor pressure difference, and thereby elevates water vapor flux and overall energy efficiency [30].

3. Transmembrane Mass and Heat Transfer Mechanisms

In the following sub-sections, the transmembrane mass and heat transfer theories in SPMD modules at the system level are discussed in details.

3.1. Transmembrane Mass Transfer Model

In the hydrophobic porous structure of MD membranes, the mass transfer rate through the membrane pores is governed by the following equation [1,31].

$$J_w = c_m(P_{mf} - P_{mp}) \quad (1)$$

in this formula, J_w (kg/(m²·s)), c_m (kg/(Pa·m²·s)), P_{mf} (Pa), and P_{mp} (Pa) represent the mass transfer flux, the mass transfer coefficient of the membrane, and the water vapor partial pressures at the feed–membrane and permeate–membrane interfaces, respectively. To calculate the water vapor partial pressures at the local membrane interface temperatures, the Antoine equation can be applied. Different transport mechanisms contribute to the movement of volatile compounds through the pores of the membrane in MD. The first significant mechanism is the Maxwell–Stefan model, which accounts for ordinary molecular diffusion, where transport is driven by molecule-to-molecule collisions. Water vapor molecules move through the air within the larger pores of the membrane, with the diffusion being influenced by the concentration difference between the two interfaces of the membrane. The following equation is used to compute the molecular mass transfer coefficient in this diffusion process [1].

$$c_{om} = \frac{1.895e^{-5}T^{2.072}\varepsilon_m M_w}{RT\tau_m\delta_m\left(\frac{P_{air,mf} - P_{air,mp}}{\ln\frac{P_{air,mf}}{P_{air,mp}}}\right)} \quad (2)$$

where T (K), ε_m , M_w (kg/mol), R (J/(mol·K)), τ_m , and δ_m (m) represent the absolute temperature, membrane porosity, molecular weight of water, universal gas constant, membrane tortuosity, and membrane thickness, respectively. Additionally, $P_{air,mf}$ (Pa) and $P_{air,mp}$ (Pa) denote the air partial pressures at the membrane's feed and permeate interfaces.

The second mechanism, referred to as Hagen–Poiseuille flow, is associated with viscous transport. This occurs when a total pressure difference exists across the larger pores within the membrane. Under this mechanism, water vapor moves through these pores as a result of viscous flow. The corresponding equation for determining the mass transfer coefficient in Hagen–Poiseuille flow is expressed in Equation (3) [1,16]:

$$c_{HP} = 0.03125 \frac{\varepsilon_m d_p^2 P_m M_w}{RT\tau_m\delta_m\mu_v} \quad (3)$$

in this formula, c_{HP} (kg/(Pa·m²·s)), μ_v (Pa·s), and d_p (m) represent the mass transfer coefficient based on the Hagen–Poiseuille equation, the dynamic viscosity of water vapor, and the membrane's average pore diameter, respectively.

The third transport mechanism, known as Knudsen diffusion, dominates within the nanoporous structure of the membrane. This mechanism becomes significant when the characteristic dimensions of the nanopores are comparable to or smaller than the mean

free path of water molecules, which depends on the prevailing temperature and pressure. In this regime, molecular collisions with the pore walls primarily govern the transport behavior, rather than intermolecular interactions. Knudsen diffusion is driven by the gradient of partial pressure across the membrane interfaces. The associated mass transfer coefficient for this mechanism can be expressed using the following equation [17,31]:

$$c_{kn} = 0.5319 \frac{\varepsilon_m d_m}{\tau_m \delta_m} \sqrt{\frac{1}{RTM_w}} \quad (4)$$

All the parameters involved in the aforementioned equations can either be directly measured through experimental techniques or determined by employing suitable empirical correlations. Although several empirical correlations, such as the Bruggeman, Millington, and Macki–Meares equations, have been proposed to estimate pore tortuosity, these models are not universally applicable to all porous media with diverse structural characteristics. To address this limitation, it is recommended to adopt specific equations tailored to the membrane structure for different domain types [16]. For loose-packed regions, Equation (5) is proposed:

$$\tau_m = \frac{1}{\varepsilon_m} \quad (5)$$

For domains encompassing closed-packed domains, the corresponding equation is:

$$\tau_m = \frac{(2 - \varepsilon_m)^2}{\varepsilon_m} \quad (6)$$

Determining the dominant diffusion mechanism—whether ordinary molecular diffusion or Knudsen diffusion—is critical for understanding membrane behavior. The Knudsen number serves as a key parameter for identifying the prevalence of these mechanisms, as it takes into account membrane-specific features, such as the average pore diameter. This dimensionless parameter is expressed as follows [1,32]:

$$Kn = \frac{\lambda}{d_p} \quad (7)$$

Here, λ [m] represents the mean free path of water molecules. At atmospheric pressure, given the typical pore size range of commercial MD membranes (10 nm to 1 μ m), the Knudsen number is generally found to lie within the range of $0.1 < Kn < 10$. This range indicates that both molecular diffusion and Knudsen diffusion are likely to coexist, resulting in a combined diffusion mechanism within the membrane.

Among the various theoretical frameworks used to describe transmembrane mass transfer within the membranes in MD processes, the Dusty Gas Model (DGM), the Schofield model, and the Knudsen-Molecular-Viscous (KM-P) model are the most prominent. These models, frequently cited in the scientific literature, incorporate the three primary mass transfer mechanisms: molecular diffusion, Knudsen diffusion, and viscous (Hagen–Poiseuille) flow. Their distinct approaches to representing the interplay of these mechanisms make them particularly valuable for different operational conditions and membrane designs [1].

The Schofield model conceptualizes mass transport as a combination of resistances, where molecular diffusion acts in series with a parallel arrangement of resistances arising from Knudsen diffusion and viscous flow. Conversely, the DGM takes a slightly different approach by positioning molecular and Knudsen diffusion resistances in series, with their combined effect placed in parallel with the viscous flow resistance. This subtle difference in the arrangement of resistances impacts the model's predictions, particularly under varying pressure and pore size conditions.

The KM-P model adopts yet another configuration, where viscous flow resistance is arranged in series with the parallel combination of molecular and Knudsen diffusion resistances. This structure underscores the dynamic interplay between transmembrane mass transfer mechanisms, particularly in membranes with significant variation in pore size or operating conditions that span the transition between Knudsen and molecular diffusion domains.

These above models, presented in Figure 2, provide versatile tools for understanding and optimizing transport phenomena in MD membranes. Each framework offers unique insights, with the choice of model often dictated by the specific characteristics of the membrane material, operating conditions, and the desired accuracy of predictions.

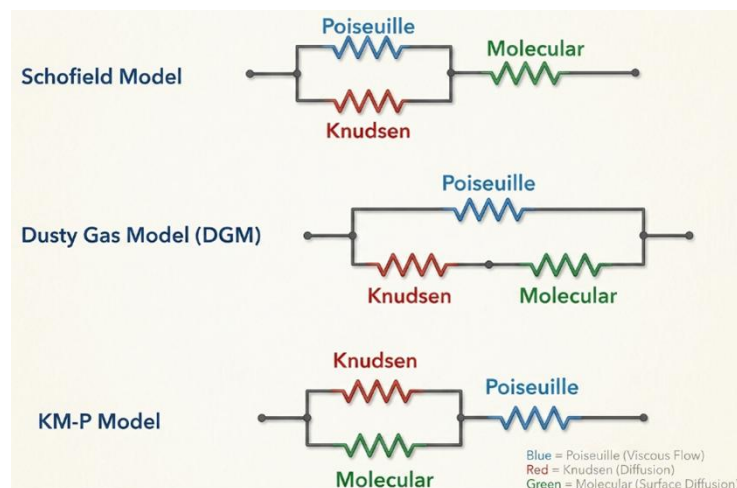


Figure 2. Commonly adopted models for the prediction of the mass transfer flux across the hydrophobic membrane in MD.

It should be noted that DGM, Schofield, and KM-P, like most classical MD transport models, assume local thermodynamic equilibrium at the feed–membrane and permeate–membrane interfaces, so that the local vapor pressure can be obtained directly from the bulk-adjacent interface temperature via the Antoine equation. This assumption holds reasonably well in CMD, where the membrane is heated through the bulk feed and the resulting temperature gradients are comparatively moderate. In SPMD, the photothermal layer instead concentrates solar absorption within a thin film directly at the liquid–vapor interface, and as discussed in Section 2, this reverses the sign of temperature polarization ($T_{mf} > T_f$) and produces a localized heat flux considerably higher than the bulk-averaged flux typical of CMD. Under such high interfacial fluxes, kinetic-theory treatments of evaporation predict, in addition to this macroscopic reversal, the formation of a thin non-equilibrium region at the interface itself, the Knudsen layer, across which a further, microscale temperature and vapor-density discontinuity can arise [33,34]. Since DGM, Schofield, and KM-P resolve neither this discontinuity nor the resulting non-linearity in the local vapor pressure profile, their accuracy may decline under the strongly localized photothermal fluxes achievable with highly absorptive coatings or concentrated solar illumination [35,36]. This is broadly consistent with the transmembrane temperature differentials and optical concentration ratio effects identified by Sharma et al. [37] as governing the onset of negative vapor flux in nanophotonics-enabled SPMD.

3.2. Transmembrane Heat Transfer, Heat Transfer in the Feed Channel, and Heat Losses

The transmembrane heat transfer and thermal efficiency of the SPMD is significantly influenced by both bulk and interfacial temperatures within the flow channels, as well as its positioning and geographical location on Earth. This system integrates a photothermal

layer that functions as a solar absorber, enabling self-sustained heating without requiring an external heat source. Solar energy is directly converted into thermal energy at the interface between the membrane and the feed stream. In addition to the heat transfer with the bulk, some energy losses occur when the system is exposed directly to the surrounding environment, as represented in the following equation [1], illustrated in Figure 3.

$$Q_m = Q_s - Q_f - Q_{loss} \quad (8)$$

where Q_m (W/m²), Q_s (W/m²), Q_f (W/m²), and Q_{loss} (W/m²) are heat transfer through the membrane, absorbed solar radiation, heat transferred to the bulk, and heat loss to the ambient. Therefore, to calculate the transmembrane heat transfer rate, Q_m , it is essential to first determine the other heat transfer components, i.e., Q_s , Q_f , and Q_{loss} . The amount of solar radiation absorbed by the photothermal layer coated on the membrane surface is influenced by several factors, including geographical location, surface tilt angle, reflection coefficients, and the composition of the coating material. The following equations are employed to ascertain heat transferred to the bulk:

$$Q_f = h_f(T_{mf} - T_{bf}) \quad (9)$$

in which, h_f (W/(K·m²)) and T_{bf} (K) represent the heat transfer coefficient of the feed and the bulk temperature of the feed, respectively.

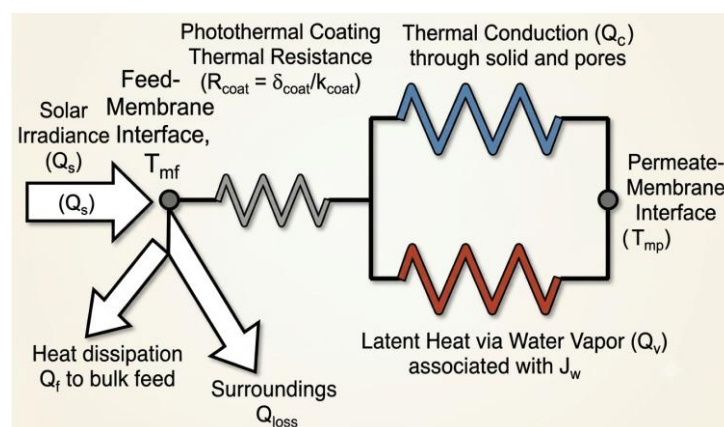


Figure 3. Equivalent thermal resistance circuit of heat transfer across the hydrophobic membrane in SPMD.

In the context of heat loss, heat transfer from the feed chamber to the surrounding environment can be represented as a series of thermal resistances. The heat dissipation process follows this sequence: convection within the feed channel, where heat moves from the bulk feed to the interface of the transparent window, conduction through the window material, and finally, a combination of convection and radiation to the surrounding atmosphere.

$$Q_{loss} = Q_{ftw} + Q_{tw} = Q_{fc} + Q_r \quad (10)$$

here, Q_{ftw} (W/m²), Q_{tw} (W/m²), Q_{fc} (W/m²), and Q_r (W/m²) represent convective heat loss from the bulk to the transparent window, heat loss through transparent window, free convection heat dissipation to the surrounding environment, and radiative heat loss to the surroundings. The heat losses described above can be mathematically represented by the following equations.

$$Q_{ftw} + Q_{tw} = U_{eq}(T_{bf} - T_{twf}) + A_g I_i \quad (11)$$

$$Q_{fc} + Q_r = h_e(T_{twf} - T_{amb}) + \sigma e(T_{twf}^4 - T_{sky}^4) \quad (12)$$

where $U_{eq} = h_f + h_{tw}$ ($W/(K \cdot m^2)$), T_{twf} (K), A_g , and I_i (W/m^2) are the equivalent heat transfer coefficient of feed and transparent window, transparent window-ambient temperature, transparent window absorptance, and Incident solar radiation, respectively. It is important to note that the heat transfer coefficient and absorptance of a transparent window are influenced by various factors, including its material composition and thickness. Also, h_e ($W/(K \cdot m^2)$), σ (5.67×10^{-8} $W/(K^4 \cdot m^2)$), e , T_{amb} (K), and T_{sky} (K) stand for heat transfer coefficient for free convection, the Stefan-Boltzmann constant, surface emissivity, ambient temperature, and sky temperature, respectively. The sky temperature is typically defined as a function of the ambient temperature ($T_{sky} = T_{amb} - 6$).

By substituting Equations (9)–(12) into Equation (8), the transmembrane heat transfer is determined. The overall heat transfer across the membrane is primarily governed by two mechanisms: (1) thermal conduction through the solid matrix of the membrane and the gas-filled pores, and (2) the transfer of latent heat associated with the water vapor generated during the evaporation process. The parallel part of Figure 3 illustrates the equivalent thermal resistance circuit for above heat transfer mechanisms in MD membranes. These mechanisms can be mathematically represented as follows [1,17]:

$$Q_m = Q_c + Q_v \quad (13)$$

$$Q_c = -\frac{k_m}{\delta_m}(T_{mf} - T_{mp}) \quad (14)$$

$$Q_v = J_w h_{fg} \quad (15)$$

here, Q_c (W/m^2) denotes the heat loss attributed to thermal conduction, Q_v (W/m^2) refers to the heat transfer carried by water vapor flux, and k_m ($W/(m \cdot K)$) represents the membrane's effective thermal conductivity. Here, h_{fg} (J/kg) signifies the latent heat of water vaporization. The mass flux through the membrane, J_w , is determined using the transmembrane mass transfer principles elaborated in a preceding section (Equation (1)). However, in photothermal systems, the coating is not merely a passive resistor but serves as an internal energy source node at the feed–membrane interface. The circuit must be modified to include solar irradiance (Q_s) as a direct heat flux input at this node, while accounting for energy losses through radiative re-emission and convective dissipation back to the bulk feed (Q_f). Furthermore, the photothermal layer introduces an additional thermal resistance ($R_{coat} = \delta_{coat}/k_{coat}$) that acts in series with the membrane's internal resistances.

In Equation (14), the thermal conductivity of a membrane, k_m , is influenced by the inherent properties of the solid material constituting the membrane as well as the thermal conductivity of the gas within its pores. Several empirical models have been developed to estimate the effective thermal conductivity of MD membranes. Among these, the Isostrain, Isostress, and flux law models, presented in Equations (16), (17), and (18), respectively, are widely cited in the literature [3].

$$k_m = \varepsilon_m k_w + (1 - \varepsilon_m) k_s \quad (16)$$

$$k_m = \left(\frac{\varepsilon_m}{k_w} + \frac{(1 - \varepsilon_m)}{k_s} \right)^{-1} \quad (17)$$

$$k_m = k_w \left(\frac{1 + (1 - \varepsilon_m)\beta}{1 - (1 - \varepsilon_m)\beta} \right) \quad (18)$$

where k_w ($W/(m \cdot K)$) denotes the thermal conductivity of water vapor passing through the membrane pores, and k_s ($W/(m \cdot K)$) represents the thermal conductivity of the polymeric material, solid phase of the membrane. In Equation (18), β represents the flux law coefficient, which is determined using the following equation:

$$\beta = \frac{\frac{k_s}{k_w} - 1}{\frac{k_s}{k_w} + 2} \quad (19)$$

It should be noted that comparative studies incorporating microstructural analyses and pore-scale modeling have demonstrated that the Isostrain model provides higher accuracy in estimating the thermal conductivity of MD membranes commonly employed in these systems [3]. This superiority arises from its ability to better capture the interactions between the membrane's microstructure and its transport properties. Beyond the structural aspects, the spatial distribution of photothermal nanoparticles—whether confined to a surface coating or distributed within the matrix as a Mixed Matrix Membrane (MMM)—fundamentally dictates the system's thermal efficiency. Applying the Isostrain model, it is evident that the inclusion of highly conductive photothermal fillers (e.g., carbon black or metallic nanoparticles) replaces a portion of the lower-conductivity polymer matrix, thereby increasing the thermal conductivity of the solid phase (k_s) [30,38]. This elevation in k_s directly translates to a higher effective membrane thermal conductivity (k_m) relative to a pristine polymer-gas composite [39].

4. Scaling in MD: Mechanisms and Mitigation Strategies

Mineral scaling, often referred to as inorganic fouling in the literature, poses a critical obstacle in MD, especially in its key applications, such as the treatment of hypersaline industrial effluents like geothermal brines [25,26]. In contrast, reverse osmosis (RO), a widely adopted water treatment technology, is often unsuitable for handling such high-salinity streams due to the elevated osmotic pressures and the structural limitations of RO membranes under extreme operating pressures. Depending on the pretreatment methods used, hypersaline wastewaters frequently contain ions that form sparingly soluble minerals, such as sulfates, carbonates, and silicates. In MD processes, water evaporation and the subsequent transport of water vapor through membrane pores lead to an increased concentration of these compounds, culminating in the formation of mineral crystal deposits on the membrane surface—a phenomenon known as mineral scaling [17].

In fact, mineral scaling refers to the formation and/or accumulation of salt, including but not limited to Ca^{2+} , Mg^{2+} , Ba^{2+} , $\text{SiO}_2(\text{aq})$, Sr^{2+} , SO_4^{2-} , CO_3^{2-} , precipitated on the membrane surface/substrate, classified into homogeneous nucleation and heterogeneous nucleation [26]. Homogeneous nucleation describes the precipitation of crystals directly from a supersaturated feed solution onto the membrane surface, leading to a rapid decline in flux. In contrast, heterogeneous nucleation arises from the interaction of ions with the membrane, causing pore blockage and potential membrane damage, which reduces water vapor flux and increases distillate conductivity [25,26].

The onset of scaling is typically detected through in situ monitoring of water vapor flux over time; a significant flux reduction often signals the formation of a scaling layer that obstructs membrane pores. Ex situ membrane autopsies provide insights into scaling mechanisms, revealing relationships between operational parameters and membrane properties. Standard characterization techniques used for these analyses include scanning electron microscopy (SEM) coupled with energy-dispersive X-ray spectroscopy (EDS), Fourier-transform infrared (FTIR) spectroscopy, atomic force microscopy (AFM), X-ray diffraction (XRD), and X-ray photoelectron spectroscopy (XPS) [40–42]. For instance, Figure 4 shows the SEM image of scaling on the top surface of a membrane, facing the feed water, after the experiment. As shown, the scaling appears as a homogeneous deposition on the membrane surface [25].

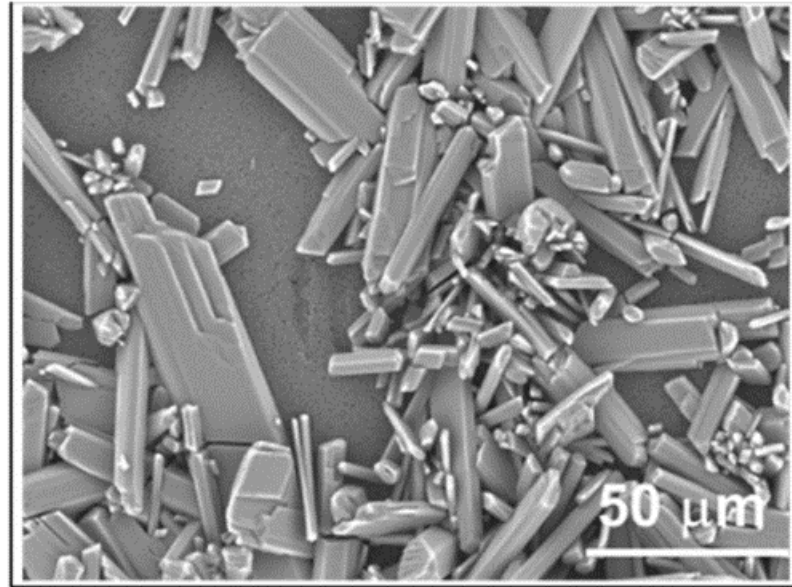


Figure 4. SEM images of scaling on the top surface of a membrane after experiment [25].

4.1. Quantitative Thermodynamics and Transport Drivers of Scaling

To establish a deterministic link between the transport phenomena, introduced in Section 3, and the scaling defined here in Section 4, the supersaturation ratio (S) at the membrane interface must be quantified as a function of the mass flux (J_w). In MD, the interfacial concentration (C_m) is elevated relative to the bulk (C_b) by the concentration polarization (CP) effect [25,26]:

$$C_m = C_b \exp\left(\frac{J_w}{\rho k_s}\right) \quad (20)$$

in which, k_s is the mass transfer coefficient. This localized supersaturation directly dictates the critical nucleation work (ΔG^*), representing the thermodynamic energy barrier for scale formation [43]:

$$\Delta G^* = \frac{16\pi\gamma^3\Omega^2}{3(k_B T_{mf} \ln S)^2} f(\theta) \quad (21)$$

here, γ is the surface energy, Ω is the molecular volume, k_B is the Boltzmann constant, and $f(\theta)$ is the geometry factor related to the contact angle. Crucially, in SPMD, the photothermal-induced interfacial temperature (T_{mf}) and the enhanced flux (J_w) act as coupled variables. While higher T_{mf} may increase solubility (potentially lowering S), the intensified J_w characteristic of photothermal systems drives a higher CP effect, which can lower the nucleation barrier (ΔG^*) and accelerate the onset of scaling. These equations provide the mathematical basis for the mitigation strategies discussed in the following sections, which focus on either increasing ΔG^* through surface energy reduction or lowering C_m through hydrodynamic control.

Various strategies have been proposed to mitigate scaling, as illustrated in Figure 5. Each mitigation approach will be explored in detail in the subsequent sections. While coupling MD with other membrane-based pretreatment methods, such as nanofiltration (NF), ultrafiltration (UF) and microfiltration (MF), has been proposed to eliminate particles and ions prone to scaling, this study concentrates solely on other standard approaches [27,44].



Figure 5. Various scaling mitigation strategies proposed for MD.

4.2. Development and Modification of Membranes

This approach to mitigating scaling focuses on transforming membrane surfaces from hydrophobic to superhydrophobic or omniphobic by engineering their surface morphology [26]. Techniques employed for such modifications include nanoimprint lithography, micro-molding phase separation (μ PS), and other methods like nonsolvent-induced phase separation, vapor-induced phase separation, templated thermally induced phase separation, and chemical coatings. The underlying mechanism is fundamentally governed by thermodynamic principles. By reducing the membrane surface energy and promoting a Cassie–Baxter wetting state, stable air pockets are retained within the membrane’s surface asperity. This is the primary thermodynamic mechanism for scaling resistance. Also, ‘slip’ phenomenon—characterized by a non-zero liquid velocity at the membrane boundary—serves as an auxiliary hydrodynamic factor. Both factors are explained in detail following [25,26,44].

When the membrane operates in a Cassie–Baxter wetting state, trapped air pockets separate the liquid feed from most of the underlying solid surface, so that only a small fraction of the apparent membrane area remains in direct solid–liquid contact. Since heterogeneous nucleation requires an available solid substrate to lower the nucleation energy barrier, this markedly reduced solid–liquid contact fraction is regarded as the primary thermodynamic reason for the superior scaling resistance of Cassie–Baxter surfaces, as it eliminates the majority of potential heterogeneous nucleation sites [25,26,44]. The concurrent slip effect—a non-zero liquid velocity along the trapped-air interface—acts as an auxiliary hydrodynamic factor, further reducing the residence time and contact duration of any crystals that do nucleate near the remaining solid–liquid contact points, but it is secondary to, and dependent on, the underlying reduction in nucleation-site density. In contrast, the Wenzel wetting state, characterized by pinned wetting and full solid–liquid contact, exposes the entire membrane area to potential heterogeneous nucleation and promotes the nucleation and growth of inorganic crystals on the membrane surface [26].

Research on surface-patterned superhydrophobic membranes, featuring multi-scale patterns, has been central to this strategy. For instance, Harandi et al. [25] and Hu et al. [26] developed corrugated polyvinylidene fluoride (PVDF) membranes (C-PVDF), which exhibited superior anti-scaling performance compared to conventional flat-sheet PVDF membranes (F-PVDF). Liu et al. [45] employed chemical fluorination (FAS-) and plasma fluorination (CF₄-) to modify PVDF membranes with micro-pillar arrays (MP-PVDF), producing two superhydrophobic membranes with distinct wetting states. The membrane

exhibiting a fully Cassie-Baxter wetting state demonstrated enhanced anti-scaling properties, validating the slip theory.

In a recent study, Hu et al. [46] fabricated fluorinated, multi-scale silicon nanoparticle-grafted corrugated PVDF membranes (FSiC-PVDF) with a water contact angle of $179.5 \pm 0.3^\circ$. These membranes were designed to resist scaling by calcium sulfate and wetting by sodium dodecyl sulfate (SDS). Silica nanoparticles (SiNPs) were synthesized and covalently bonded to the corrugated membrane surface, with additional surface energy reduction achieved through chemical fluorination. Compared to conventional F-PVDF and C-PVDF membranes, the omniphobic FSiC-PVDF demonstrated stable flux under high-concentration calcium sulfate and SDS solutions. Its superior performance was attributed to (1) the perturbation effect caused by pulse flow, (2) the increased flow velocity along the parallel corrugation, which reduced crystal deposition and SDS accumulation near membrane pores, and (3) the re-entrant structure created by SiNPs, which introduced slip boundaries, air pockets, and non-zero flow velocity, significantly lowering contaminant interaction with the membrane surface. Figure 6 presents the wetting state factor mapping for C-PVDF and FSiC-PVDF membranes, alongside a schematic representation of silica nanoparticle coatings on the corrugated membranes [46]. It also depicts how pulse flow and the corrugated structure contribute to the enhanced scaling resistance observed in these membranes.

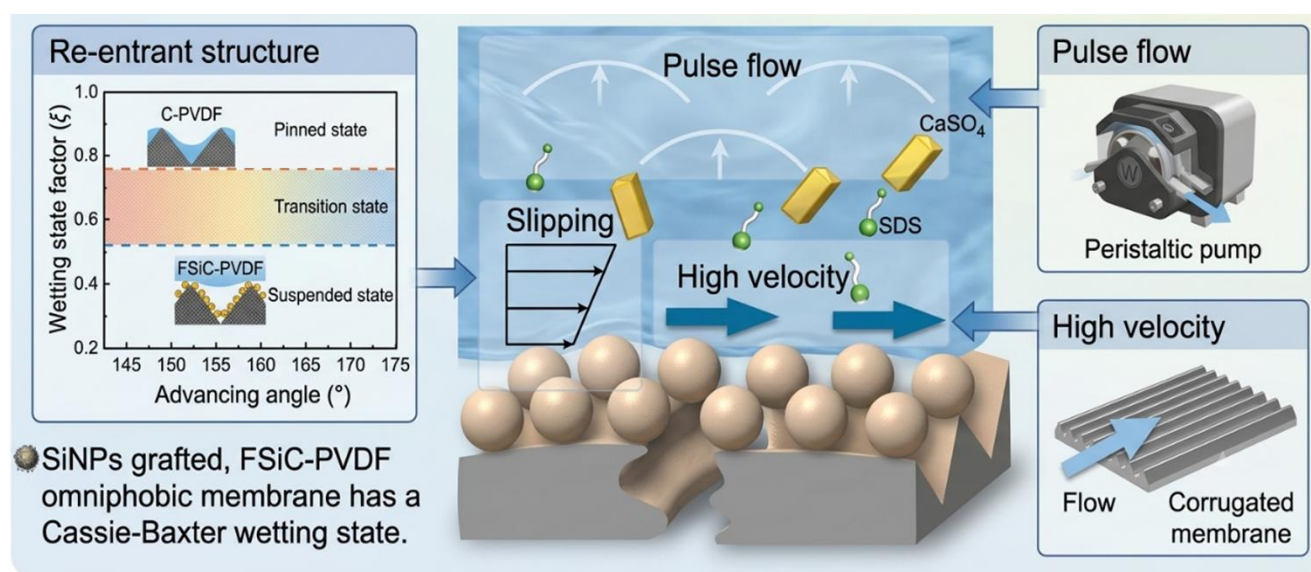


Figure 6. Map of the wetting state factor of C-PVDF and FSiC-PVDF and schematic representation of silica nanoparticle coatings on the corrugated membranes [46].

4.3. Introduction of Nano/Micro Bubbles to Feed Water

Another effective strategy for scaling control involves introducing a gas–liquid two-phase flow through bubble generation [47]. Research has shown that bubble-induced secondary flows can substantially increase the maximum shear stress near the membrane surface, which helps mitigate temperature and concentration polarization and reduces scale deposition on the membrane. Additionally, bubble-based technologies, when appropriately implemented, are membrane-safe and environmentally sustainable [38,48].

The efficiency of bubble technology in minimizing scaling in membrane systems is closely linked to the size and distribution of the bubbles produced. Microbubbles (MBs), defined as air bubbles with diameters ranging from 1 to 100 μm , exhibit unique properties compared to larger bubbles [24,49]. These properties include an extended lifespan in water, a negatively charged surface, and a high specific surface area. Due to these

characteristics, MBs have been successfully applied to agitate and remove particulates from membrane surfaces in various membrane separation processes, including MD. Adding MBs to the feed water enhances turbulence at the membrane interface, thereby alleviating concentration polarization and dislodging scalants from the surface. Furthermore, the negative surface charge of MBs has been suggested to decrease scaling in MD systems [49].

Nanobubbles (NBs), which are smaller than 200 nm in diameter, offer an alternative to MBs for scaling mitigation. NBs are stable gas cavities in liquids and possess unique attributes such as high interfacial area, neutral or low buoyancy, prolonged residence time, strong negative surface charge, and elevated internal pressure [50,51]. Unlike MBs and larger bubbles, NBs can persist in solution for extended periods, sometimes months, due to their neutral buoyancy and stable structure [47]. The higher internal pressure in smaller bubbles, as described by the Young-Laplace equation, accelerates gas diffusion out of MBs, causing them to collapse rather than gradually shrink into NBs. In contrast, the strong negative surface charge of NBs prevents aggregation, promoting their stable dispersion in the feed water.

The use of NBs in MD feed streams is expected to significantly enhance shear forces at the membrane surface compared to MBs. Despite their neutral buoyancy, NBs interact dynamically with surrounding fluids, generating shear forces that disrupt the boundary layer. This disruption reduces concentration polarization and scaling layer formation. Additionally, the pronounced negative charge of NBs may attract counter-ions to the gas-water interface, decreasing salt precipitation.

Despite these benefits, the implementation of bubble-based mitigation in SPMD involves inherent risks that necessitate a critical evaluation. In high-salinity and high-temperature feed solutions, the rapid collapse of bubbles—driven by intense internal pressures—can generate localized cavitation effects. These events produce high-pressure micro-jets and shockwaves directed at the membrane surface, which may cause eroding and compromise the polymeric surfaces, as recently demonstrated for microbubble-induced erosion of polymer surfaces [52]. Furthermore, these localized pressure spikes can momentarily exceed the membrane's liquid entry pressure (LEP), potentially triggering pore wetting and premature separation failure [52].

4.4. Addition of Anti-Scalant with Anionic and Neutral Moieties or Cationic Amino Groups

The application of anti-scalants represents a chemical approach to mitigating scaling in MD processes. These specialized agents disrupt the nucleation, growth, and aggregation of mineral crystals, thereby reducing their likelihood of depositing on the membrane surface [53]. Nonetheless, the use of anti-scalants has been associated with the development of microbial biofilms on membrane surfaces. This microbial fouling can present a substantial challenge to the long-term operational stability and efficiency of MD systems. Furthermore, chemical softening would be economically unfeasible for a large-scale MD plant [54].

4.5. Optimization of Operational Parameters

Optimizing operational parameters in MD is another strategy for scaling mitigation [25,55]. Key parameters such as feed temperature, flow rate, pulse rate, membrane effective area, module design are adjusted to minimize the conditions that promote scale formation. Fine-tuning these parameters can significantly improve MD performance and minimize scaling risks [3,32].

4.6. Periodic Utilization of Air-Backwash Protocols

An employed cleaning strategy in MD involves the periodic use of air-backwash protocols. Unlike pressure-driven membrane filtration processes that utilize water for backwashing, MD membranes require air-backwash to maintain their hydrophobicity and prevent wetting [27,56]. Research has indicated that intermittent air-backwashing of hydrophobic membranes demonstrates limited effectiveness in addressing gypsum scaling, as scale layers adhere strongly to the membrane surface. However, combining intermittent air-backwash with superhydrophobic membranes has been found to effectively prevent gypsum scaling [44,57]. Notably, while superhydrophobic membranes alone can delay the onset of scaling, they are insufficient to fully eliminate it without the addition of air-backwashing.

5. Fouling in MD: Mechanisms and Mitigation Strategies

Fouling is a common challenge in membrane processes and is generally classified into organic, inorganic, colloidal, and biological types [58]. Within MD systems, inorganic fouling is identified as mineral scaling. Since scaling has already been analyzed in detail earlier in this study, the focus of this section will now shift to organic, colloidal, and biological fouling. Generally speaking, fouling in membrane processes refers to the accumulation of above unwanted materials, i.e., organic, colloidal, and biological, on the membrane surface or within its pores, leading to performance decline [59]. This phenomenon diminishes membrane functionality, increases energy demands, and reduces operational lifespan, emphasizing the importance of effective fouling management for sustainable process efficiency. From a materials perspective, MD membranes are particularly susceptible to organic fouling due to long-range hydrophobic interactions between the membrane material and common hydrophobic organic foulants, such as proteins, humic acids, and emulsified oil droplets [60,61]. Oil fouling is especially significant in MD applications, as the process is widely proposed for treating oil- and gas-produced water [58,62,63].

Colloidal particles, which are fine suspended materials, contribute significantly to fouling in various feed water solutions [17]. These particles range in size from a few nanometers to several micrometers [64]. While larger particles can be effectively removed through membrane filtration technologies, smaller colloidal particles often pose more severe fouling challenges. Colloidal foulants can be broadly classified into inorganic and organic macromolecular groups. The inorganic fraction of colloidal fouling primarily consists of materials such as silica, aluminum silicate minerals, clay, silt, iron oxides/hydroxides, and other debris, which are commonly found in natural water sources. In contrast, organic colloidal foulants predominantly include macromolecules such as polysaccharides, proteins, and natural organic matter. The specific composition and type of colloidal particles vary depending on the source of the water. For instance, lakes, rivers, and groundwater sources are more prone to colloidal fouling compared to desalination processes, where advanced pre-treatment technologies are often employed to screen out larger molecules [61,65]. Several factors influence colloidal fouling, including the properties of the colloidal particles (e.g., size, shape, and charge), the strength of electrostatic interactions between colloids, other foulants, and the membrane surface, as well as the frequency of collisions between particles. These interactions can result in the formation of a fouling layer on the membrane, which increases concentration polarization and introduces additional mass transfer resistance, ultimately reducing the permeate flux [66,67].

Biological fouling, or biofouling, results from the growth of microorganisms like bacteria, fungi, and algae, often involving biofilm formation [68]. Biofouling is particularly relevant to MD when the feed water contains a high concentration of biological microorganisms. These microorganisms are commonly found in wastewater from industries such as pharmaceuticals, food and beverage production, and municipal wastewater treatment

facilities, which come into direct contact with the membrane surface [68,69]. While the high-salinity and high-temperature conditions in MD systems might suggest a reduced risk of biofouling, certain bacteria and microorganisms are resistant to these harsh conditions. Moreover, moderate temperatures can even foster the growth of thermophilic bacteria, further complicating fouling management [44,70].

In fact, the extent of fouling is impacted by the characteristics of the feed water, such as its concentration, physiochemical properties, and pH, as well as membrane attributes and operational conditions, including hydrodynamics. Understanding these factors is critical for designing effective strategies to mitigate fouling and optimize membrane performance. From an operational standpoint, the low pressure used in MD minimizes the formation of dense and compact foulant layers, making them less irreversible compared to those formed in pressure-driven processes like RO or NF [2,58]. However, the high interplay between hydrophobic/superhydrophobic membranes and organic constituents, as mentioned above, necessitates a comprehensive approach to mitigating fouling for efficient MD operation. This has become increasingly significant with advancements in the development of novel superhydrophobic membranes designed to mitigate scaling and wetting, comprehensively investigated in the previous section. As previously discussed, the Cassie-Baxter wetting state is characterized by the presence of air pockets that form a physical barrier between the liquid phase and the solid membrane surface. This results in a reduced contact area between the liquid and the membrane [26]. The trapped air pockets enhance the membrane's hydrophobicity, which in turn strengthens the long-range hydrophobic interactions between the membrane and organic foulants, such as proteins, humic acids, and oils. Consequently, these intensified interactions promote the adhesion and accumulation of organic materials on the membrane surface.

Similarly to mineral scaling, several strategies have been suggested to mitigate fouling in MD, as shown in Figure 7. The following sections will provide a detailed exploration of each of these control methods.

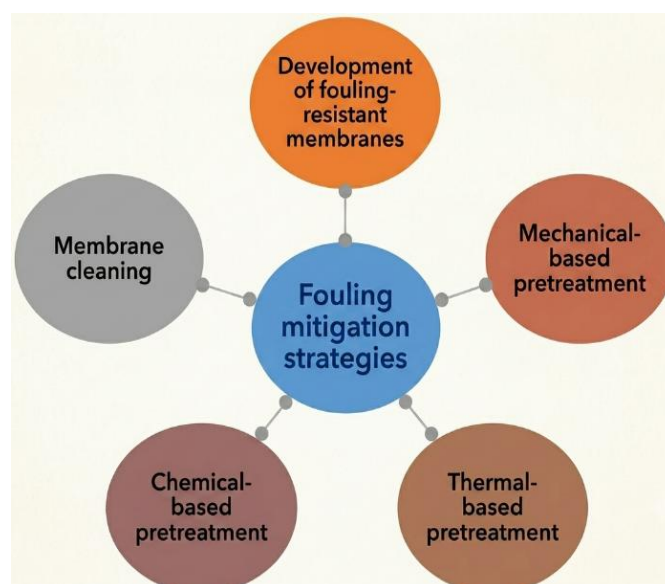


Figure 7. Various fouling mitigation strategies proposed for MD.

5.1. Development of Fouling-Resistant Membranes

Many studies on MD fouling have increasingly focused on oil fouling, as it poses a significant challenge when MD is employed for desalinating oil- and gas-produced water. The strong hydrophobic interactions inherent to hydrophobic MD membranes make them highly susceptible to oil fouling, which can severely compromise membrane performance.

Oil fouling is particularly detrimental to hydrophobic membranes, often rendering them unsuitable for sustained operation [44,57].

Omniphobic membranes, by contrast, are designed to resist both hydrophobic and oleophobic fouling due to their unique surface properties. However, it is essential to note that wetting characteristics are typically defined in air. Underwater, an omniphobic membrane exhibits oleophilic behavior, as the low surface energy materials used in its fabrication result in strong interactions with oil droplets, akin to those observed in hydrophobic membranes. The key distinction lies in the reentrant structure of omniphobic membranes, which prevents oil droplets from penetrating the pores. While oil droplets can still adhere to the surface and block vapor transport, this fouling is reversible through cleaning, as the absence of pore wicking simplifies the removal process [46].

As mentioned earlier, a novel superhydrophobic fluorinated multi-scale silicon nanoparticle grafted corrugated membrane (FSiC-PVDF) was developed to improve anti-fouling and anti-scaling performance, in our previous research. This membrane demonstrated an exceptionally high water contact angle of 179.5° , along with a strong omniphobicity characterized by a contact angle of 144.9° for mineral oil. The superior omniphobic performance was attributed to a multiscale structural design, combining spherical silicon nanoparticles (SiNPs) and surface corrugation with a 17-FAS coating. SiNPs adsorbed on the corrugated membrane surface contribute to nanoscale roughness, and provide hydroxyl groups as active sites for fluorination. The former established a re-entrant structure, while the latter reduced surface energy. Together, these features maintained the Cassie-Baxter wetting state, ensuring robust fouling resistance [46].

An alternative approach to mitigate oil fouling involves applying a hydrophilic coating on a hydrophobic membrane surface. While this strategy may offer some resistance to oil fouling in simpler feed water compositions, it is generally less effective for complex feed waters containing a mix of organic and inorganic foulants. Beyond these techniques, several other coating strategies with various materials have been explored to develop fouling-resistant MD membranes, aiming to enhance durability and performance in challenging conditions [44,71,72].

5.2. Chemical-Based Pretreatment

Chemical pretreatment techniques, such as coagulation-flocculation, chemical softening, and pH adjustment, are commonly used to mitigate fouling in membrane processes. These methods remove undesirable suspended particles and minimize fouling by neutralizing particle charges or inducing chemical reactions. They are effective against various types of fouling, including inorganic, organic, colloidal, and biological fouling, as well as oxidative fouling caused by different agents [17].

The coagulation-flocculation method primarily targets colloidal particles in feed water [17]. Coagulants are used to destabilize colloidal particles, while flocculants facilitate their aggregation into larger flocs that can be easily removed. Inorganic or polymeric coagulants, such as polyaluminum chloride (PACl), ferric and ferrous salts, lime, and cationic polymers, are commonly used. Among these, aluminum and iron salts are the most widely employed in water treatment. During coagulation, the positive charges of inorganic coagulants neutralize the negative charges of particles, reducing electrostatic repulsion and promoting aggregation. The growth of flocs depends on factors such as pH, temperature, coagulant dose, shear rates, and the type of coagulant used. This technique effectively removes a wide range of suspended particles, including microplastics, as well as dissolved matter from water [73–75].

pH adjustment is another essential chemical pretreatment strategy. Adjusting the pH of feed water based on its composition can reduce fouling during subsequent treatment

processes. It is particularly recommended as a preparatory step before the primary treatment stage in MD systems [17,76–78].

Chemical softening is among the most popular methods for removing inorganic contaminants. In this process, calcium hydroxide is added to precipitate substances responsible for carbonate hardness, such as calcium and other metals. The reaction between calcium hydroxide and dissolved CO_2 in the feed water produces calcium carbonate, which can be removed easily. This method is particularly effective for addressing scaling issues caused by metal ions [73,74,79].

In addition to these chemical-based pretreatment approaches, other techniques may also be viable for mitigating fouling, depending on the specific characteristics of the feed water and operational requirements.

5.3. Mechanical-Based Pretreatment

Physical or mechanical pretreatment methods are widely utilized to separate solid impurities and remove both coarse and fine particles that contribute to fouling in MD. Commonly employed techniques include filtration, hydrocyclone, adsorption, and membrane bioreactors, each with distinct mechanisms for minimizing fouling risks [17].

Filtration is one of the most prevalent mechanical pretreatment strategies. Gravity filtration, one of the simplest methods, is particularly effective for feed waters with high levels of solids. This technique relies on filtration media such as sand, gravel, anthracite, or walnut shell to remove solids from the feed water. Membrane-based filtration, including MF, UF, and NF, offers more advanced pretreatment options [5]. These processes reduce the concentration of colloids, suspended particles, organic matter, microorganisms, and bulky particles in the feed water, making them highly compatible with MD systems for minimizing fouling and preventing membrane damage. Among these membrane filtration methods, MF membranes, with the largest pore sizes, are primarily effective at removing large particles and microorganisms. UF membranes, which have smaller pores, not only filter out larger particles and microorganisms but also exclude bacteria and macromolecules such as proteins. NF membranes, characterized by their fine porous structures with pore sizes on the nanometer scale, demonstrate superior separation performance, effectively removing hardness, organic matter, and other contaminants [5]. These filtration methods are often applied as pretreatment steps to enhance MD performance by minimizing fouling [80].

Hydrocyclone technology, another mechanical approach, is commonly used for separating oil and grease from water based on differences in density. Adsorption techniques, on the other hand, target the removal of dissolved organic substances and heavy metals like iron and manganese from feed water. Despite their effectiveness, ion-exchange pretreatment methods are less favourable for large-scale operations due to the high costs associated with resin regeneration [17,81].

Biological pretreatment methods, such as membrane bioreactors (MBRs), utilize microorganisms to degrade pollutants in water. These systems integrate biological treatment with membrane filtration, providing an effective means of reducing organic fouling and improving feed water quality for MD processes [73,74,82].

In general, researchers proposed using more than one pre-treatment process before the MD, and for more efficient processes.

5.4. Thermal-Based Pretreatment

Thermal pretreatment involves heating the feed water to its boiling point to improve water quality and minimize fouling in subsequent membrane processes. A primary objective of this method is the removal of bicarbonates from the feed solution, thereby reducing the potential for inorganic scaling on the membrane surface [83]. Additionally, thermal

pretreatment is effective in addressing biological fouling. In feed solutions containing protein-based foulants, boiling the water followed by filtration has been shown to significantly lower the risk of biofilm formation. Research has demonstrated that combining thermal pretreatment with filtration effectively decreases total organic carbon (TOC) and turbidity levels, leading to a reduced likelihood of protein accumulation on the membrane surface. This approach enhances membrane performance by mitigating fouling-related challenges. However, it is important to consider that thermal processes are highly energy-intensive, which can make them economically impractical for large-scale applications [83].

5.5. Membrane Cleaning

Membrane cleaning is sometimes necessary to restore membrane performance by removing fouling deposits. Cleaning processes aim to partially or completely eliminate particles that block membrane pores or accumulate on the surface, thereby improving operational efficiency. Various membrane cleaning methods are employed to address fouling. Among these, chemical and physical approaches are the most widely recognized. The effectiveness of these methods is typically evaluated based on resistance removal and permeate flux recovery [84,85].

Chemical cleaning involves the use of agents like acids, caustic soda, oxidants, chelating agents, or specialized surfactants. These chemicals act to weaken the cohesive forces binding foulants to the membrane surface, facilitating their removal. On the other hand, physical cleaning employs mechanical actions, such as backwashing or other application of mechanical forces, to dislodge and remove fouling layers adhered to the membrane surface [86].

5.6. Trade-Offs, Compatibility, and Comparative Promise of Mitigation Strategies

Considered together, the scaling and fouling mitigation strategies reviewed above (Sections 4 and 5) differ substantially in their trade-offs, compatibility with one another, and likely impact on long-term membrane performance. Chemical approaches—antiscalant dosing, chemical softening, and ion-exchange pretreatment—offer relatively low upfront energy cost but carry recurring operational costs and, in the case of antiscalants, a documented tendency to promote biofilm formation [53,54], partially offsetting their anti-scaling benefit. Thermal pretreatment is effective against both scaling precursors and biological foulants but is highly energy-intensive, working against the core energy-efficiency rationale of SPMD [83]. Surface-engineering approaches (omniphobic, superhydrophobic, and corrugated membranes) address the root thermodynamic cause of scaling—nucleation site availability—rather than treating its symptoms, and therefore do not require recurring chemical or thermal input once fabricated; however, their benefit is compatibility-dependent, since intermittent air-backwash has been shown to be largely ineffective against gypsum scaling on conventional membranes but highly effective when combined specifically with superhydrophobic surfaces [44,56]. Physical/hydrodynamic strategies (nano/microbubbles, pulse flow) are membrane-compatible and reversible in principle, but as discussed in Section 4.2, may introduce their own risk to membrane surface integrity under sustained operation. Repeated chemical cleaning cycles, meanwhile, pose a documented risk of gradually degrading membrane hydrophobicity and any surface nanocoating over the membrane's operational lifetime, an effect that is likely to compound with the coating durability concerns discussed in Section 8. Based on the balance of these trade-offs, the combination of durable surface engineering with periodic air-backwash currently appears the most promising strategy identified in the literature for sustained scaling resistance with the lowest recurring energy penalty, while purely chemical or thermal pretreatment routes remain comparatively difficult to justify at full operational scale.

6. Fouling and Scaling in SPMD: Effect of Photothermal Coatings

In SPMD, photothermal materials, e.g., carbon nanoparticles (CNPs), gold nanoparticles (GNPs), etc., are applied directly to the membrane surface to harvest sunlight and generate localized heating at the liquid–vapor interface. Research has shown that this localized heating reduces the energy demands of SPMD compared to conventional MD, where the bulk feed water is heated. By concentrating heat at the membrane interface, SPMD minimizes temperature polarization and lowers the overall energy consumption [23,87].

In addition to energy efficiency, photothermal coating materials in SPMD has demonstrated the ability to reduce scaling and organic fouling. Previous studies have evaluated the anti-scaling/fouling properties of photothermal membranes used in SPMD. Results indicated that membranes with photothermal coatings exhibited greater resistance to scaling and fouling compared to uncoated, pristine membranes. It is hypothesized that the self-heating nature of the photothermal coating alters surface characteristics critical to scale formation [23]. Specifically, the increased hydrophilicity of the photothermal layer may play a key role in preventing the adhesion and deposition of scaling/fouling species present in the feed solution. However, the adoption of hydrophilic photothermal coatings introduces a fundamental physical contradiction in MD operations: while a hydrophilic surface effectively repels organic foulants and scalants, it significantly increases the membrane's susceptibility to pore wetting by lowering the LEP [88]. The literature reconciles this trade-off through advanced interfacial engineering, most notably via the development of Janus membranes. In these asymmetric architectures, a thin hydrophilic photothermal top-layer is used to harvest solar energy and provide a fouling-resistant interface, while a thick, highly hydrophobic substrate ensures the stability of the vapor-filled pores and prevents liquid penetration [89]. Furthermore, researchers have demonstrated that incorporating hierarchical re-entrant structures within the photothermal layer can stabilize air pockets at the interface, effectively maintaining a Cassie-Baxter wetting state even when the surface chemistry is modified [25,26]. By separating the anti-fouling functionality (at the top interface) from the anti-wetting requirement (within the membrane matrix), these engineered SPMD systems overcome the systemic risks of surface hydrophilization while maximizing separation efficiency.

This innovative approach to scaling/fouling mitigation highlights the potential of SPMD to enhance desalination and wastewater treatment processes by leveraging the dual benefits of energy efficiency and fouling resistance. However, the observed anti-scaling/fouling performance of photothermal coatings, while notable, is not sufficiently robust on its own. Therefore, it is promising to combine photothermal coatings with additional strategies discussed in earlier sections, i.e., development scaling/fouling resistant membranes, periodic cleaning, etc., holds significant promise for further reducing the likelihood of scaling and fouling in SPMD systems [6,23]. Beyond its established role in scaling mitigation, localized photothermal heating may also offer an intrinsic route to suppressing biofouling, as photothermally induced heat has been shown to inactivate microorganisms and confer antimicrobial resistance in related membrane platforms, including reverse osmosis, ultrafiltration, and MXene/nanoparticle-functionalized photothermal MD membranes [90,91]. This raises the possibility of a favorable synergy between photothermal heating and antiscalant dosing, in which the intrinsic antimicrobial action of the photothermal layer could offset the biofilm-promoting side effect of antiscalants noted earlier. However, this outcome should not be assumed automatically. As discussed in Section 5, moderate temperature elevation can, in some conditions, favor the growth of thermophilic microorganisms rather than suppress it [41,66], and the two mechanisms (localized thermal stress versus antiscalant-mediated nucleation inhibition) act via fundamentally different pathways. The net effect of combining photothermal heating with antiscalant

dosing on biofouling is therefore likely to be system- and condition-specific, and dedicated studies isolating this interaction remain lacking, representing a useful direction for future SPMD research. Mathematical modelling using both heat and mass transfer equations, are fundamental in describing and understanding the non-isothermal MD process. The involved equations incorporate complex interactions between the hot feed stream, the membrane, and the cold permeate, depending on the considered MD configuration (DCMD, AGMD, VMD, SGMD, etc.).

7. Numerical Modeling and Simulation Approaches

7.1. Coupled Radiative and Thermal Models for SPMD

Although SPMD is becoming increasingly important for solar-driven desalination, only a small number of studies have concentrated on its mathematical and numerical simulation. Elmaghraoui et al. [92] developed a theoretical model to describe the photothermal response of plasmonic nanofillers embedded in MD membranes. Based on heat transfer and radiative absorption equations, they studied energy losses and vaporization cooling effects within the photothermal layer, and investigated the effect of nanoparticle geometry and material properties on local heating efficiency. In a comparative numerical analysis of two VMD setups, Ma et al. [93,94] used a photothermal membrane for direct sun absorption and a traditional absorbing plate for external heating. They revealed that localized interfacial heating in the photothermal membrane results in the significant increases in both vapor flux and thermal efficiency, while minimize bulk heat loss. A computer model was created by Sharma et al. [37] to study nanophotonics-enabled solar membrane distillation, with a focus on the phenomenon of negative vapor flow under intense sun illumination. Investigated permeate gap thickness, transmembrane temperature differentials, and optical concentration ratios, they specified the ideal operating conditions to maximize vapor generation and reduce performance instability. In addition, the work by Elrakhawi et al. [22] presented a mathematical model of a nanophotonics-enhanced solar membrane distillation system and validated their model with experimental data. Using MATLAB and finite difference discretization method, they investigated detailed heat and mass transfer including sweeping-air transport, and identified major heat-loss pathways. They also established exponential correlations between permeate production and solar irradiance, and quantified heat-transfer coefficients for the system.

7.2. Numerical Transient Simulations for Fouling and Scaling

Scientific modelling plays a crucial role in improving our understanding of complex mechanisms such as fouling and scaling in membrane-based systems [95–101]. Over the years, numerous computational approaches, as illustrated in Figure 8, have been introduced for different MD configurations and module designs, including CFD, RSM, ANN, ML/DL techniques, and hybrid CFD-AI frameworks [102–106]. However, only a limited number of studies have addressed the dynamic simulation of fouling and scaling on membrane surfaces during separation and treatment operations. Such simulations require a comprehensive analysis of the interactions among multiple physical phenomena—fluid flow, solute and solvent transport through membranes, energy exchange within modules, and the deposition of foulants or scalants on the membrane surface.

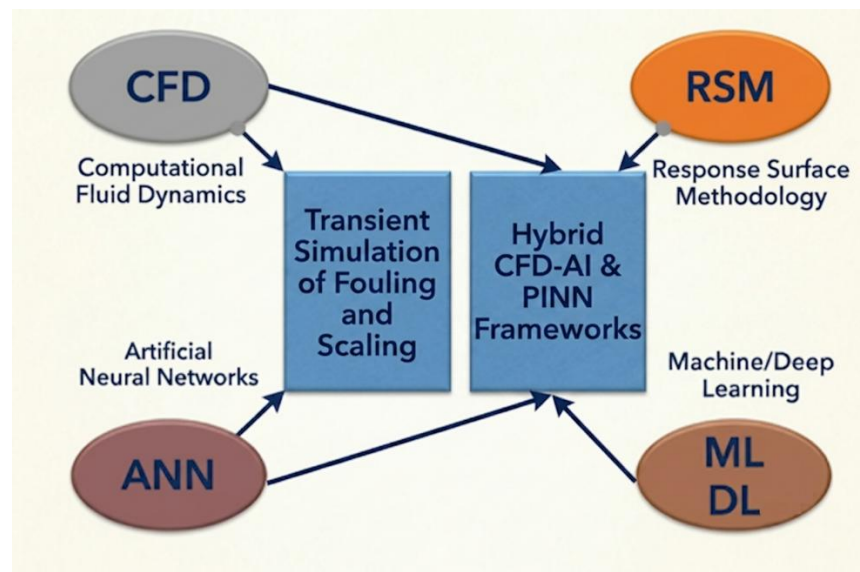


Figure 8. Computational approaches for transient simulation of fouling/scaling in membrane-based water treatment technologies.

CFD is the most popular approach among those available for MD modeling that it uses the governing equations of motion (Navier–Stokes) and mass, momentum, and energy conservation rules to forecast fluid behavior. Coupled equations for continuity, energy, momentum, and species transport can be solved by CFD models to determine distribution of pressure, velocity, temperature, and concentration throughout the membrane module [3,32]. To incorporate fouling and scaling into CFD frameworks, the model must account for the interplay between these conservation principles and the progressive accumulation of deposits on the membrane surface. This accumulation is often represented mathematically through adsorption/desorption relationships [43,107]. However, the adsorption and desorption coefficients are case-specific and depend on factors such as nucleation, crystallization, and membrane material properties. Determining these parameters typically requires experimental data or reliable empirical correlations. Consequently, most CFD-based studies simplify the problem by neglecting this coupling and focus on steady-state predictions rather than transient fouling and scaling behaviour. In fact, a truly holistic dynamic simulation must account for the feedback loop where the growing scale layer thickness ($\delta_{sc}(t)$) alters the transport coefficients. The effective mass transfer coefficient ($C_{m,eff}$) and overall heat transfer coefficient (U_{eff}) decline over time according to a resistance-in-series model [39]:

$$\frac{1}{C_{m,eff}} = \frac{1}{C_m} + \frac{\delta_{sc}(t)}{P_{sc}} \quad (22)$$

$$\frac{1}{U_{eff}} = \frac{1}{h_f} + \frac{\delta_m}{k_m} + \frac{\delta_{sc}(t)}{k_{sc}} \quad (23)$$

where k_{sc} and P_{sc} represent the thermal conductivity and vapor permeability of the scale layer. As δ_{sc} increases, the added thermal and physical resistance reduces the effective driving force, explaining the non-linear flux decline observed in long-term SPMD operations.

RSM is frequently used to optimize MD processes, including scaling and fouling mitigation techniques. RSM offers a conceptual framework for analyzing situations in which a response is influenced by several factors, establishing quantitative correlations, and visualizing variable contributions using computational and graphical methods. awareness the various contamination mechanisms in MD systems requires an awareness of the

complex connections among affecting parameters, which RSM helps discover and illustrate in the context of fouling and scaling prediction [108–110]. Research employing RSM in MD seeks to improve important performance metrics such water productivity per module volume, permeate flux, energy efficiency, and cleaning efficacy in addition to reducing the thickness of foulant or scalant layers. RSM is based on statistical design of experiments (DoE), as opposed to CFD, which is based on physical assumptions and governing equations. All operating parameters can be changed simultaneously with this method, making it possible to identify interaction effects and how they affect process performance [111,112].

ANN and ML, branches of artificial intelligence, are designed to predict outcomes by identifying patterns within large datasets through algorithmic models. Today, these techniques have become highly prevalent across numerous scientific and industrial domains [113,114]. In MD systems, ANN and ML can help pinpoint critical variables, assess how operating conditions influence fouling behavior and overall performance, and provide insights across different MD configurations, from conventional setups to SPMD. Research findings consistently highlight the significance of ANN and ML in this field, demonstrating its potential to deepen our understanding of fouling and scaling in all membrane-based water treatment processes and improve predictive capabilities [102,104,113–115]. Abuwatfa et al. [116] reviewed the existing literature on the application of ANNs for predicting membrane fouling. This review provided an in-depth discussion of the advantages, limitations, potential applications, and areas where these models can be improved for predicting fouling in pressure-driven membrane processes such as UF, NF, and RO. In another review study, Shahouni et al. investigated deeply the advancement in AI models for membrane-based water treatment technologies, emphasising the superior predictive capabilities of AI models compared to traditional methods. Key findings include the development of AI models for various membrane separation techniques and the integration of AI concepts such as ML and ANNs to simulate membrane fouling, water flux and micropollutant behaviour, aiming to enhance wastewater treatment and optimise treatment and desalination processes. In conclusion, this review summarised the applications of AI in predicting the behaviour of membranes as well as their strengths, weaknesses and future directions of AI in membranes for water purification and desalination processes. In another comprehensive study, Shahouni and colleagues [117] evaluated more recent advancements in the use of AI to membrane-based water treatment systems. They indeed studied applicability of more AI-driven models employing various ANNs and ML techniques for various membrane separation processes that were used to describe the behavior of micropollutants, water flux, and membrane fouling. By using principal component analysis (PCA) to transmembrane pressure data obtained from a pilot-scale UF system, Naessens et al. [118] presented and validated a novel method for fouling monitoring. Their investigation looked at fouling's evolution over time and its relationship to the cleaning techniques used as well as the incoming seawater's quality. The created models showed that there was no discernible difference between the improved backwashing technique and the traditional one in terms of cleaning efficacy. By lowering the frequency of cleaning cycles without sacrificing performance, this result lends credence to the notion that optimal cleaning can be applied sustainably. Shim et al. [119] created a long short-term memory (LSTM) model to examine how fouling progression and filtration efficiency vary over time. They focused on the many pathways connected to natural organic matter (NOM) in their controlled laboratory studies on membrane fouling in NF systems in order to create the training dataset. Four representative NOM chemicals were chosen as model foulants: tannic acid, sodium alginate, bovine serum albumin, and humic acid. Additionally, fouling layer generation on the membrane surface was measured using optical coherence tomography (OCT) to get real-time two-dimensional pictures of the fouling layer.

Permeate flux and fouling layer thickness were predicted as output variables by the LSTM model, which was trained using these experimental observations. During both the training and validation stages, the model's root mean square errors were less than 1 L/m²·h for flux and less than 10 µm for layer thickness, indicating its high accuracy. In another work and in order to track the formation of fouling layers on membranes during forward osmosis (FO) in real time, Im et al. [120] also used OCT. According to the OCT pictures, the fouling layer looked thin, compact, and comparatively smooth at the beginning. The layer developed into a thicker structure with a rougher surface texture as the procedure went on. They used a dataset of real-time fouling OCT photos to build a deep learning-based convolutional neural network in order to analyze these changes. The model's prediction performance was very accurate and closely matched experimental observations. In particular, thickness had a coefficient of determination (R²) of 0.90, porosity of 0.86, roughness of 0.92, and density of 0.90. It is worth emphasizing that, among the studies discussed above, the LSTM model of Shim et al. [119] and the CNN-based model of Im et al. [120] represent genuine dynamic simulations of foulant layer evolution, tracking layer thickness and related structural properties as continuous functions of time, in contrast to the steady-state focus that dominates current CFD-based approaches. Moving-mesh and phase-field methods, which explicitly resolve a growing solid–liquid interface and are well established for simulating crystal growth in other fields [121], have not yet, to our knowledge, been applied to dynamic scale or foulant layer growth in membrane distillation, representing a promising avenue for future physics-based dynamic modeling. In parallel, hybrid CFD-AI frameworks, in which machine learning models are trained on or coupled with CFD-generated flow and concentration fields, are emerging as an important development trend for membrane-based separation processes generally [122,123], and could offer a practical route to achieving dynamic, physically grounded fouling/scaling predictions in SPMD without the full computational cost of transient multiphase CFD. Although extensive research and most discussed studies in this review have focused on fouling and scaling in other membrane-based water treatment technologies such as UF, NF, and RO, this concept and approach can also be applied to MD and its variants, including SPMD.

8. Practical Implementation, Durability, and Techno-Economic Perspectives

While the preceding sections address the mechanistic and computational foundations of SPMD, translating these developments into deployable systems raises practical questions that have received comparatively little attention in the literature to date. First, the long-term durability of photothermal coatings under real outdoor solar exposure remains insufficiently characterized: most reported CB, plasmonic, and 2D-material (e.g., MoS₂) coatings are evaluated over laboratory timescales of hours to days, and questions of coating delamination, nanoparticle release into the permeate or environment, and gradual loss of photothermal efficiency under prolonged UV and thermal cycling are rarely addressed systematically [124]. Second, economic feasibility depends not only on the thermal energy savings that photothermal coatings provide relative to the ~90% thermally dominated energy demand of conventional MD, but also on the added cost, synthesis complexity, and expected service life of the coating itself; direct cost comparisons remain scarce, though available evidence suggests that carbon-based and MoS₂-based coatings are considerably less expensive than noble-metal plasmonic alternatives such as Ag nanoparticles, without a proportional loss in performance [124]. Third, despite encouraging pilot-scale demonstrations under field solar irradiance and stand-alone, heat-exchanger-free configurations [21], the great majority of SPMD studies remain at bench or laboratory scale, and multi-month or seasonal outdoor validation, alongside standardized

technology readiness level (TRL) assessment, is largely absent from the current literature. Addressing these three areas—coating durability, economics, and field-scale validation—will be essential for moving SPMD from a promising laboratory concept toward a commercially viable desalination technology.

9. Conclusions

In summary, this comprehensive review has established a unified framework for SPMD, systematically connecting core transport physics, interface operational challenges, material-based mitigation strategies, and advanced computational forecasting paradigms. The main highlights and insights synthesized in this work are summarized as follows:

- **Transmembrane Mass & Heat Transport Dynamics:** The review critically evaluated classical theoretical models—specifically the KM-P model, DGM, and Schofield model—for capturing coexisting molecular and Knudsen diffusion resistances across diverse nanoporous geometries. Beyond classical equilibrium assumptions, this work emphasized that under high photothermal flux, mass transfer is governed by non-equilibrium, Knudsen-layer behavior at the liquid-vapor interface. Resolving this microscale discontinuity and its non-linear local vapor pressure profile represents a key scientific frontier required to accurately model mass transfer beyond typical DGM or KM-P strategies. Coupled heat transfer is governed by bulk and interfacial temperatures, where microstructural models like the Isostrain model effectively capture effective thermal conductivity. In fact, the spatial distribution of photothermal nanoparticles fundamentally dictates the system's thermal efficiency. Applying the Isostrain model, it is evident that the inclusion of highly conductive photothermal fillers replaces a portion of the lower-conductivity polymer matrix, thereby increasing the thermal conductivity of the solid phase.
- **Interfacial Scaling & Fouling Challenges:** Despite the thermodynamic benefits of reversing temperature polarization, this review examined the serious operational challenges of mineral scaling and organic/biological fouling common to both conventional MD and SPMD modules. Phase change at the photothermal interface triggers severe pathways of bulk homogeneous and surface-confined heterogeneous crystal nucleation, which dynamically compromise the membrane's operational lifespan and drive wetting transitions from a stable Cassie-Baxter suspended state to a flooded, pinned Wenzel state.
- **Advanced Mitigation Strategies & Photothermal Layer Dynamics:** A wide array of mitigation approaches was evaluated, ranging from surface-engineered omniphobic membranes (e.g., silica nanoparticle-grafted multi-scale corrugated structures) to hydrodynamic and chemical controls (nano/micro-bubble injections, pulse flow, anti-scalants, and periodic air-backwash). The active photothermal layer (e.g., carbon black or plasmonic nanoparticles) not only drives localized solar energy capture but actively alters crystallization kinetics. Key engineering bottlenecks that warrant focused attention include the cavitation-related risks of bubble-based cleaning, the long-term durability of coatings under outdoor solar exposure, and reconciling coating hydrophilicity with wetting resistance via Janus-type membrane architectures.
- **Computational Modeling & Predictive Paradigms:** Contemporary simulation frameworks were benchmarked, contrasting deterministic multi-phase Computational Fluid Dynamics (CFD) with empirical Response Surface Methodology (RSM) and data-driven Artificial Intelligence/Machine Learning (AI/ML) models. On the computational side, developing hybrid CFD-AI frameworks and physics-informed neural networks (PINNs) that embed governing transport equations directly into data-driven models represents a critical bridge between mechanistic accuracy and dynamic predictive capability [125–127].

- **Techno-Economic and Field Implementation Barriers:** Moving SPMD from laboratory scale to field deployment requires overcoming practical barriers, including photothermal coating durability, scaling up modules without performance decay, and conducting rigorous techno-economic analyses to justify costs against conventional desalination processes.

Ultimately, this holistic review highlights that overcoming the systemic boundaries of SPMD relies on integrating advanced surface engineering with multi-scale computational modeling, paving the way for scalable, fouling-resistant, and optimized solar-driven desalination infrastructure.

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References

1. Khayet, M.; Matsuura, T. *Membrane Distillation: Principles and Applications*; Elsevier: Amsterdam, The Netherlands, 2011.
2. Winter, D. *Membrane Distillation: A Thermodynamic, Technological and Economic Analysis: 1 (Schriftenreihe der Reiner Lemoine-Stiftung)*; Shaker: Düren, Germany, 2014.
3. Harandi, H.B.; Asadi, A.; Fathi, H.; Sui, P.-C. Combined macroscopic and pore scale modeling of direct contact membrane distillation with micro-porous hydrophobic membranes. *Desalination* **2021**, *514*, 115171. <https://doi.org/10.1016/j.desal.2021.115171>.
4. Drioli, E.; Ali, A.; Macedonio, F. Membrane distillation: Recent developments and perspectives. *Desalination* **2015**, *356*, 56–84.
5. Harandi, H.B.; Asadi, A. Transport Mechanisms in Membranes Used for Desalination Applications. In *Transport Perspectives for Porous Medium Applications*; IntechOpen: London, UK, 2023.
6. Dongare, P.D.; Alabastri, A.; Pedersen, S.; Zodrow, K.R.; Hogan, N.J.; Neumann, O.; Wud, J.; Wang, T.; Deshmukh, A.; Elimelech, M.; et al. Nanophotonics-enabled solar membrane distillation for off-grid water purification. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 6936–6941. <https://doi.org/10.1073/pnas.1701835114>.
7. Said, I.A.; Fuentes, N.; He, Z.; Xin, R.; Zuo, K.; Li, Q. Low-cost desalination of seawater and hypersaline brine using nanophotonics enhanced solar energy membrane distillation. *Environ. Sci. Water Res. Technol.* **2020**, *6*, 2180–2196. <https://doi.org/10.1039/d0ew00254b>.
8. Said, I.A.; Wang, S.; Li, Q. Field Demonstration of a Nanophotonics-Enabled Solar Membrane Distillation Reactor for Desalination. *Ind. Eng. Chem. Res.* **2019**, *58*, 18829–18835. <https://doi.org/10.1021/acs.iecr.9b03246>.
9. Said, I.A.; Fuentes, N.; He, Z.; Xin, R.; Zuo, K.; Walker, W.S.; Li, Q. Treatment of brackish water reverse osmosis brine using only solar energy. *Environ. Sci. Water Res. Technol.* **2021**, *7*, 1840–1851. <https://doi.org/10.1039/d1ew00291k>.
10. Bodell, B.R. Silicone Rubber Vapor Diffusion in Saline Water Distillation. US 285,032, 3 June 1963.
11. Weyl, P.K. Recovery of Demineralized Water from Saline Waters. US3340186A, 5 September 1967.
12. Findley, M.E.; Tanna, V.V.; Rao, Y.B.; Yeh, C.L. Mass and heat transfer relations in evaporation through porous membranes. *AIChE J.* **1969**, *15*, 483–489.
13. Bodell, B.R. Distillation of Saline Water Using Silicone Rubber Membrane. US3361645A, 2 January 1968.
14. Cheng, D.Y. Method and Apparatus for Distillation. US 4482431, 13 November 1984.
15. Esato, K.; Eiseman, B. Experimental evaluation of Gore-Tex membrane oxygenator. *J. Thorac. Cardiovasc. Surg.* **1975**, *69*, 690–697.
16. Zare, S.; Kargari, A. Membrane properties in membrane distillation. In *Emerging Technologies for Sustainable Desalination Handbook*; Elsevier: Amsterdam, The Netherlands, 2018; pp. 107–156.

17. Bazargan Harandi, H.; Zhang, L.; Kargari, A.; Sui, P.; Wang, Y.; Mutailipu, M.; Lu, H.; Li, Q. Optimum chain desalination process design for treatment of high TDS brine: A case assessment for future treatment of extracted brine from Shenhua CO₂ storage site. *Greenh. Gases Sci. Technol.* **2023**, *13*, 470–492. <https://doi.org/10.1002/ghg.2217>.
18. Kaplan, R.; Mamrosh, D.; Salih, H.H.; Dastgheib, S.A. Assessment of desalination technologies for treatment of a highly saline brine from a potential CO₂ storage site. *Desalination* **2017**, *404*, 87–101. <https://doi.org/10.1016/j.desal.2016.11.018>.
19. Summers, E.K.; Lienhard, V.J.H. A novel solar-driven air gap membrane distillation system. *Desalin. Water Treat.* **2013**, *51*, 1344–1351. <https://doi.org/10.1080/19443994.2012.705096>.
20. Dongare, P.D.; Alabastri, A.; Neumann, O.; Nordlander, P.; Halas, N.J. Solar thermal desalination as a nonlinear optical process. *Proc. Natl. Acad. Sci. USA* **2019**, *116*, 13182–13187. <https://doi.org/10.1073/pnas.1905311116>.
21. Said, I.A.; Chomiak, T.R.; He, Z.; Li, Q. Low-Cost High-Efficiency Solar Membrane Distillation for Treatment of Oil Produced Waters. *Sep. Purif. Technol.* **2020**, *250*, 117170.
22. Elrakhawi, M.; Tayel, A.F.; Abdelrazek, A.; He, Z.; Li, Q.; Said, I.A. Modeling and experimental validation of nanophotonics-enhanced solar membrane distillation technology for treating reverse osmosis brine. *Appl. Water Sci.* **2025**, *15*, 11.
23. Bellier, M.; Ali, M.E.A.; Abo El fadl, M.M.; Perreault, F. Photothermal Carbon Black Nanoparticle Coating Increases Scaling Resistance in Solar Membrane Distillation. *ACS ES&T Water* **2024**, *4*, 5925–5932. <https://doi.org/10.1021/acsestwater.4c00882>.
24. Ali, M.E.A.; Alghanayem, R.; Varela, A.; Bellier, M.; Perreault, F. Scaling mitigation in direct contact membrane distillation using air microbubbles. *Desalination* **2023**, *549*, 116348. <https://doi.org/10.1016/j.desal.2022.116348>.
25. Bazargan Harandi, H.; Hu, J.; Asadi, A.; Sui, P.-C.; Zhang, L.; He, T. Experimental and theoretical analysis of scaling mitigation for corrugated PVDF membranes in direct contact membrane distillation. *J. Memb. Sci.* **2023**, *686*, 122001. <https://doi.org/10.1016/j.memsci.2023.122001>.
26. Hu, J.; Harandi, H.B.; Chen, Y.; Zhang, L.; Yin, H.; He, T. Anisotropic gypsum scaling of corrugated polyvinylidene fluoride hydrophobic membrane in direct contact membrane distillation. *Water Res.* **2023**, *244*, 120513. <https://doi.org/10.1016/j.watres.2023.120513>.
27. Horseman, T.; Su, C.; Christie, K.S.S.; Lin, S. Highly Effective Scaling Mitigation in Membrane Distillation Using a Superhydrophobic Membrane with Gas Purging. *Environ. Sci. Technol. Lett.* **2019**, *6*, 423–429. <https://doi.org/10.1021/acs.estlett.9b00354>.
28. Wang, Z.; Horseman, T.; Straub, A.P.; Yip, N.Y.; Li, D.; Elimelech, M.; Lin, S. Pathways and Challenges for Efficient Solar-Thermal Desalination. *Sci. Adv.* **2019**, *5*, eaax0763.
29. Zuo, K.; Wang, W.; Deshmukh, A.; Jia, S.; Guo, H.; Xin, R.; Elimelech, M.; Ajayan, P.M.; Lou, J.; Li, Q. Multifunctional nanocoated membranes for high-rate electrothermal desalination of hypersaline waters. *Nat. Nanotechnol.* **2020**, *15*, 1025–1032. <https://doi.org/10.1038/s41565-020-00777-0>.
30. Jawed, A.S.; Nassar, L.; Hegab, H.M.; van der Merwe, R.; Al Marzooqi, F.; Banat, F.; Hasan, S.W. Recent developments in solar-powered membrane distillation for sustainable desalination. *Heliyon* **2024**, *10*, e31656. <https://doi.org/10.1016/j.heliyon.2024.e31656>.
31. Bazargan Harandi, H.; Asadi, A.; Shen, Z.; Sui, P.-C. Integration of Direct-Contact Membrane Distillation with Flat-Plate Solar Collector versus Proton-Exchange Membrane Fuel Cell: Dynamic Simulations and Comparative Analysis. *J. Energy Eng.* **2022**, *148*, 04022005 [https://doi.org/10.1061/\(ASCE\)EY.1943-7897.0000825](https://doi.org/10.1061/(ASCE)EY.1943-7897.0000825).
32. Harandi, H.B.; Asadi, A.; Shen, Z.; Rahnama, M.; Djilali, N.; Sui, P.-C. Modeling of heat and mass transfer in direct contact membrane distillation: Effect of counter diffusion velocity. *Desalin. Water Treat.* **2021**, *216*, 71–82. <https://doi.org/10.5004/dwt.2021.26816>.
33. Vaartstra, G.; Lu, Z.; Lienhard, J.H.; Wang, E.N. Revisiting the Schrage Equation for Kinetically Limited Evaporation and Condensation. *J. Heat Transfer* **2022**, *144*, 4054382. <https://doi.org/10.1115/1.4054382>.
34. Schrage, R.W. *A Theoretical Study of Interphase Mass Transfer*; Columbia University Press: New York, NY, USA, 1953.
35. Shaoyi, S.; Mingxuan, L.; Linsong, J.; Yongqian, D.; Ali Hamid, M.O.; Yang, Z.; Haotian, Q.; Maozhao, X. Analysis of turbulent structural characteristics and dynamic heat transfer mechanisms in a packed structure wake rectifier using large eddy simulation method. *Chem. Eng. Sci.* **2026**, *334*, 124305. <https://doi.org/10.1016/j.ces.2026.124305>.
36. Jia, B.; Zhao, Z.; Wang, X.; Chen, C.; Ma, X.; Wu, J.; Yang, L.; Politaeva, N. Local film thickness in relation to the droplet topological structure of droplet falling film on micro-nano structured horizontal tubes. *Case Stud. Therm. Eng.* **2026**, *83*, 108125. <https://doi.org/10.1016/j.csite.2026.108125>.

37. Sharma, M.K.; Muhammad, A.; He, Z.; Younas, M.; Sameti, M.; Rezakazemi, M.; Li, Q. Understanding the phenomena of negative vapor flux in Nanophotonics-Enabled solar membrane distillation. *Chem. Eng. J.* **2024**, *483*, 149005. <https://doi.org/10.1016/j.cej.2024.149005>.
38. Chen, G.; Lu, Y.; Krantz, W.B.; Wang, R.; Fane, A.G. Optimization of operating conditions for a continuous membrane distillation crystallization process with zero salty water discharge. *J. Memb. Sci.* **2014**, *450*, 1–11. <https://doi.org/10.1016/j.memsci.2013.08.034>.
39. Yu, Q.; Xie, M.; Chen, R.; Li, K.; Zhang, L.; Pan, B.; Pan, X.; Zhang, J.; Qu, D. High-efficiency solar-driven photothermal membrane distillation via permeate-side interfacial heating. *Desalination* **2026**, *628*, 120073. <https://doi.org/10.1016/j.desal.2026.120073>.
40. Xie, M.; Gray, S.R. Gypsum scaling in forward osmosis: Role of membrane surface chemistry. *J. Memb. Sci.* **2016**, *513*, 250–259. <https://doi.org/10.1016/j.memsci.2016.04.022>.
41. Su, C.; Horseman, T.; Cao, H.; Christie, K.S.S.; Li, Y.; Lin, S. Robust Superhydrophobic Membrane for Membrane Distillation with Excellent Scaling Resistance. *Environ. Sci. Technol.* **2019**, *53*, 11801–11809. <https://doi.org/10.1021/acs.est.9b04362>.
42. Karanikola, V.; Boo, C.; Rolf, J.; Elimelech, M. Engineered Slippery Surface to Mitigate Gypsum Scaling in Membrane Distillation for Treatment of Hypersaline Industrial Wastewaters. *Environ. Sci. Technol.* **2018**, *52*, 14362–14370. <https://doi.org/10.1021/acs.est.8b04836>.
43. Swaidan, B.; Hassan Ali, M.I.; Abu Al-Rub, R.K.; Alhseinat, E.; Arafat, H.A. Deep insights on gypsum scaling in DCMD using computational fluid dynamics: Role of spacer design. *Desalination* **2025**, *612*, 118967. <https://doi.org/10.1016/j.desal.2025.118967>.
44. Horseman, T.; Yin, Y.; Christie, K.S.; Wang, Z.; Tong, T.; Lin, S. Wetting, Scaling, and Fouling in Membrane Distillation: State-of-the-Art Insights on Fundamental Mechanisms and Mitigation Strategies. *ACS ES&T Eng.* **2021**, *1*, 117–140. <https://doi.org/10.1021/acsestengg.0c00025>.
45. Liu, L.; Charlton, L.; Song, Y.; Li, T.; Li, X.; Yin, H.; He, T. Scaling resistance by fluoro-treatments: The importance of wetting states. *J. Mater. Chem. A* **2022**, *10*, 3058–3068. <https://doi.org/10.1039/D1TA07695G>.
46. Hu, J.; Harandi, H.B.; Liu, S.; Zhang, Y.; He, T. Scaling and wetting resistant silica nanoparticle grafted multi-scale corrugated omniphobic membranes for membrane distillation. *Desalination* **2024**, *592*, 118122. <https://doi.org/10.1016/j.desal.2024.118122>.
47. Farid, M.U.; Kharraz, J.A.; Lee, C.-H.; Fang, J.K.-H.; St-Hilaire, S.; An, A.K. Nanobubble-assisted scaling inhibition in membrane distillation for the treatment of high-salinity brine. *Water Res.* **2022**, *209*, 117954. <https://doi.org/10.1016/j.watres.2021.117954>.
48. Cui, Z.; Chang, S.; Fane, A. The use of gas bubbling to enhance membrane processes. *J. Memb. Sci.* **2003**, *221*, 1–35. [https://doi.org/10.1016/S0376-7388\(03\)00246-1](https://doi.org/10.1016/S0376-7388(03)00246-1).
49. Sakr, M.; Mohamed, M.M.; Maraqa, M.A.; Hamouda, M.A.; Aly Hassan, A.; Ali, J.; Jung, J. A critical review of the recent developments in micro–nano bubbles applications for domestic and industrial wastewater treatment. *Alexandria Eng. J.* **2022**, *61*, 6591–6612. <https://doi.org/10.1016/j.aej.2021.11.041>.
50. Agarwal, A.; Ng, W.J.; Liu, Y. Principle and applications of microbubble and nanobubble technology for water treatment. *Chemosphere* **2011**, *84*, 1175–1180. <https://doi.org/10.1016/j.chemosphere.2011.05.054>.
51. Lugli, F.; Höfinger, S.; Zerbetto, F. The Collapse of Nanobubbles in Water. *J. Am. Chem. Soc.* **2005**, *127*, 8020–8021. <https://doi.org/10.1021/ja0505447>.
52. Li, D.; Bolikava, V.; Shi, Y.; Jin, S.; Unitt, R.; Sheerin, E.D.; Kang, P.; Xiao, L.; Pan, X.; Hill, C.; et al. Microbubble-induced erosion releases micro- and nanoplastics into water. *Sci. Adv.* **2025**, *11*, eaea4729. <https://doi.org/10.1126/sciadv.aea4729>.
53. Yin, Y.; Jeong, N.; Minjarez, R.; Robbins, C.A.; Carlson, K.H.; Tong, T. Contrasting Behaviors between Gypsum and Silica Scaling in the Presence of Antiscalants during Membrane Distillation. *Environ. Sci. Technol.* **2021**, *55*, 5335–5346. <https://doi.org/10.1021/acs.est.0c07190>.
54. Xu, D.; Zhu, Z.; Tan, G.; Xue, X.; Li, J. Mechanism insight into gypsum scaling of differently wettable membrane surfaces with antiscalants in membrane distillation. *J. Memb. Sci.* **2022**, *652*, 120499. <https://doi.org/10.1016/j.memsci.2022.120499>.
55. Alawad, S.M.; Lawal, D.; Khalifa, A.E. Optimization of the design and operating parameters of a large-scale vacuum membrane distillation system to improve process performance. *J. Water Process Eng.* **2023**, *56*, 104369. <https://doi.org/10.1016/j.jwpe.2023.104369>.
56. Julian, H.; Ye, Y.; Li, H.; Chen, V. Scaling mitigation in submerged vacuum membrane distillation and crystallization (VMDC) with periodic air-backwash. *J. Memb. Sci.* **2018**, *547*, 19–33. <https://doi.org/10.1016/j.memsci.2017.10.035>.
57. Wang, Z.; Lin, S. Membrane fouling and wetting in membrane distillation and their mitigation by novel membranes with special wettability. *Water Res.* **2017**, *112*, 38–47. <https://doi.org/10.1016/j.watres.2017.01.022>.

58. Alkhatib, A.; Ayari, M.A.; Hawari, A.H. Fouling mitigation strategies for different foulants in membrane distillation. *Chem. Eng. Process.-Process Intensif.* **2021**, *167*, 108517. <https://doi.org/10.1016/j.cep.2021.108517>.
59. Malaeb, L.; Ayoub, G.M. Reverse osmosis technology for water treatment: State of the art review. *Desalination* **2011**, *267*, 1–8. <https://doi.org/10.1016/j.desal.2010.09.001>.
60. Tijing, L.D.; Woo, Y.C.; Choi, J.-S.; Lee, S.; Kim, S.-H.; Shon, H.K. Fouling and its control in membrane distillation—A review. *J. Memb. Sci.* **2015**, *475*, 215–244. <https://doi.org/10.1016/j.memsci.2014.09.042>.
61. Tang, C.Y.; Chong, T.H.; Fane, A.G. Colloidal interactions and fouling of NF and RO membranes: A review. *Adv. Colloid Interface Sci.* **2011**, *164*, 126–143. <https://doi.org/10.1016/j.cis.2010.10.007>.
62. Naidu, G.; Jeong, S.; Kim, S.J.; Kim, I.S.; Vigneswaran, S. Organic fouling behavior in direct contact membrane distillation. *Desalination* **2014**, *347*, 230–239. <https://doi.org/10.1016/j.desal.2014.05.045>.
63. Kim, H.C.; Dempsey, B.A. Membrane fouling due to alginate, SMP, EfOM, humic acid, and NOM. *J. Memb. Sci.* **2013**, *428*, 190–197. <https://doi.org/10.1016/j.memsci.2012.11.004>.
64. Al-Amoudi, A.; Lovitt, R.W. Fouling strategies and the cleaning system of NF membranes and factors affecting cleaning efficiency. *J. Memb. Sci.* **2007**, *303*, 4–28. <https://doi.org/10.1016/j.memsci.2007.06.002>.
65. Coetser, S.E.; Cloete, T.E. Biofouling and biocorrosion in industrial water systems. *Crit. Rev. Microbiol.* **2005**, *31*, 213–232. <https://doi.org/10.1080/10408410500304074>.
66. Buffle, J.; Wilkinson, K.J.; Stoll, S.; Filella, M.; Zhang, J. A generalized description of aquatic colloidal interactions: The three-colloidal component approach. *Environ. Sci. Technol.* **1998**, *32*, 2887–2899. <https://doi.org/10.1021/es980217h>.
67. Winter, D.; Koschikowski, J.; Wiegand, M. Desalination using membrane distillation: Experimental studies on full scale spiral wound modules. *J. Memb. Sci.* **2011**, *375*, 104–112. <https://doi.org/10.1016/j.memsci.2011.03.030>.
68. Vrouwenvelder, H.S.; Van Paassen, J.A.M.; Folmer, H.C.; Hofman, J.A.M.H.; Nederlof, M.M.; Van Der Kooij, D. Biofouling of membranes for drinking water production. *Desalination* **1998**, *118*, 157–166. [https://doi.org/10.1016/S0011-9164\(98\)00116-7](https://doi.org/10.1016/S0011-9164(98)00116-7).
69. Qiu, H.; Peng, Y.; Ge, L.; Villacorta Hernandez, B.; Zhu, Z. Pore channel surface modification for enhancing anti-fouling membrane distillation. *Appl. Surf. Sci.* **2018**, *443*, 217–226. <https://doi.org/10.1016/j.apsusc.2018.03.004>.
70. Hausmann, A.; Sanciolo, P.; Vasiljevic, T.; Weeks, M.; Schroën, K.; Gray, S.; Duke, M. Fouling of dairy components on hydrophobic polytetrafluoroethylene (PTFE) membranes for membrane distillation. *J. Memb. Sci.* **2013**, *442*, 149–159. <https://doi.org/10.1016/j.memsci.2013.03.057>.
71. Xiao, Z.; Guo, H.; He, H.; Liu, Y.; Li, X.; Zhang, Y.; Yin, H.; Volkov, A.V.; He, T. Unprecedented scaling/fouling resistance of omniphobic polyvinylidene fluoride membrane with silica nanoparticle coated micropillars in direct contact membrane distillation. *J. Memb. Sci.* **2020**, *599*, 117819. <https://doi.org/10.1016/j.memsci.2020.117819>.
72. Xie, M.; Luo, W.; Gray, S.R. Surface pattern by nanoimprint for membrane fouling mitigation: Design, performance and mechanisms. *Water Res.* **2017**, *124*, 238–243. <https://doi.org/10.1016/j.watres.2017.07.057>.
73. Fakhru'l-Razi, A.; Pendashteh, A.; Abdullah, L.C.; Biak, D.R.A.; Madaeni, S.S.; Abidin, Z.Z. Review of technologies for oil and gas produced water treatment. *J. Hazard. Mater.* **2009**, *170*, 530–551. <https://doi.org/10.1016/j.jhazmat.2009.05.044>.
74. Iggunu, E.T.; Chen, G.Z. Produced water treatment technologies. *Int. J. Low-Carbon Technol.* **2014**, *9*, 157–177.
75. Farahbakhsh, K.; Svrcek, C.; Guest, R.K.; Smith, D.W. A review of the impact of chemical pretreatment on low-pressure water treatment membranes. *J. Environ. Eng. Sci.* **2004**, *3*, 237–253. <https://doi.org/10.1139/s03-078>.
76. Karakulski, K.; Gryta, M. Water demineralisation by NF/MD integrated processes. *Desalination* **2005**, *177*, 109–119. <https://doi.org/10.1016/j.desal.2004.11.018>.
77. Wang, J.; Qu, D.; Tie, M.; Ren, H.; Peng, X.; Luan, Z. Effect of coagulation pretreatment on membrane distillation process for desalination of recirculating cooling water. *Sep. Purif. Technol.* **2008**, *64*, 108–115. <https://doi.org/10.1016/j.seppur.2008.07.022>.
78. He, F.; Sirkar, K.K.; Gilon, J. Studies on scaling of membranes in desalination by direct contact membrane distillation: CaCO₃ and mixed CaCO₃/CaSO₄ systems. *Chem. Eng. Sci.* **2009**, *64*, 1844–1859. <https://doi.org/10.1016/j.ces.2008.12.036>.
79. Qu, D.; Wang, J.; Wang, L.; Hou, D.; Luan, Z.; Wang, B. Integration of accelerated precipitation softening with membrane distillation for high-recovery desalination of primary reverse osmosis concentrate. *Sep. Purif. Technol.* **2009**, *67*, 21–25. <https://doi.org/10.1016/j.seppur.2009.02.021>.
80. Karakulski, K.; Gryta, M.; Morawski, A. Membrane processes used for potable water quality improvement. *Desalination* **2002**, *145*, 315–319. [https://doi.org/10.1016/S0011-9164\(02\)00429-0](https://doi.org/10.1016/S0011-9164(02)00429-0).
81. Dong, H.; German, M.; Tian, L.; SenGupta, A.K. Multifunctional ion exchange pretreatment driven by carbon dioxide for enhancing reverse osmosis recovery during impaired water reuse. *Desalination* **2020**, *485*, 114459. <https://doi.org/10.1016/j.desal.2020.114459>.

82. Xing, C. Physical and biological characteristics of a tangential-flow MBR for municipal wastewater treatment. *J. Memb. Sci.* **2001**, *191*, 31–42. [https://doi.org/10.1016/S0376-7388\(01\)00472-0](https://doi.org/10.1016/S0376-7388(01)00472-0).
83. Gryta, M. Fouling in direct contact membrane distillation process. *J. Memb. Sci.* **2008**, *325*, 383–394. <https://doi.org/10.1016/j.memsci.2008.08.001>.
84. Yang, J.Y.; Li, Y.S.; Huang, B. Research on refurbishing of the used RO membrane through chemical cleaning and repairing with a new system. *Desalination* **2013**, *320*, 49–55. <https://doi.org/10.1016/j.desal.2013.04.008>.
85. Sohrabi, M.R.; Madaeni, S.S.; Khosravi, M.; Ghaedi, A.M. Chemical cleaning of reverse osmosis and nanofiltration membranes fouled by licorice aqueous solutions. *Desalination* **2011**, *267*, 93–100. <https://doi.org/10.1016/j.desal.2010.09.011>.
86. Porcelli, N.; Judd, S. Chemical cleaning of potable water membranes: A review. *Sep. Purif. Technol.* **2010**, *71*, 137–143. <https://doi.org/10.1016/j.seppur.2009.12.007>.
87. Oh, Y.; Kim, J.; Lee, E.; Lee, J.; Jeong, S. Effect of fabrication technique on membrane distillation performance of photothermal membrane: Electrospinning vs electrospraying. *Desalination* **2023**, *564*, 116799. <https://doi.org/10.1016/j.desal.2023.116799>.
88. Feng, D.; Chen, Y.; Wang, Z.; Lin, S. Janus Membrane with a Dense Hydrophilic Surface Layer for Robust Fouling and Wetting Resistance in Membrane Distillation: New Insights into Wetting Resistance. *Environ. Sci. Technol.* **2021**, *55*, 14156–14164. <https://doi.org/10.1021/acs.est.1c04443>.
89. Yu, J.; Sun, D.; Li, B.; Yue, D.; Ge, Y.; Xu, R.; Liang, H.; Song, X.; Zhai, D. Flower-like CuO light traps as anti-wetting armor of Janus membrane for spraying wastewater treatment by photothermal membrane distillation. *J. Memb. Sci.* **2023**, *688*, 122113. <https://doi.org/10.1016/j.memsci.2023.122113>.
90. Cao, S.; Wu, X.; Zhu, Y.; Gupta, P.; Martinez, A.; Zhang, Y.; Ghim, D.; Wang, Y.; Liu, L.; Jun, Y.-S.; et al. MXene aerogel for efficient photothermally driven membrane distillation with dual-mode antimicrobial capability. *J. Mater. Chem. A* **2021**, *9*, 22585–22596. <https://doi.org/10.1039/D1TA05058C>.
91. Jun, Y.-S.; Wu, X.; Ghim, D.; Jiang, Q.; Cao, S.; Singamaneni, S. Photothermal Membrane Water Treatment for Two Worlds. *Acc. Chem. Res.* **2019**, *52*, 1215–1225. <https://doi.org/10.1021/acs.accounts.9b00012>.
92. Elmaghraoui, D.; Politano, A.; Jaziri, S. Photothermal response of plasmonic nanofillers for membrane distillation. *J. Chem. Phys.* **2020**, *152*, 114102. <https://doi.org/10.1063/1.5139291>.
93. Ma, Q.; Ahmadi, A.; Cabassud, C. Direct integration of a vacuum membrane distillation module within a solar collector for small-scale units adapted to seawater desalination in remote places: Design, modeling & evaluation of a flat-plate equipment. *J. Memb. Sci.* **2018**, *564*, 617–633. <https://doi.org/10.1016/j.memsci.2018.07.067>.
94. Ma, Q.; Ahmadi, A.; Cabassud, C. Optimization and design of a novel small-scale integrated vacuum membrane distillation—Solar flat-plate collector module with heat recovery strategy through heat pumps. *Desalination* **2020**, *478*, 114285. <https://doi.org/10.1016/j.desal.2019.114285>.
95. Melnik, R. Universality of Mathematical Models in Understanding Nature, Society, and Man-Made World. In *Mathematical and Computational Modeling: With Applications in the Natural and Social Sciences, Engineering, and the Arts*; John Wiley & Sons: Hoboken, NJ, USA, 2015; pp. 1–16.
96. Herrera, I.; Pinder, G.F. *Mathematical Modeling in Science and Engineering*; Wiley: New York, NY, USA, 2012.
97. Fetsov, S.S.; Lutsenko, N.A. A novel computational model and OpenFOAM solver for simulating thermal energy storages based on granular phase change materials: Advantages and applicability. *J. Energy Storage* **2023**, *65*, 107294. <https://doi.org/10.1016/j.est.2023.107294>.
98. Haselman, J.T.; Nichols, J.W.; Mattingly, K.Z.; Hornung, M.W.; Degitz, S.J. A biologically based computational model for the hypothalamic-pituitary-thyroid (HPT) axis in *Xenopus laevis* larvae. *Math. Biosci.* **2023**, *362*, 109021. <https://doi.org/10.1016/j.mbs.2023.109021>.
99. Liu, Y.; Sun, S.; Lin, C. High-precision computational modeling of soil-rock mixtures considering realistic shape of rock blocks. *Eng. Geol.* **2023**, *323*, 107236. <https://doi.org/10.1016/j.enggeo.2023.107236>.
100. Gharehdash, S.; Sainsbury, B.-A.; Shelyag, S.; Barzegar, M. An integrated field scale computational model for hydraulic conductivity of high energy explosive driven fracturing. *Int. J. Rock Mech. Min. Sci.* **2023**, *165*, 105368. <https://doi.org/10.1016/j.ijrmms.2023.105368>.
101. Aytac, E. Forecasting Turkey's Hazelnut Export Quantities with Facebook's Prophet Algorithm and Box-Cox Transformation. *ADCAIJ Adv. Distrib. Comput. Artif. Intell. J.* **2021**, *10*, 33–47. <https://doi.org/10.14201/ADCAIJ20211013347>.
102. Ma, J.; Xu, H.; Wang, A.; Wang, A.; Gao, L.; Ding, M. Machine learning-guided underlying decisive factors of high-performance membrane distillation system: Membrane properties, operation conditions and solution composition. *Sep. Purif. Technol.* **2023**, *327*, 124964. <https://doi.org/10.1016/j.seppur.2023.124964>.

103. Imdakm, A. A Monte Carlo simulation model for membrane distillation processes: Direct contact (MD). *J. Memb. Sci.* **2004**, *237*, 51–59. <https://doi.org/10.1016/j.memsci.2004.03.005>.
104. Mittal, S.; Gupta, A.; Srivastava, S.; Jain, M. Artificial Neural Network based modeling of the vacuum membrane distillation process: Effects of operating parameters on membrane fouling. *Chem. Eng. Process.-Process Intensif.* **2021**, *164*, 108403. <https://doi.org/10.1016/j.cep.2021.108403>.
105. Cheng, D.; Gong, W.; Li, N. Response surface modeling and optimization of direct contact membrane distillation for water desalination. *Desalination* **2016**, *394*, 108–122. <https://doi.org/10.1016/j.desal.2016.04.029>.
106. Qi, J.; Lv, J.; Li, Z.; Bian, W.; Li, J.; Liu, S. A Numerical Simulation of Membrane Distillation Treatment of Mine Drainage by Computational Fluid Dynamics. *Water* **2020**, *12*, 3403. <https://doi.org/10.3390/w12123403>.
107. Ling, B.; Xie, P.; Ladner, D.; Battiato, I. Dynamic Modeling of Fouling in Reverse Osmosis Membranes. *Membranes* **2021**, *11*, 349. <https://doi.org/10.3390/membranes11050349>.
108. Yan, X.; Wang, G.; Ma, C.; Li, J.; Cheng, S.; Yang, C.; Chen, L. Effects of pollutants in alkali/surfactant/polymer (ASP) flooding oilfield wastewater on membrane fouling in direct contact membrane distillation by response surface methodology. *Chemosphere* **2021**, *282*, 131130. <https://doi.org/10.1016/j.chemosphere.2021.131130>.
109. Mahallati, M.N. Advances in modeling saffron growth and development at different scales. In *Saffron*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 139–167.
110. Deng, H.; Yang, X.; Tian, R.; Hu, J.; Zhang, B.; Cui, F.; Guo, G. Modeling and optimization of solar thermal-photovoltaic vacuum membrane distillation system by response surface methodology. *Sol. Energy* **2020**, *195*, 230–238. <https://doi.org/10.1016/j.solener.2019.11.006>.
111. Roslan, S.N.A.B.; Alias, N.H.; Othman, N.H.; Aziz, M.H.A.; Marpani, F.; Mat-Shayuti, M.S.; Shahrudin, M.Z.; DjokoKusworo, T. Application of response surface methodology for modelling of direct contact membrane distillation system: A review. *Desalin. Water Treat.* **2022**, *257*, 169–184. <https://doi.org/10.5004/dwt.2021.28015>.
112. Tibi, F.; Park, S.-J.; Kim, J. Improvement of Membrane Distillation Using PVDF Membrane Incorporated with TiO₂ Modified by Silane and Optimization of Fabricating Conditions. *Membranes* **2021**, *11*, 95. <https://doi.org/10.3390/membranes11020095>.
113. Yang, C. Neural networks for predicting air gap membrane distillation performance. *J. Indian Chem. Soc.* **2023**, *100*, 100921. <https://doi.org/10.1016/j.jics.2023.100921>.
114. Behnam, P.; Shafieian, A.; Zargar, M.; Khiadani, M. Development of machine learning and stepwise mechanistic models for performance prediction of direct contact membrane distillation module—A comparative study. *Chem. Eng. Process.-Process Intensif.* **2022**, *173*, 108857. <https://doi.org/10.1016/j.cep.2022.108857>.
115. Shirzadi, M.; Li, Z.; Yoshioka, T.; Matsuyama, H.; Fukasawa, T.; Fukui, K.; Ishigami, T. Performance analysis and optimization of sweep gas membrane distillation module using high-resolution computational model and machine learning. *Chem. Eng. J.* **2023**, *473*, 145078. <https://doi.org/10.1016/j.cej.2023.145078>.
116. Abuwatfa, W.H.; AlSawaftah, N.; Darwish, N.; Pitt, W.G.; Hussein, G.A. A Review on Membrane Fouling Prediction Using Artificial Neural Networks (ANNs). *Membranes* **2023**, *13*, 685. <https://doi.org/10.3390/membranes13070685>.
117. Shahouni, R.; Abbasi, M.; Dibaj, M.; Akrami, M. Utilising Artificial Intelligence to Predict Membrane Behaviour in Water Purification and Desalination. *Water* **2024**, *16*, 2940. <https://doi.org/10.3390/w16202940>.
118. Naessens, W.; Maere, T.; Gilabert-Oriol, G.; Garcia-Molina, V.; Nopens, I. PCA as tool for intelligent ultrafiltration for reverse osmosis seawater desalination pretreatment. *Desalination* **2017**, *419*, 188–196. <https://doi.org/10.1016/j.desal.2017.06.018>.
119. Shim, J.; Park, S.; Cho, K.H. Deep learning model for simulating influence of natural organic matter in nanofiltration. *Water Res.* **2021**, *197*, 117070. <https://doi.org/10.1016/j.watres.2021.117070>.
120. Im, S.J.; Viet, N.D.; Jang, A. Real-time monitoring of forward osmosis membrane fouling in wastewater reuse process performed with a deep learning model. *Chemosphere* **2021**, *275*, 130047. <https://doi.org/10.1016/j.chemosphere.2021.130047>.
121. Emmerich, H.; Löwen, H.; Wittkowski, R.; Gruhn, T.; Tóth, G.I.; Tegze, G.; Gránásy, L. Phase-field-crystal models for condensed matter dynamics on atomic length and diffusive time scales: An overview. *Adv. Phys.* **2012**, *61*, 665–743. <https://doi.org/10.1080/00018732.2012.737555>.
122. Thajudeen, K.Y.; Ahmed, M.M.; Alshehri, S.A. Integration of machine learning and CFD for modeling mass transfer in water treatment using membrane separation process. *Sci. Rep.* **2024**, *14*, 23970. <https://doi.org/10.1038/s41598-024-74530-1>.
123. Volpe, F.; Battaglia, G.; Cipollina, A.; Micale, G.; Tamburini, A. A Hybrid CFD Platform for Colloidal Fouling Prediction in Electrodialysis. *Membranes* **2025**, *15*, 375. <https://doi.org/10.3390/membranes15120375>.
124. Eljaddi, T.; Cabassud, C. Wetting-Based Comparison of Ag, Carbon Black, and MoS₂ Composite Membranes for Photothermal Membrane Distillation. *Membranes* **2023**, *13*, 780. <https://doi.org/10.3390/membranes13090780>.

125. Ghorbani Bam, P.; Rezaei, N.; Roubanis, A.; Austin, D.; Austin, E.; Tarroja, B.; Takacs, I.; Villez, K.; Rosso, D. Digital Twin Applications in the Water Sector: A Review. *Water* **2025**, *17*, 2957. <https://doi.org/10.3390/w17202957>.
126. van Rooij, F.; Scarf, P.; Do, P. Planning the restoration of membranes in RO desalination using a digital twin. *Desalination* **2021**, *519*, 115214. <https://doi.org/10.1016/j.desal.2021.115214>.
127. Di Bella, A.; Raissi, M.; Santoro, D.; Roccaro, P. Physics-informed neural networks in water and wastewater systems: A critical review. *Water Res.* **2026**, *293*, 125449. <https://doi.org/10.1016/j.watres.2026.125449>.

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