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| Research Article

Mathematical Modeling of Reverse Osmosis Systems, The Effects of Operating Conditions and Cleaning Techniques: A Review

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Annotation
Reverse osmosis (RO) remains the dominant desalination technology, offering relatively low energy consumption and high water quality. Despite its widespread deployment, challenges such as fouling, energy intensity, and limited predictive control hinder its long-term sustainability. This review critically examines advances in RO system modeling, the influence of operating conditions, and the role of artificial neural networks (ANNs) and cleaning strategies. We compare mechanistic, empirical, and hybrid modeling approaches, evaluating their predictive capacity and limitations. ANN-based methods are assessed for their ability to capture nonlinearities and enhance operational optimization, but their dependence on large datasets and poor interpretability remain unresolved challenges. Cleaning strategies, ranging from conventional chemical treatments to novel physical and forward-osmosis-based approaches, are analyzed for effectiveness, costs, and environmental impact. By synthesizing strengths, weaknesses, and knowledge gaps across these domains, this review highlights future directions, including the integration of physics-informed machine learning, real-time monitoring for predictive fouling control, and sustainable, non-chemical cleaning innovations.

Keywords: Reverse osmosis; Membranes; Desalination; Modeling; Operational conditions; Fouling; Neural networks.

1. INTRODUCTION

The 21st century is called the "century of water shortage," and the first and second decades of the 21st century are called the "water crisis decades[1].This is because the population is growing steadily and there is a greater need for fresh water. Many countries in the Middle East, Southeast Asia, and North Africa are having a hard time getting enough water. These areas are called "water-stressed" because of pollution of water sources and not enough rain[2]. Experts say that by 2030, this lack of water might affect as many as 40% of the world's people. It was very important to improve technology for desalinating saltwater and brackish water to solve this problem. Desalination is a process that transforms saline water into fresh water by removing dissolved salts and other contaminants. Consequently, desalination is commonly used to treat salty or brackish water. According to Alghoul et al.,2009 [3], the process involves filtering saline feed water to separate brine a highly concentrated salt solution from water with a lower salt content.

Desalination of seawater and brackish water is now the main way to get fresh water, and more and more people are using it around the world, especially in the Gulf region. In the 1950s, Kuwait built the first large-scale desalination plant. The world's largest reverse osmosis (RO) facility, which can process 274,000 m^3 of water per day, was also built in southern Arizona[4] . In the last few decades, techniques that rely on concentration, such dialysis and pervaporation, have become more popular for separating things in industry and the environment. Even Nevertheless, pressure-driven membrane processes are still the most common membrane technology for cleaning water[5, 6] .

Reverse osmosis (RO) is a method used by communities that lack sufficient safe drinking water[7]. It works well to get rid of salt and uses less energy than other heat treatments[8-10]. RO is the most common way to get rid of salt in brackish and seawater. It also has many beneficial things about it that make it useful for cleaning water[8, 11-13]. RO systems have an issue with membrane fouling since they need to be cleaned all the time, which uses more energy and pressure. To make sure that reverse osmosis systems work well and last a long time, you need to know how to clean them properly and other things that affect how they work [14]. Mathematical models and artificial neural networks (ANNs) are essential instruments for forecasting reverse osmosis performance and determining optimal operating settings[9]. This paper examines various methodologies for modeling reverse osmosis systems, evaluates their efficacy across diverse contexts, and explores prospective technical advancements. The research examines new developments in closed-circuit and batch reverse osmosis technologies, alongside traditional approaches, aiming to enhance the energy efficiency of desalination processes for seawater and brackish water. A lot of people talk about how to model systems, how they change when operations change, and how artificial neural networks can help make modeling more precise.

2. HISTORICAL BACKGROUND OF REVERSE OSMOSIS

People started writing about osmosis, a natural process, in the 1700s. It wasn't until the mid-1900s that people began using reverse osmosis (RO) to filter water. In the 1950s and 1960s, scientists found that water could be moved across a semipermeable barrier using hydraulic pressure. This allowed them to remove salt from saltwater[15]. The first functioning RO membranes were made from cellulose acetate, a biopolymer made from cellulose. In 1959, Loeb and Sourirajan at UCLA produced the first high-performance asymmetric membrane and received a patent for it[16] . RO systems have a big impact on both society and engineering. In the 1970s, people constructed membranes out of thin-film composites (TFC). Polysulfone or polyethersulfone substrates are used to hold up TFC polyamide membranes in most large RO systems nowadays [17]. Scientists are looking at a new kind of material for their RO research: membranes composed of graphene, especially ones that include graphene oxide (GO) in them. Scientists have been trying to make things more porous so they can keep salt out better and not get soiled as easily[18]. The stagewise Process Design Framework for RO was created in 1969. People have since learned how to make seawater RO systems better for many different jobs. [19]. Researchers are now using these early results in theory and practice to study reverse osmosis. Based on the data, it has led to better modeling tools, novel membrane materials, and ways to make desalination systems work better in the business.

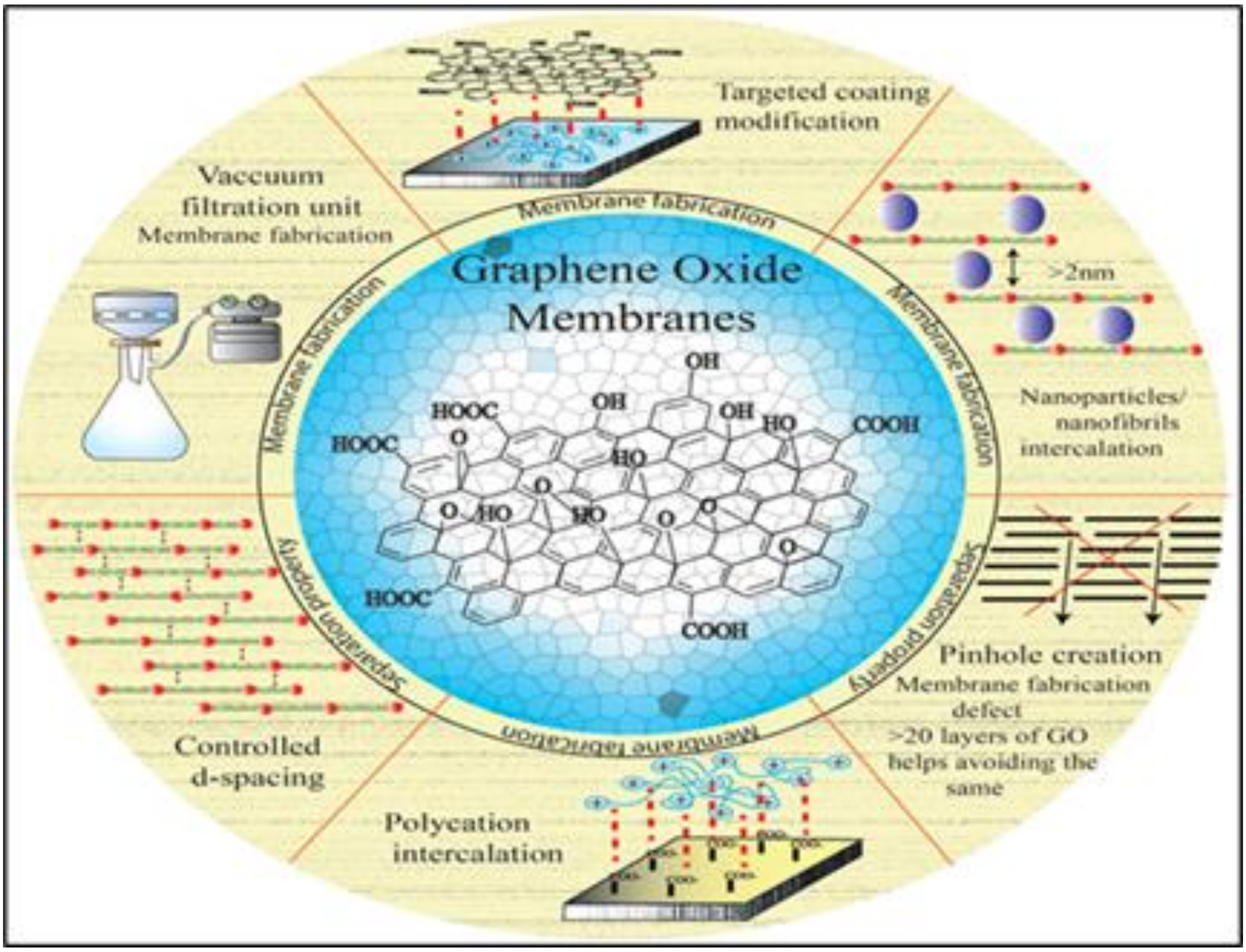

Figure1.Schematic of a graphene-oxide (GO) membrane, showing stacked GO layers with functional groups (orange, green) creating nanochannels for water while blocking ions[18] .

The evolution of RO underwent various stages: (a) cellulose-acetate membranes (b) polyamide TFC membranes, (c) nanoscale additives or coatings on polymeric membranes (d) new 2D/material-based membranes. Prominent milestones are the 1962 invention of the phasing (asymmetric CA film) and the 1972 PA TFC breakthrough and the current development of nano-enhanced membranes. The next step we make is a comparison of the role of RO to other technologies.

3. MEMBRANE DESALINATION

Membrane separation techniques use membranes to remove rid of metals, germs, viruses, salts, and other things that shouldn't be in water. These membranes can be made from various materials, such as cellulose, acetate, and non-polymeric substances. However, polymeric materials are the most commonly utilized for desalination[20] . Pressure or electricity can power membrane technologies. Electrodialysis (ED) and electrodialysis reversal (EDR) use electricity, while ultrafiltration (UF), microfiltration (MF), nanofiltration (NF), reverse osmosis (RO), and forward osmosis (FO) use pressure. The efficiency of these pressure-driven systems differs based on their capacity to segregate molecules of disparate sizes[20]. are all techniques that use pressure. There are many types of pressure-driven processes based on how well they can separate molecules of different sizes. Figure (2) shows some of the chemicals that different membrane technologies can separate.

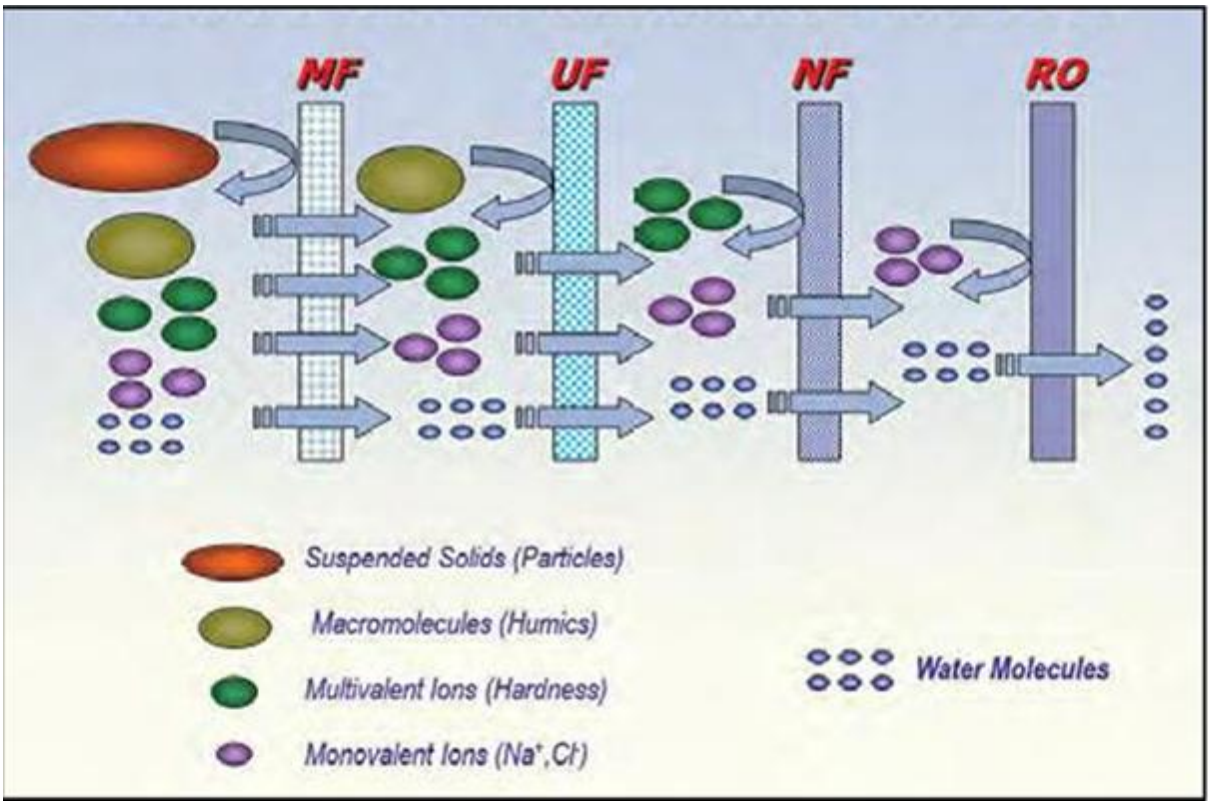

Figure 2. Membrane processes driven by pressure[21].

Membrane distillation (MD) is another type of membrane technology that uses heat to extract salt from water. Membrane technologies have become some of the most promising new ways to treat water in the last few decades. They have a number of benefits over typical thermal desalination technologies, such as[22]:

- A process that keeps separating things
- A mix of different desalination technologies
- Works in mild conditions
- Scaling up that makes sense
- Properties of the membrane that can be changed.

4. IMPACT OF OPERATIONAL CONDITIONS ON RO PERFORMANCE

The operating parameters regulate the performance of an RO system. Table 1 summarizes the key parameters and their usual values, along with how they affect important factors like water flow, salt removal, recovery (R), and energy use.

Tabel 1. Recapitulates the main parameters and typical values thereof and their corresponding influence

Parameter	Typical Range	Effect on Performance
Pressure (ΔP)	Brackish: 5–15 bar Seawater: 50–80 bar	↑ ΔP → roughly ↑ permeate flux (nearly linearly). However, excess pressure delivers negative marginal gains; the higher the pressure, the higher the osmotic pressure (flux ∝ $\Delta P - \Delta\pi$). Higher pressure also contributes to greater energy consumption[23].
Feed salinity	0.5–35 g/L (TDS)	↑ feed salt → ↑ osmotic pressure $\Delta\pi$ → ↓ net driving pressure → ↓ flux [23].

		Scaling and fouling (e.g. CaCO 3, Mg(OH) 2) is also increased in high salinity and may restrict recovery. The high recovery (~ 80 %) of brackish feeds (≤5 g/L) is easily accomplished; seawater feeds (~ 35 g/L) are ordinarily restricted to a 50% at most recovery to prevent the very salty brine[24] .
Temperature (T)	~5–40 °C (often 15–30 °C)	↑ T → ↓ water viscosity and ↑ diffusion → ↑ flux (typically ~3–5% flux gain per °C). Flux can be reduced drastically and energy per m^3 can be increased by use of cold feed. T should be very high (>40 o C) mostly mitigated not to damage membranes (PA starts to break down at~45o C)[25] .
Cross-flow velocity	Mild turbulent (Re≥2000)	↑ flow velocity → thinner boundary layer → reduced concentration polarization and fouling. Using high velocity (e.g., ≈1–2 m/s in spacers) raises the flux a little and drives salt to a greater distance, but at the expense of pumping power. The low velocity leads to harsh polarization and fouling[24] .
Recovery (fraction)	10–85% (typ. 40–60%)	↑ recovery → ↑ feed concentration in remaining solution → ↑ osmotic pressure → ↓ flux in later stages. At high recovery, energy per unit water tends to be high. It is better to have high recovery (to reduce waste), but only practical recovery is possible because scaling is risky (e.g. 40–50% for SWRO, 60–85% for BWRO)[26].
pH and chemistry	4–11 (adjusted)	Natural feed pH (often 7–8) is adjusted as needed. The pH can influence scale precipitation (e.g. CaCO 3 precipitate at pH 8.5), and membrane charge/rejection (e.g. PA is negative above pH4)[27, 28] . PA membranes are susceptible to damage at acidic or extreme pH (eg. >10), so pretreatment is usually de-hardening or pH-neutralizing[28].

In mathematical terms RO flux is commonly approximated by the solution diffusion relation. Simply put, the term [29] :

Jw=A (ΔP-Δπ) (1)

where J_w is the permeate volume flux (rate of flow in L/m² h), A is known as the water permeability coefficient (an intrinsic membrane parameter), ΔP is the applied hydraulic pressure, and Δπ is the difference between the osmotic pressure in the feed and permeate[30]. This linear approximation holds when ΔP > Δπ.

The term salt rejection has a definition of [31]:

Rs=(1-CpCf)*100% (2)

Where C_f and C_p, are TDS or NaCl salt concentrations in feed and permeate. RO membranes would perform normally with a high Rs (95 99%). The osmotic pressure increases approximately linearly with the salt concentration (Van't Hoff relation).

5. MEMBRANE MATERIALS AND PRODUCTION TECHNIQUES

The RO membranes themselves are the point of research. Performance (flux, rejection, durability) depends on the material in the active layer and the way it is made. These include the following:

1. **Cellulose Acetate (CA):** Cellulose Acetate (CA) is a biopolymer with low cost, chlorine resistance, and limited permeability, but its sustainability interest has declined, and RO is now primarily used with PA[32].

2. **Polyamide Thin Film Composite(PA-TFC):** The typical TFC PA RO membrane is composed of three different layers (Figure 3) . PA-TFC membranes consist of a thin layer of special PA material on a porous polymer support, typically polysulfone or polyethersulfone, with a nonwoven backing[33, 34]. They have high salt and permeability rejection. Recent innovations include nanostructured supports, surface coating, and layer-by-layer assembly to increase fouling resistance and improve chlorine stability[33].

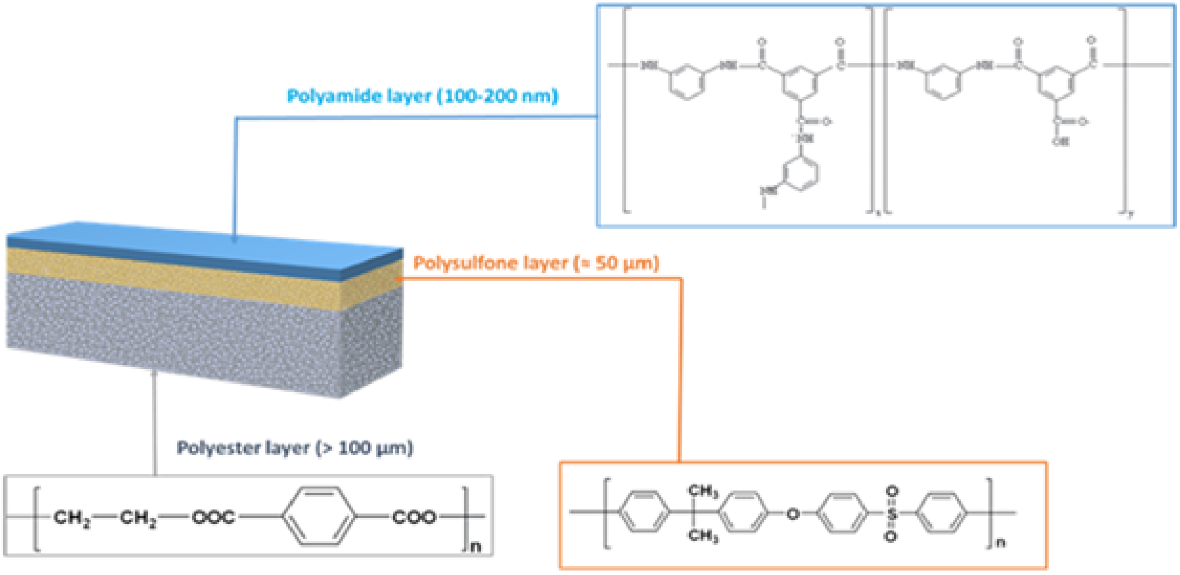

Figure 3. A diagram of the TFC membrane's structure and what it's made of.

3. **New Materials (Graphene, Nanocomposites):** Over the past decade, researchers have been exploring innovative membrane materials like graphene and nanocomposites. Graphene offers atomic thickness and adjustable nanochannels, while aquaporin-based biomimetic membranes simulate natural cell membranes. Mixed-matrix membranes combine inorganic nanoparticles with a polymer for easy water flow and substance filtering. Graphene-based and aquaporin-inspired biomimetic membranes are also emerging, offering adaptable interlayer separation for high water flux[18, 35-37].

Membrane research is rapidly progressing, focusing on improving flux, selectivity, and fouling tolerance, with membrane development being a key contributor to improved RO performance.

6. MEMBRANE CLEANING

The quality of RO feedwater has improved a lot because to new desalination pretreatment methods like MF and UF. However, it is not always possible to get rid of all the contaminants[38]. Because of this, SWRO plants often clean their equipment on a regular basis to get rid of built-up foulants using physical, chemical, and biochemical (enzymatic) methods[38-41] .This also helps to recover or keep water flow and permeability[42, 43]. Cleaning MF and UF membranes is not very expensive compared to pre-treatment. It can be done in situ (cleaning in place (CIP), chemically enhanced backflush (CEB), and cleaning in air (CIA)) or ex situ[38, 43-45].As shown in figure 4.

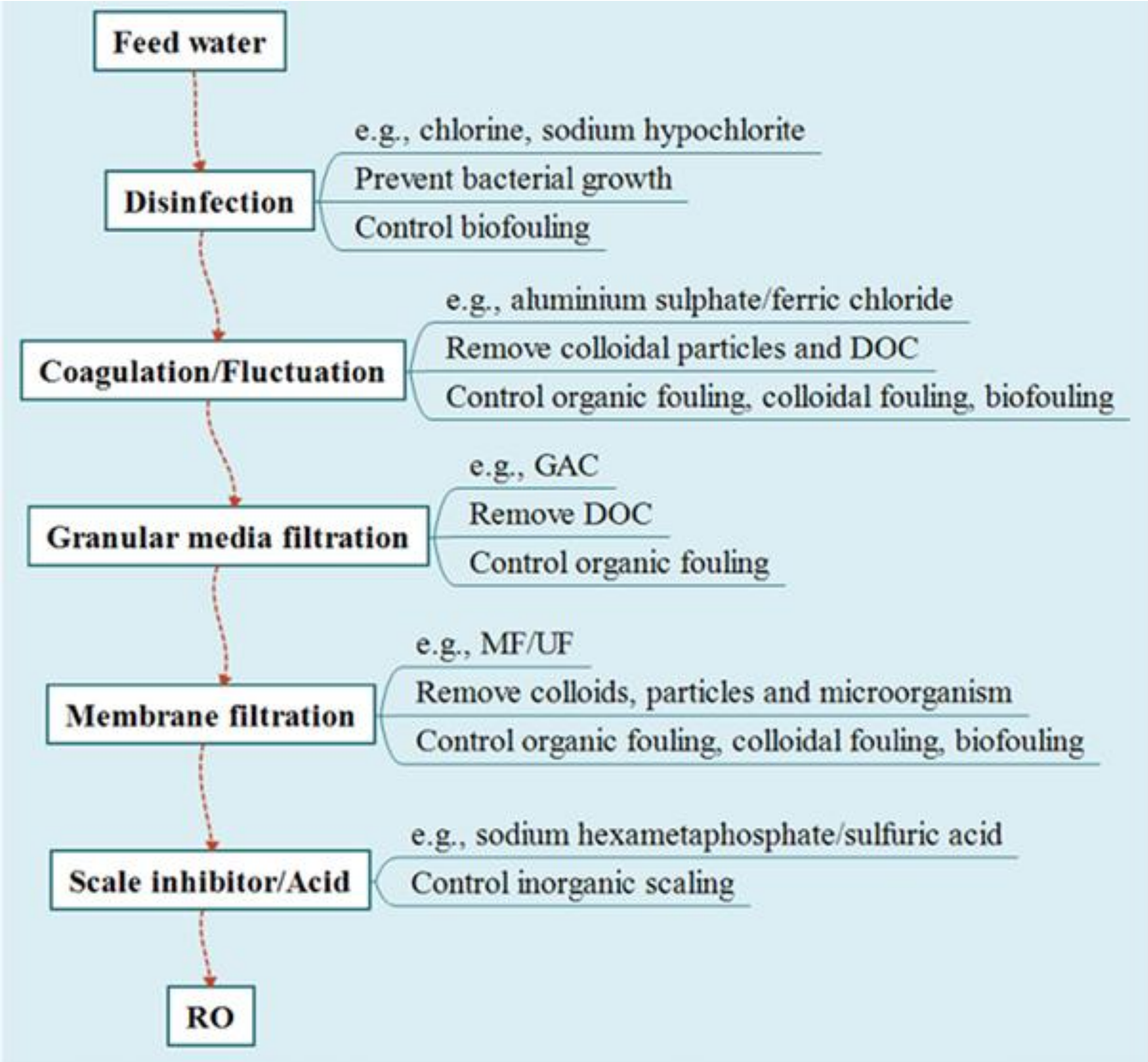

Figure 4. A schematic depiction of the RO pretreatment processes and how they help control fouling[41].

6.1 Physical and chemical cleaning

Physical cleaning involves using hydraulic, mechanical, and electrical forces to remove weakly connected deposits from MF and UF membranes. Chemical cleaning uses acidic, alkaline, chelating, and oxidant agents to remove dirt. Biochemical agents can break down biopolymers like proteins and lipids. The desalination industry uses various methods to make things cleaner, but consumers may not always know the chemicals used[38, 40, 41, 43, 46, 47].

There are usually six processes in chemical cleaning[38]:

1. The bulk reaction of cleaning agents, which includes hydrolysis, ionization, and other reactions[38].
2. The transport of cleaning agents to the membrane surface[38].
3. The transition through foulant layers to the membrane surface[38].
4. The reaction with foulants[38].
5. The transport of modified foulants to the interface[38].

6. The transport of modified foulants to the bulk solution[38].

Sodium hydroxide, alkaline treatments, acidic substances, chelating agents, oxidizing agents, and enzymatic agents are used to clean membranes. Factors like cleaning types, chemical agents, and operating parameters affect the effectiveness of cleaning. Overwashing, incorrect cleaning agents, and poor cleaning conditions can affect membrane life. To maintain good cleaning conditions, it's crucial to identify fouling, select appropriate methods and chemicals, and maintain optimal cleaning conditions[38, 45].

6.2. Agents based on chlorine and hydrogen peroxide

Chloramines, hypochlorous acid (HOCl), and other free chlorine-based compounds are the most prevalent ones used to speck and clean SWRO membrane surfaces. These chemicals clean up dirt that comes from living things. Oxidants turn the functional groups of organic pollutants into aldehydes, ketones, and carboxylic acids. This makes them more likely to stick to the membrane surface and less likely to stick to water. A lot of research is about chlorinated oxidants, which can cause problems like swelling, damage, and chemicals left behind from cleaning.There isn't as much study on using hydrogen peroxide to clean polysulphone and polyvinylchloride membranes, but it is less likely to hurt RO membranes and doesn't leave behind any harmful chemicals [43, 45].

7. PREVIOUS STUDIES

7.1. Mathemtical modeling of (RO) process

Mathematical modeling is the act of turning real-world issues into math equations and then utilizing math programming to find solutions[48, 49]. Optimization modelling is a common application of mathematical modelling, which involves maximizing or minimizing an objective function by selecting input values and stratifying constraints[50, 51]. As computers get better and systems get more complicated, mathematical modeling and optimization become important parts of the design process[52]. Models are "abstractions of reality" in engineering, which means they help us understand things better and make better predictions[53]. To do engineering modeling, you need to know how a whole system works and what its most important parts are. But it's hard to make reliable models with realistic assumptions and limits because real systems are unpredictable and pilot plants are expensive[54].

Interest in optimization modelling techniques in desalination has significantly increased in the last decade, particularly in pressure-driven membrane separation[49]. Models let us guess how well something will work, provide us a better grasp of how permeation and separation work, and let us keep an eye on processes and investigate the things that affect performance. The kind of material and structure affect the kind of mass transport through the membrane, which in turn affects the mathematical model used to describe mass transfer[49, 55]. Recent improvements in the RO process include better nanofiltration membranes, new ways to model NF, and advanced engineering models for solutions with multiple ions[56]. Nanofiltration modeling had a drop in interest between 2009 and 2016, but it has since come back, with more than twice as many papers with "nanofiltration" and "modeling" in the title[49, 57] .Multiple researchers have developed mathematical frameworks which describe physical processes taking place in RO operations.

Lonsdale et al.,1965[58] created the fundamental solution-diffusion model, created by Lonsdale et al., suggests that solvent and solute diffuse separately from high-concentration and pressure sides at different rates, facilitated by membrane texture. Solute flux is independent of pressure differential, and understanding transport parameters is important when estimating fluxes. However, this model overlooks the impact of pressure on solute flux and membrane properties. The diffusion and distribution of water and sodium chloride in cellulose acetate osmotic membranes vary with acetyl content, and more detailed models are needed to explain the dependence of water and salt permeability on acetyl content.

Boudinar et al.,1992[59] created a computer program that indicates how the spiral grass modules work more efficiently. The application can get concentrations, pressure and flow speed anywhere in the module, as it takes into account the unique spiral structure and other physical factors in the module. The verification method has used experimental data from two different types of SPW modules: Roga-4160HR and Filmtech FT30SW2.5. The simulation results carefully reflected the experimental results, with the Roga-4160HR module showing low variability. The study indicates that the use of more accurate correlation for mass transfer coefficients may increase the accuracy of the performance forecast.

Avlonitis et al.,1991,1993,2007[60-62] developed a stable-distributed model with a stable state, utilizing the existing model solution and thin film theory, applicable to spiral-west reverse osmosis (RO) modules. Scientists came up with easy equations that can be used to find wear properties for any Reynolds number.People think these equations can be used on any membrane that uses spacers that are similar.

Abbas and Al-Bastaki,2001[63] created a detailed model to estimate how well spiral-wound membrane modules would work, taking into account both turbulent and laminar flow patterns. The model presumes uniform diffusivity during the procedure. The plant's overall water permeability coefficient reduced by almost 25% after 500 days of continuous operation, and its salt rejection dropped by 1.9%.The researchers also came up with simple equations to show how the plant's performance changed over time, which were quite close to the data they saw.

Marriott and Sørensen,2003 [64] created a distributed dynamic model for a spiral wound RO module by using mass balance, momentum, and energy equations and ignoring several shared assumptions. This model illustrates the flow dynamics within the module and is applicable to any membrane separation process. But the change in bulk concentration inside the feed channel because of solvent flow through the membrane was not fully taken into account.

Abbas,2005 [65] proposed a semi-rigorous methodology for evaluating the performance of a reverse osmosis (RO) desalination facility designed with three tapering stages. The developed model is capable of predicting the plant's future operational performance, which is helpful for long-term planning and optimization.

Geraldes et al.,2005 [66] improved a distributed model for stable state for spiral-on-facing osmosis (RO) processes by incorporating both the mass and movement transport in the membrane module. The model is fundamentally based on the solution -spread principle, and the spreading current in the feed canal and permission of pressure in the permet channels to streamline the analysis. This method makes it possible to evaluate the Ro process in a more useful and concentrated way, while it still maintains the necessary level of accuracy.

Majali et al.,2008 [67] created two models for two pilot-scale RO plants to see how well they worked. First, a basic semi-empirical model was made for a RO Sharjah plant that turned brackish water into fresh water. This model estimates the flow rate, concentration, and pressure profiles, however it doesn't take into account the area of the membrane. Second, a permeability model was suggested to forecast how well a RO plant in Qatar that removes salt from saltwater would work. The model interestingly predicts the area of the membrane.

Guillen et al.,2009[68] The research employs a modeling technique that connects small-scale and large-scale transport mechanisms in spiral wound materials to enhance the performance of reverse osmosis and nanofiltration systems. Model simulations show that the shape of the feed spacer doesn't have much of an influence on mass transfer. However, thinner filaments that are spaced out more do help reduce hydraulic losses. Filaments with thinner shapes might operate better in water that isn't very salty than in water that is very salty.

Kaghazchi et al.,2010 [69] examined two industrial seawater reverse osmosis (RO) systems. Two industrial seawater reverse osmosis systems were simulated and their efficacy evaluated using FilmTec SW30HR-380 modules.The models precisely illustrated the functionality of the plants, and their operational approaches affected their performance.

Altaee,2012 [70] created a numerical model to test how to succeed in transforming a multi-tattox with reverse osmosis pressure car water to fresh water. The model was pretty good at creating predictions, achieved for 85% time. When NaCl was added, it was properly estimated how fast the permit was driving and how much salt was in the solution. This study shows that a properly calibrated model can accurately guess how effectively multi -stage the reverse osmosis system works.

Al-Obaidi et al.,2018 [71] Study was a Jordan Multi-Pass Serpil Serving Emosis Osmosis Dislocation Efficiency, which is the osmosis shift system for Bracsh water, uses a mathematical model based on the solution proliferation theory. The model takes into account the continuous properties of the membrane, pressure in the environment, concentration polarization and concentration pollution. It also recognizes feed flow rate and operating pressure as important factors affecting the salinity of the product.

Ncube et al.,2019 [72] contend that current research mostly concentrates on improving the sustainability and efficiency of reverse osmosis (RO) desalination systems using sophisticated modeling and optimization techniques. More and more people are employing cutting-edge tools like genetic algorithms and neural networks. PID controllers are still widely used because they can make systems run better and reduce steady-state failures.

Chen and Qin,2019[51] developed a math model to see how a reverse osmosis membrane separates water from glucose. The model was validated with data from a glucose solution that had already been treated and found to be correct. It uses the irreversible thermodynamic Spiegler-Kedem model and the concentration-polarization model .The model accurately shows how the RO membrane concentration process works and the mass transfer coefficient in the CP layer.

Hadadian et al.,2021[29] created a simulation model for multi-element reverse osmosis(RO) systems arranged in series so it can integrate with optimization and control systems. A custom program received mass and energy balances and circular permeability data for validation through testing on a small-scale RO unit. The simulated permeate flow predictions together with salt rejection results of this model agreed closely with Dow's ROSA software and experimental data by remaining approximately 4 percent and 20 percent off respectively. The model was considered suitable for performance assessments even though there were limited mismatches with experimental results (probably caused by instrumentation errors or unaccounted fouling effects). Open-source availability allowed further development of the model according to the authors. The simulation outcomes matched ROSA results by more than 96% while showing acceptable correspondence to experimental data which proved model precision.

Ncube et al.,2021 [73] This article is about how to develop and improve a seawater reverse osmosis desalination plant in Cape Town, South Africa. The method used ideas from mass and transport theory to create models and simulations. The results showed that the specific energy use went up by 7.3% and the permeate productivity went up by 18%. The plant reached its theoretical improvement by raising the input flow rate to 24 m3/h.This meant that the facility could make 86% of what it used to and use less energy. This made it cheaper to run the whole thing.

Salahudeen,2022 [74] developed model equations to guess the process parameters for reverse osmosis, which is a method for removing salt from water. The equations link the solute concentration to the difference in process pressure and other factors, such as polarity, water flux, osmotic pressure, water output rate, power density, and specific energy use. Simulations indicated that it was possible to get the highest power density, specific energy use, water production rate, solute rejection factor, and bulk fluid concentration .

Saeed and Alhawaj,2024 [75] The purpose of this study was to build a computer model that could guess how well a reverse osmosis (RO) system would work with different types of membranes. When the model and the WAVE software were compared, they were extremely similar.The model could always guess essential variables regarding pretreatment feed solutions, like the recovery rate, feed pressure, permeate flow rate, and permeate concentration. There were two distinct amounts of saltwater and seawater in the feed water: 32,000 mg/L and 40,000 mg/L. No matter who manufactured the membrane, the model can find the most important components for the RO system.

Mehrizi et al.,**2024**[76] created a generalized model based on which a two-stage RO desalination system is developed. Both membrane permeation and development of the solution boundary layer were represented using solution-diffusion theory, film theory, and mass balances. The MATLABS had been solved of non-linear equations with characteristics of the membrane, providing predictions regarding necessary feed pressure and system performance level at designated recovery rates. The researchers evaluated their model utilizing real plant information and ROSA software and achieved results within a 4% margin of error. The model operated two steps with similar recovery to reach low feed pressure than standard design, resulting in energy saving capacity. The model recommends design software calculations, while showing how the recovery operation can be distributed can effectively reduce the feed pressure.

In the summary, these studies show that mathematical modeling of reverse osmosis is important to understand, predict and increase the desalination processes. Models can be as simple as equations for dissolution spread or complicated as dynamic simulation covering the entire plant.

Table 2. A summary of the models created for the Reverse Osmosis (RO) process

Author and year	Main characteristics	Shortcomings
Lonsdale et al., 1965[58]	• A model for the diffusion of cellulose acetate membranes that is the same throughout. • Explained how things move via membrane films in the RO process. • The nonporous surface layers of the membrane dissolve the solvent and solute.	• Constant pressure in the membrane channels.
Avlonitis et al.,1991[60]	• Taking into account the pressure drop that happened in the brine and permeate channels. • The friction parameters for brine and permeate and the membrane water permeability constant were combined.	• The concentration polarization and the osmotic pressure were ignored.
Boudinar et al., 1992[59]	• Included the primary factors that impact how well a SW module works	•Neglected the pressure drop along the permeate tube. • Constant fluid density.
Avlonitis et al., 1993[61]	• Thought of the thin film theory to explain concentration polarization. • The concentration gradient along the membrane feed channel was built in.	•Neglected the solute–solute interaction in multi component solutions.
Abbas and Al-Bastaki, 2001[63]	• Study looked at both turbulent and laminar flow regimes. • Indicated a reduction in water flux due to membrane fouling.	• Didn't pay attention to how the solute interacted with itself. • Took out the explanation of how the membrane transfer mechanism works.
Marriott and Sørensen, 2003[64]	• Talked about the flow patterns inside a SW module and the main elements of the membrane. • The friction parameter described the drop in pressure of the flow. • The stationary film model showed the concentration polarization.	• The permeate flow area was assumed constant.
Abbas, 2005[65]	• Looked at a neural network model (NNM) to get a guess about how well the RO would work.	• The diffusivity, density , and viscosity were assumed constant.
Geraldes et al., 2005[66]	• Enhanced a steady-state distributed model for a seawater reverse osmosis process. • The movement of mass and momentum inside the membrane modules was achieved.	• Didn't pay attention to the change in pressure inside the permeate channels. • Didn't pay attention to the diffusion flow on the feed side.
(Majali et al., 2008)[67]	• Created semi-empirical and permeability models for two kinds of pilot scale RO plants.	• It was assumed that the feed and permeate channels had fully mixed conditions. • The semi-empirical model assumed that the salt retention and water recovery were fixed.
Guillen & Hoek, 2009[68]	• Utilizes modeling to link small-scale and large-scale transport mechanisms. • Improves reverse osmosis and nanofiltration systems.	• Feed spacer shape doesn't significantly affect mass transfer.

	• Thinner filaments reduce hydraulic losses. • Thinner filaments work better in low salinity waters.	
Kaghazchi et al., 2010[69]	• Utilized FilmTec SW30HR-380 modules. • Models demonstrated plant functionality and performance impact.	• Focus on steady-state only.
Altaee2012 [70]	• Developed for desalinating seawater. • Demonstrated 85% accuracy in performance alignment. • Accurately predicted element permeate flow rate and salt composition. • Demonstrates potential for multi-stage RO performance prediction.	• Steady-State Focus • No Discussion of Model Limitations
Al-Obaidi et al.2018 [71]	• Model assumes steady-state operation, constant membrane characteristics, one atmospheric pressure at permeate channel, film-theory model for membrane wall concentration calculation, and isothermal process. • Model considers concentration polarization and feed spacer's impact on pressure drop along feed channel.	• Steady-State Focus • Limited Range of Sensitivity Analysis
Ncube et al.2019 [72]	• Utilizing genetic algorithms and neural networks. • Using PID controllers for improved dynamic response and reduced steady-state errors.	• Lack of Original Experimental or Simulation Data • No Discussion of Practical Challenges
Chen and Qin 2019[51]	• Developed model to understand water-glucose separation. • Validated using treated glucose solution data. • Utilizes irreversible thermodynamic Spiegler-Kedem model and concentration-polarization model. • Accurately depicts RO membrane concentration process and mass transfer coefficient in CP layer.	• Limited Scope: Laboratory-Scale Only • One-Dimensional Flow Assumption • No Long-Term or Fouling/Scaling Analysis
Hadadian et al.2021[29]	• Created a model for multi-element RO systems for integration with optimization and control systems. • Custom program received mass and energy balances and circular permeability data for validation. • Model's permeate flow predictions and salt rejection results matched Dow's ROSA software and experimental data by approximately 4% and 20%, respectively. • Model suitable for performance assessments with limited mismatches with experimental results. • Open-source availability allowed further model development. • Simulation outcomes matched ROSA results by over 96%, proving model precision.	• No Long-term or Real-world Plant Validation • Steady-State Focus

	• Thinner filaments reduce hydraulic losses. • Thinner filaments work better in low salinity waters.	
Kaghazchi et al., 2010[69]	• Utilized FilmTec SW30HR-380 modules. • Models demonstrated plant functionality and performance impact.	• Focus on steady-state only.
Altaee2012 [70]	• Developed for desalinating seawater. • Demonstrated 85% accuracy in performance alignment. • Accurately predicted element permeate flow rate and salt composition. • Demonstrates potential for multi-stage RO performance prediction.	• Steady-State Focus • No Discussion of Model Limitations
Al-Obaidi et al.2018 [71]	• Model assumes steady-state operation, constant membrane characteristics, one atmospheric pressure at permeate channel, film-theory model for membrane wall concentration calculation, and isothermal process. • Model considers concentration polarization and feed spacer's impact on pressure drop along feed channel.	• Steady-State Focus • Limited Range of Sensitivity Analysis
Ncube et al.2019 [72]	• Utilizing genetic algorithms and neural networks. • Using PID controllers for improved dynamic response and reduced steady-state errors.	• Lack of Original Experimental or Simulation Data • No Discussion of Practical Challenges
Chen and Qin 2019[51]	• Developed model to understand water-glucose separation. • Validated using treated glucose solution data. • Utilizes irreversible thermodynamic Spiegler-Kedem model and concentration-polarization model. • Accurately depicts RO membrane concentration process and mass transfer coefficient in CP layer.	• Limited Scope: Laboratory-Scale Only • One-Dimensional Flow Assumption • No Long-Term or Fouling/Scaling Analysis
Hadadian et al.2021[29]	• Created a model for multi-element RO systems for integration with optimization and control systems. • Custom program received mass and energy balances and circular permeability data for validation. • Model's permeate flow predictions and salt rejection results matched Dow's ROSA software and experimental data by approximately 4% and 20%, respectively. • Model suitable for performance assessments with limited mismatches with experimental results. • Open-source availability allowed further model development. • Simulation outcomes matched ROSA results by over 96%, proving model precision.	• No Long-term or Real-world Plant Validation • Steady-State Focus

Ncube et al.2021 [73]	• Utilizes mass and transport theory for model creation and simulations.	• No Consideration of Process Dynamics
Salahudeen 2022[74]	• Simulations show highest power density, specific energy use, water production rate, solute rejection factor, and bulk fluid concentration.	• Narrow Range of Operating Conditions • Steady-State Focus
Saeed and Alhawaj 2024[75]	• Created a model to predict RO system performance with various membrane types. • Model and WAVE software compared closely. • Model predicted key variables like recovery rate, feed pressure, permeate flow rate, and permeate concentration. • Model was tested with saltwater and seawater in feed water. • Model identified crucial RO system components regardless of membrane manufacturer.	• No Experimental or Field Data Comparison • Steady-State Focus
Mehrizi et al.2024[76]	• Developed a two-stage model using solution-diffusion theory, film theory, and mass balances. • Solved non-linear equations using MATLABS to predict feed pressure and system performance. • Evaluated model using real plant information and ROSA software, achieving results within a 4% margin of error. • Model showed energy conservation potential by operating two stages with equal recoveries. • Recommendation matched software calculations, demonstrating effective reduction of feed pressure through distributed recovery operations.	• Steady-State Focus • Homogenous Recovery Rate Assumption

7.2. Effect of operating conditions on reverse osmosis (RO) process.

The conditions under which a reverse osmosis (RO) system works have a big effect on how well it works. Permeate flux and solute rejection are two common ways to measure this .Important operational parameters include feed concentration (salinity), recovery rate , feed pressure, feed temperature, crossflow velocity, turbidity, pH, and how much the membrane is fouled[77] .This section gives a full picture of how these factors affect the RO process's efficiency and effectiveness.

Costa and Dickson,1991[78] created two models for designing and predicting how well reverse osmosis (RO) systems will work while the temperature is constant. The first model uses a weighted average method that takes into account concentration polarization and averages system conditions along the length of the module. This model tends to make fewer conservative guesses about system variables, which helps keep the necessary membrane area from being too high. The second concept breaks the membrane module into a number of "cells," each of which is thought to have the same requirements. When the feed flow rates are large, the estimates of permeate concentration from this cell-based model are quite close to those from a model with a constant mass transfer coefficient. However, for low feed flow rates, employing a constant mesh step coefficient yields significantly disparate predictions of the permeate concentration. Both approaches are beneficial for evaluating and enhancing the efficacy of RO systems.

Hyung and Kim,2006[79] investigated the effect of pH and temperature on drilling in membrane functions in seawater reverse osmosis (SWR), aimed at following the World Health Organization (WHO) standards. Bench-scal cross-current filtration study showed that drilling rejection works through a separate mechanism. To assess these effects, he used an irreversible thermodynamic model that accurately predicts the performance of the membrane under different pH and temperature conditions. This model will help identify optimal techniques for removing drills from SWRO processes and for developing drills in the development of these processes.

Alsalhy et al.,2013 [80] aimed at checking methods to improve the effect of the reverse osmosis (RO) filter in synthetic saline treatment, aims to increase water flow and optimize pollutants. The study used a central total design (CCD) to evaluate the effect of operational parameters, such as water masculine, and temperature, temperature, temperature, and temperature, and water masculine, temperature, temperature and volumes. The results showed that the continuous coast of gas and fluid in various streams improved the production of filtered water and improved the efficiency of salt removal. The results showed that the use of the continuous coil of gas and fluid in different streams increases the amount of water that is filtered heavily. 3,406 kg/m/h to 5,676 kg/m/h and salt repair rate from 85% to 91%. The system had a snail flow pattern, an injection factor of 0.878, air velocity of 1,5923 m/second and liquid speed of 0.221 m/second.

Ruiz-Garcia &de la Nuez Pestana,2019 [81] A study found that there was a major impact on the concentration of filtered water (CP) in the real world SWMs used for the amount of energy required (SEC) required as feed spacing and BWRO-Disliener. The optimal form of feed spacers depends on how well the system works and how light water can flow. The best water permeability coefficient (A) varies as the best water permeability that is fed. To improve the calm process, manufacturers must see both permeability coefficients for the same membrane and separate feeding spacing design. The study recommends that in order to achieve more reliable results, manufacturers must test more than one SWMM with separate lining spacers. It will also be advantageous to learn more about how the futting changes over time. This will help us learn more about how the actual BWRO work feeds the feeding spacing piece in the desalination system.

Boulahfa et al.,2020[82] The goal of this study is to make the coagulation-flocculation process better and find out how it impacts the quality of the water that is treated before it goes into the RO unit. Reverse osmosis (RO) demineralization works best when the water is ready. This keeps the membranes from getting dirty. The plant that was studied has both a normal pretreatment and a reverse osmosis (RO) process. They checked the water's cloudiness, how much metal was still in it, and the silt density index (SDI). This study also looks at the permeate flow, feed pressure, pressure drop and permeate conductivity to see how well the RO membrane has been working for almost a year. The results reveal that making the pretreatment better minimizes the quantity of aluminum and SDI that the 5 μm cartridge filters leave behind. The RO membranes functioned great the whole time, too. The paper stresses how crucial it is to receive aid from people who work in the field when you build and take care of equipment.

Ansari et al.,2021 [83] The study evaluated a 50 m^3/d reverse osmosis system for brackish water under different salinity and pressure conditions. Results showed nonlinear permeate flow and a link between flow rates and feed pressure. The volume of salt waste fluctuated, peaking at a discharge pressure of 13 bar. The water permeability coefficient varies with temperature, feed pressure, salinity and the amount of recycled water.

Yousif et al.,2022[84] Research considered a reverse osmosis (RO) function in al -Makal Port, Iraq, and developed a model. Water was considered safe, with a recovery rate of 72% and a permet flux within the permitted area. However, it felt the challenges of salt removal and significant pressure loss, and requires recurrence or chemical cleaning. The simulated TDS was accurate within the acceptable margin of the forecast error. Optimal settings are identified for the plant performance, and the membrane must be replaced every five years. Research indicated that false TDS predicts carefully estimated the actual TDs, with 17%margin of error, considered acceptable.

Shigidi et al.,2022 [85] The study examined the effect of reverse osmosis by removing nickel ions from fake wastewater. Conclusions indicated that the temperature and pressure of the feed directly affect the permit current and the percentage of removal. The temperature improvement factor (TCF) fell as the pressure subsided and the supply temperature increased. Experiments confirmed this.

Saeed et al.,2023 [86] The research investigates the application of membranes in desalination using reverse osmosis (RO), a technique noted for its inefficiency and substantial expense. It says that forward osmosis (FO) drives can be used with RO to use less energy. The results showed that the feed solution levels, draw solution, and concentration polarization all have a big effect on how effectively the system performs. FO-RO hybrid systems operate better. The hybrid FO-RO system used a lot less energy, between 87.57% and 87.81%.

Zahedipoor et al.,2024[87] The study's purpose was to improve the lab's performance by lowering concentration polarization on the reverse osmosis membrane. The study used Taguchi design of experiment (DoE) and Minitab 16 to look at several factors that affect the process of desalination. The polyamide composite membrane demonstrated maximum efficacy in salt removal under particular conditions. The membrane's diminished concentration polarization expedited the water flow through it.

Fu et.al.,2024[88] The study discusses an integrated EDRO system, a new inductance technique that adds reverse osmosis (RO) and electrodialysis (ED) to a unit. This technique improves the procession process by increasing the RO concentration, reducing the amount of water, using lightweight material transfer, and increasing filtration efficiency. The ion access membrane also holds several solutions as the pressure increases. In the same entrance concentration, this process occurs at a speed of 14.95%. When calm and ED work together, they require less energy than working alone. This means that scientists need to learn more about how ions move and how well they perform all the time when there are other things in water that don't have salt in them.The study also recommends using hollow fiber membranes or other calm membranes suitable for jobs to make the membrane area larger and improve the performance of RO.

Alzahmi,2024 [77] The study looks at how well a single-module feed-forward reverse osmosis system works in different conditions. Results show that increased salt concentration reduces permeate but maintains unit cost. By adhering to feed temperature restrictions, wall concentration can be reduced by 20%.

H.A. Khanfar,2025[89]The thesis looks at how desalination plants work and how well they do their jobs using a reverse osmosis method .Over 120 experiments were conducted, revealing that the GARO2 desalination plant in Karma Ali improved at different rates. However, increased energy required for operation increased. A second scenario was created using the Winflows 4.04 program, but the performance improvement was limited. Four mathematical models representing different objective functions were developed using Genetic Algorithm Programming, extracting correlations for variables and choosing the most valuable ones with a close correlation coefficient.

Overall, these studies indicate that the configuration and operation of RO systems significantly influence their performance. Changing things like flow dynamics, pretreatment, feed spacer shape, pressure, temperature, and hybrid designs can make the water cleaner, use less energy, and last longer in desalination plants.

7.3. Artificial neural networks (ANN) Appley to Model of reverse osmosis(RO) process

Artificial neural networks (ANN) are a form of computational models inspired by the human brain's networks of neurons. Engineers use ANNs as flexible function approximators to learn a complex non-linear relationship with the data[90, 91]. Current uses of ANNs with RO systems include modeling the performance based on input parameters (flux, salt rejection, fouling rates) to predict the performance, as well as to optimize the performance of RO processes whether no analytical model exists or one is too cumbersome[9, 92].. This section summarizes the applications of ANNs for RO modeling or optimization.

Al-Shayji,1998[93] demonstrated the application of artificial neural networks in simulating a reverse osmosis desalination project. The study analyzed two multiple-input single-output (MISO) topologies and one multiple-input multiple-output (MIMO) network architecture, concluding that utilizing a single model for predicting both outputs is more cost-effective. Engineers select the input variables, and factor analysis was employed to reduce the number of variables by concentrating on the most critical dependent variable.The study indicated that models with more technical experience (using four input variables) made better predictions than those with fewer inputs.

Jafar et al.,2002[94] employed multilayer perceptron (MLP) and radial basis function neural networks (RBFNN) to model the performance of two reverse osmosis (RO) desalination facilities. With eight input variables, they predicted both the permeate flow rate and total dissolved solids (TDS). Data clustering and histogram equalization techniques were used to optimize the selection of centers and widths for the RBFNN. The redistributed RBFNN worked better than both the MLP and the standard (fixed) RBFNN models. It got better results with fewer neurons and weights.This indicates that the redistributed RBFNN method is more efficient and makes better predictions.

Murthy and Vora,2004a[95] used ANN modeling on a system that separated NaCl and water using RO to forecast the permeate flux and solute rejection. The flow rate was anticipated to be within ± 1% of the actual value, except for the first and last values at low pressure. The rejection rate was within ± 1.5%.

Abbas and Al-Bastaki,2005 [96] held a nervous network model for reverse osmosis (RO) of seawater and saltwater, taking into account a variety of operating parameters to make the model more wider. The authors tested the projection features using the best model with NOK 0.989 to estimate the permission flux for untrained data. But when it came to this extra plan, the model's estimates were incorrect.

Lee et al.,2009[97] used operating data from 2005 to improve the performance of Fujarah seawater Reverse Osmosis (SWRO) function using artificial neural networks (Ann). The Ann model had important factors such as temperature, completely -resolution solids (TDS), transmembrane Pressure (TMP), flow rate and TDS capacity. From the beginning of the year (n = 200), the dataset was divided into training, verification and testing for model development and evaluation. The analysis has shown that both feed the water temperature and the transmembrane pressure(TMP), overall the total dissolved solids (TDS) and the flow rate. Research indicated that the feed temperature can be significantly reduced to the total disintegrated solids (TDS) by changing the temperature either through the heat exchanger or through the step by step regulation. This reflects the ability of SET-based Ann-models to handle the complexities of SWRO discs and recommends its use to increase construction operation, reduce scaling and fouling and increase general efficiency.

Righton,2009[98] developed a nerve model for the treatment of groundwater and wastewater using reverse osmosis (RO). In addition, two inverted osmosis desalination functions were simulated using Ann -function, which receives accurate prognosis for permeat flux and salt rejection.

Libotean et al.,2009[99] emonstrated that the Ann model allows can predict the operational efficiency of a reverse osmosis system based on short-term fluctuations in the permission flux and salt passage. The three forecasts were an assessment of the function: the standard time-series correlation (STSC) approach, sequential prognosis and marching prognosis. We compared the support vector regression (SVR) model with the MLP model. The study indicated that the model can be used to provide a prognosis with satisfactory accuracy by using a short -term memory span of up to 24 hours.

Khayet et al.,2011[100] study examined the reverse osmosis (RO) desalination system using both the response surface methodology (RSM) and artificial neural networks (ANN).This used the RSM model to create feed solutions that had both low and high salt levels.That saw things like sodium chloride volume, temperature, flow rate, and pressure.The ANN model created a global model, which showed better calm performance than the RSM model.The reverse osmosis pilot plant did the best work when it was used to remove salt water.

DJ. Jassim [101] This study looks into using artificial neural networks (ANN) to model and simulate reverse osmosis systems (ROS)for water extraction. This study uses experimental data and operating characteristics to train models, employs feed-forward back propagation, and tests different transfer functions for hidden layers.

Moradi et al.,2013a[102] The new surface force pore flow model is a way to anticipate how well RO membranes will operate. The study utilized a sort of computer software called artificial neural networks to test how well they work by comparing the model's attributes to the membrane's properties. This employed a three-layer network that learns by comparing what it believes it knows to what it already knows. This looked at the network's guesses and the real data. The average inaccuracy for the test data was less than 0.0007, and the connection was more than 0.99. The study reveals that artificial neural networks (ANNs) can properly guess how well RO membranes would work by trying out a lot of various setups and choosing the best one. This is clearly true for separation, pure solvent flow, and total flow.

Barello et al.,2014 [103] The study employs a neural network-based correlation to determine the dynamic water permeability constant K_w for a dirty reverse osmosis desalination plant. The feed-forward network with many layers has four neurons and one hidden layer. This model can guess K_w values that are close to ones that have already been found. This is add more source data to the correlation or use it with fresh data. The paper also looks into Inel's Flow, hidden layers, neurons, and transfer functions, which are all aspects of network design. The results show that a small number of layers and a 3-neuron arrangement make the best predictions.

Garg and Joshi,2014[104] also compared RSM and ANN modeling. They projected the recovery of water, the rejection of TDS, and the specific energy consumption (SEC). We determined the best input parameter values for both models by lowering SEC and raising TDS rejection and water recovery. The findings indicated that ANN predictions were significantly more aligned with the validation experiments for the optimal conditions.

Salgado-Reyna et al.,2015[105] used artificial neural network modeling to predict the permeate flow rate of a proposed reverse osmosis pilot system under nine separate operations and feed scenarios. Training was done separately to create the best other models for each case. 9 had the best operatingconditions of all examples, with maximum permeate flow and the lowest TDs in the effluent. For this example, different types and layouts of the network were tried to find the best best-performing ANN architecture.

Aish et al.,2015[106] used several linear regression (MLR), multilayer perception (MLP) and radial basic Function Neural Network (RBFNN) models, to estimate the flow rate and flow rate for the reverse osmosis (RO) in Gaza's stripe. The Levenberg-Marquard algorithm performed the best of the training methods examined for MLP. This used orthogonal at least squares and Gaussian radial base functions to train RBFNN. All three methods provided TDS species that were similar to experimental data, but the MLP model was best in predicting permeate flow. Several statistical tests showed that the output and electrical conductivity were very strongly related, but the feed pressure was only related to the weak shape. These prediction algorithms were successfully tested for further estimates of one week using real data.

Madaeni et al.,2015 [107] investigated the application of the nerve network to simulate the decline in performance in three converted osmosis systems for increased process control and adaptation. That employed a multilayer perceptron (MLP) to guess how the permit would float and how well it would work with power.The percentage capacity in all three systems was reduced through the use of both Genetic Algorithm (GA) adaptation and artificial neural network (ANN) simulation. The study found ways to accommodate things that improve transmembrane pressure (TMP) and feed flow rate. This means that by following these best practices, the facility can do the work much better.

Pardeshi et al.,**2016**[108] developed a Taguchi-neural network model to evaluate the efficiency of both a forward osmosis (FO) the groundwater process in both active layer facing draw side

(AL-DS) and active layer facing feed side (AL-FS) orientations. When the draft solution was 2 m NaCl, the researchers predicted reverse solute flux selectivity (RSFS) for the flat sheet membrane in the laboratory. This used the Taguchi method to organize tests. As a result, 16 studies found place, with 4 components with 4 separate levels for each direction. ANN was used to find the best settings to reduce RSFS, and it was tested on the real world. The ANOVA analysis of the data indicated that the temperature of the draft solution was the most important factor affecting the FO performance.

Cabrera et al.,2017[109] developed an artificial neural network (ANN) model for a reverse osmosis desalination facility powered by a wind turbine. The model was used to look at how changes in the power supply affected the flow of feed and the setpoints for operational pressure.10-fold cross-validation and evolutionary algorithm optimization were used to determine the best architecture for an artificial neural network, including the number of neurons and hidden layers. The ANN learns from data that is divided into 16 power blocks and four levels of temperature and conductivity in the water supply. The artificial neural network used the wind turbine's fluctuating power to predict the flow and pressure setpoint .This made sure that the recovery rate stayed within a certain range so that the desalination process could be controlled.

Ruiz- García and Feo-García,2017 [110] utilized neural networks to simulate the operations of desalination plants that use seawater reverse osmosis, concentrating on the estimation of their operation and maintenance (O&M) expenses. They evaluated 12 desalination facilities in Spain, considering factors such as production capacity, recovery rate, and specific energy consumption (SEC). The neural network model was used to predict and analyze cost profiles by varying the recovery rate at different plant capacities. The study also pointed out that there isn't much research on using artificial neural networks (ANN) to predict forward osmosis compared to other membrane processes.

Farahbakhsh et al.,2019[111] utilized artificial neural network (ANN) modeling to analyze the antifouling characteristics of membranes containing poly pyrrole (PPy)-coated multiwalled carbon nanotubes (MWCNTs) within a reverse osmosis (RO) process. Two separate neural network models were developed—one for membranes made with raw MWCNTs-PPy and another for those with oxidized MWCNTs-PPy. The ANN models revealed that the oxidized MWCNTs-PPy membrane exhibited consistently higher water flux. The models also predicted that molecular aggregation on the membrane surface would reduce both salt rejection and water flow over time.

Jawad et al.,2020[112] developed an Ann model to provide a generic prediction of the membrane current for small-scale FO desalination. The model was tested against many linear regressions and well known mathematical models, and it worked well. The Ann model studied many neurons in their hidden layers and used 9 input parameters, who use 9 entrance parameters. The study combined a lot of existing research on FO lab-scale studies to train and test the ANN model.

The authors used a unique function by combining the ANN-RSM model with data from**Hawari et al**.,**2016,2021**[113, 114] which was to investigate the concentration, temperature and effect of concentration, temperature and speed on the flow of the membrane. Trained artificial neural network (Ann) was used. Parameter is used to develop an Response Surface Methodology (RSM) model for optimization, even without practical data, especially sewn for RSM. It achieves achievable because artificial neural network (AN) modeling does not require a certain experimental design to succeed, making it easier to find the best process parameters.

Mahadeva et al.,2022[115] This study is about utilizing artificial neural networks (ANN) to find out how much money desalination facilities will make. Models trained using the backpropagation method performed better after 127 tests. The softmax-purelin function, two hidden layers, the Levenberg–Marquardt training function, dataset partitions, and the mean square error are all excellent choices. This method makes it easier and more reliable for desalination plants to execute their functions. This method also serves as an excellent tool for monitoring the availability of water over time.

Brooke et al.,2022[116] The research presents a new way to use Ms. utilizing response surface methods and artificial neural networks to make models, boost performance, and guess how reverse osmosis desalination would work on limited water. Reverse osmosis (RO) works well, but it uses a lot of energy.The technique and equipment need to be better, especially for water with low salinity (TDS = 500–5000 mg/L), because desalination uses less energy in this instance than in saltwater. The main things that affect how well the system works are the amount of salt, the temperature of the water, and the amount of pressure. These were all changed to see how well the system could remove salt and make water.The best results happened when temperatures were 38.8°C, pressures were 150.57, and salt levels were 577 mg/L.Both ANN and RSM did a good job of predicting what would happen in the future ($R^2 = 0.99$).The root mean square errors for these predictions were 2.41 and 5.85. ANN turned out to be better because it can always get better and doesn't need special tests, even though RSM was more accurate. The results show that using combined modeling methods can improve reverse osmosis systems, no matter what kind of membrane or water is used.

Mahadeva et al.,2023 [117] used the MWOA-ANN approach where the ANN models had fairly good performance, although somewhat inferior to the standard ANN model and the response surface model (the best model had minimal prediction error of from about 0.5 %). The results showed that the ANN models trained with the hybrid metaheuristic were better than the old ones. This meant that the prediction errors in RO plant performance were very low, making the digital twin of the process very dependable.

Wang et al.,2024[118] The paper discusses the use of math in improving reverse osmosis (RO) desalination in salty brackish waters. The model uses Response Surface Methodology (RSM) and Artificial Neural Network (ANN) models to predict RO system performance. The ANN model surpasses the RSM model, exhibiting a high correlation coefficient and a low rejection rate. The aim is to improve the process in two stages for ongoing implementation.

Alardhi et al.,2024[119] The study employs two machine learning methods, response surface methodology (RSM) and artificial neural networks (ANN), to optimize the reverse osmosis (RO) process. Researchers employed a central composite design (CCD) to identify the factors influencing the reduction of total dissolved solids (TDS) in wastewater treatment. The RSM-CCD investigation established the optimal initial conductivity, flow rate, feed pressure, and temperature for reducing conductivity. The ANN model, featuring hidden layers, performed effectively, demonstrating that both RSM and ANN may enhance RO procedures.

In recent years, ANN modeling has been extensively employed to simulate the RO process. The comparison analyses revealed that MLR is an insufficient modeling instrument for representing the RO process. Studies demonstrate that both MLP-ANN and RBFANN yield enhanced accuracy relative to other methodologies.This suggests that the effectiveness of any model is likely dependent on the specific data used for training and the training algorithm, which often vary among research. ANN models surpassed RSM models, perhaps because to their autonomy from experimental design and inflexible training techniques, which often vary from one study to another. ANN models were better than RSM models, which could be because they didn't depend on experimental design or a strict training algorithm. One ANN model can handle all kinds of data, but you might need more than one RSM model to explain how the data changes. You can use RSM and GA with ANN to make the outputs of the ANN model bigger or smaller by linking them together. Instead of utilizing trial and error, GA optimization can also be used to improve the network architecture, such as the number of hidden layers and neurons. Factor analysis can help cut down on the number of input variables to the ANN by ranking them by importance. This can make the model simpler, which means it will be more accurate and take less time to train. Another significant feature examined for ANN is its interpolation and extrapolation functionalities. The results for interpolation look really good, however the results for extrapolation are not very good. This could be because there isn't enough data to train on. Creating an ANN with varied amounts of training data and measuring how well it can extrapolate would be a nice method to prove this idea.

Table 3. shows the features of ANN models made for the reverse osmosis process.

Process	Method	Input	Output	Network Architecture	Activation	Training algorithm	Performance	References
RO desalination plant	MLP	feed temperature, feed pressure, feed flow rate, feed pH	product flux, product conductivity	4–30-15–2	tan-sigmoid	Gradient-descent algorithm	R^2 =0.916704 , R^2=0.9512 2	**[93]**
Groundwater desalination plant	RBFN	eight-variable vector	permeate flow rate, permeate TDS	8-13 -28 -2		Least Mean Square (LMS) and Radial Basis Function Networks (RBFN) algorithms.	Error =1.73 Error = 2.32	**[94]**
Lab-scale separation of sodium chloride - water system	MLP	concentration, pressure, flow rate	rejection, flux	3–10-10–2	log-sigmoid	Levenberg- Marquardt	Absolute error<1%	**[119]**
RO water desalination unit	MLP	feed pressure, temperature and salt concentration	permeate rate	3–5-1	log-sigmoid	Levenberg- Marquardt	R^2=0.998	**[97]**
Seawater desalination plant	MLP	feed temperature, feed total dissolved solids, TMP, feed flow rate, time	permeate TDS, flow rate	5–12-2	log-sigmoid	Back propagation algorithm	R^2=0.96, R^2 =0.75	**[98]**
Separation of sodium chloride and calcium carbonate	MLP	pressure, various feed concentrations, flow rates, concentration of the permeate and reject streams	permeate flux, solute rejection percentages		log-sigmoid	Levenberg- Marquardt	R^2= 0.9989	**[101]**
Brackish water desalination plant	MLP	flow rate, conductivity, feed pressure, pH, temperature	permeate flux, salt passage	5–3-1	tan-sigmoid	Levenberg- Marquardt	Mean absolute error =0.9%	**[120]**
RO desalination pilot plant	MLP	Feed concentration, temperature, flow rate, pressure	permeate flux, rejection	4–5-3–1	log-sigmoid	Levenberg- Marquardt	R^2 =1	**[102]**
RO Brackish water desalination plant	MLP	operating pressure, feed temperature, feed concentration, operating time, feed flow rate,	permeate flow rate and permeate concentration.	5-10-2	log-sigmoid	Levenberg-Marquardt	R^2= 0.99342	**[103]**
RO desalination plant	MLP	average longitude concentration, operational condition, and the parameters of the MD-SF–PF model.	separation factor (f), pure solvent flux (NP) and total flux (NT)	3-9-1-3	tan-sigmoid	Levenberg–Marquardt	R^2= 0.99966 for f, 0.998 for NP and 0.998 for NT	**[104]**
RO desalination	MLP	pressure, temperature, concentration, pore radius, friction constants, potential parameter, ratio of average pore length to fractional pore area	separation factor, solvent flux, total flux	9–20-3	tan-sigmoid	Levenberg- Marquardt	R^2 =0.9966, 0.998, 0.9982	**[121]**
RO desalination using artificial groundwater	MLP	pH, feed temperature, pressure, concentration	water recovery, TDS rejection, specific energy consumption	4–5-3	log-sigmoid	Back propagation algorithm	R^2 =0.9611	**[106]**
RO desalination process	MLP	time, salinity, operating pressure, membrane type	water permeability	10 hidden layers with 4 neurons	tan-sigmoid	Levenberg- Marquardt	R^2 =0.9964	**[105]**
RO wastewater pilot plant	MLP	inlet concentration, TDS inlet concentration, time	permeate flow	3–4-3–1	tan-sigmoid	Levenberg- Marquardt	R^2 =0.998	**[107]**
Large and small- scale brackish water desalination	RBFNMLP	water temperature, pH, conductivity, pressure	TDS, permeate flow	4–6-2	Gaussian kernel/tan sigmoid	Levenberg- Marquardt	R^2=1, 0.9873 R^2 =1, 0.9904	**[95]**
RO water treatment in a power plant	MLP	time, TMP, conductivity, flow rate	permeate flow, conductivity	4–11-5–2	log-sigmoid	Levenberg- Marquardt	R^2 =0.94, 0.99	**[99]**

FO of ground water using 2 M NaCl as draw solution	MLP	feed CFV and temperature, draw solution CFV and temperature	reverse solute flux selectivity (RSFS)	4–8-1 4–7-1	exponential	BFGS quasi- Newton backpropagation	R^2=0.9943 R^2=0.9988	[108]
RO desalination plant	MLP	production capacity, water flux recovery, energy consumption, price of electrical tariff	operating and maintenance cost	5–4-1	tan-sigmoid	Levenberg- Marquardt	R^2=1	[109]
Small scale pilot plant seawater desalination plant	MLP	power, temperature, conductivity	Pressure, flow	3–71-17–13–69- 13–1	sigmoid	Resilient backpropagation algorithm	Mean absolute error =0.405% Mean absolute error =0.867%	[100]
Brackish water desalination plant	MLP	temperature, TMP, time, concentration	water flux	4-16-1		Levenberg- Marquardt	R^2=0.9947 5	[110]
Modeling of Lab- scale FO desalination	MLP	membrane type, membrane orientation, molarity feed solution (FS), molarity draw solution (DS), MW, FS velocity, DS velocity, FS temperature, DS temperature	membrane flux	9–25-25–40-1	log-sigmoid, tan-sigmoid, log-sigmoid	Levenberg- Marquardt	R2 =0.973	[111]
Bench-scale FO unit using different concentrations of NaCl solutions	MLP	osmotic pressure difference, FS velocity, DS velocity, FS temperature, DS temperature	membrane flux	5–10-1	tan-sigmoid	Levenberg- Marquardt	R^2 =0.98036	[113]
desalination plant	MLP	-	permeate flux	4-2-1	SoftMax-purlin	Levenberg–Marquardt	R^2 = 0.994	[114]
RO Desalination	single hidden layer	Feed water salinity, pressure, and temperature	salt rejection efficiency and permeate flux	3- 1-2	TRANSIG-PURELIN	Bayesian regularization	R^2 =0.999	[115]
Reverse Osmosis (RO) desalination plant	MWOA-ANN	feed flow rate, evaporator inlet temperature, feed salt concentration, condenser inlet temperature	the permeate flux	4-11-1	Log-purlin	Modified Whale Optimization Algorithm (MWOA)	R^2 =0.991	[116]
RO Desalination	RSM (Second-order polynomial) +GA-BP ANN (Genetic Algorithm + BP)	Feed TDS, Feed water flow rate, Concentration/desalination ratio	Rejection, Membrane flux, Performance index, SEC	3-10-4			R^2 = 0.9936 (performance index), R^2 = 0.9932 (SEC), RMSE = 0.85 (rejection)	[117]
RO Desalination	**RSM (with CCD)**	**Flow rate, initial conductivity, pressure, temperature**	**Final conductivity (TDS)**	**4-2-1**	-	**Backpropagation**	R^2 **=0.99**	**[118]**

7.4. membrane cleaning

The effectiveness of RO membrane cleaning through chemical procedures and physical methods stands essential for performance recovery after scale or fouling events. This section reviews research that investigated chemical cleaner formulations alongside mechanical cleaning methods or their blended approaches for RO membranes.

MH Tran-Ha, DE Wiley,1998[122] This study found that impurities in water used for cleaning a polysulphone ultrafiltration membrane affect its efficiency. A cationic surfactant, CTAB, was used. The presence of ions like calcium, sodium, chloride, nitrate, and sulfate improved flux recovery during cleaning. Higher ionic strengths also improved cleaning efficiency.

MA Saad,2004[123] research shows the problems that RO plant operators, end-users, and membrane producers have when it comes to keeping an eye on and finding membrane fouling and scaling growth in real time. The current industry-standard way to analyze performance is to look at how RO flux decrease parameters change over time. The Silent Alarm™ technology is an early-warning system that lets you find fouling or scaling on RO membranes early, so you can take action right away. This method makes the total cost of desalinated water a lot better.

Sadeddin et al.,2011[124] The study explores the use of electro-coagulation (EC) to remove total suspended solids (TSS) and turbidity from feed water of a reverse osmosis unit. EC treatment improves water quality by reducing fouling symptoms like water flow, pressure loss, and silt density index. The results show that EC treatment significantly improves water quality, surpassing normal standards in reverse osmosis units.

Baskar et al.,2014 [125] A study looked into ways to use chemicals to clean spiral wound reverse osmosis membranes that have gotten unclean from textile wastewater. The study used different amounts and timings of H2SO4, HCl, NaOH, and EDTA. The amount of foulant that was removed likewise increased raised as the cleaning period, chemical concentration, surfactant concentration, and temperature went up. The results demonstrate that the length of time, concentration, and temperature of cleaning affect different types of dirt. However, further tests are needed to de ermine the optimum cleaning chemicals.

Tu et al.,2015 [126] The study looks at how washing with chemicals impacts the performance of a reverse osmosis membrane. It cleans with surfactants, chelating agents, and its own proprietary cleaning solutions. The study also looks at how different ways to clean membranes and how easily water may pass through them alter things. The results show that washing the membrane changes its ability to repel water and boron and sodium a lot, but not too much. The most significant thing is the solution's pH.

Beyer et al.,2017 [127] This study used membrane autopsy and measured total organic carbon (TOC) to learn more about membrane fouling and cleaning in three reverse osmosis (RO) facilities. Researchers found that these plants were damaged by permanent foulants, which made them perform worse in terms of normalized pressure drop and water permeability, even after they were cleansed with chemicals. Standard cleaning methods cut TOC by an average of 45%, and in certain cases by as much as 80%. But none of the cleaning methods got rid of all the foulants on the membrane elements. The study shows that we need new ways of cleaning that focus on resistant foulants in order to enable membrane regeneration to work very well. You can utilize cross-flow cells to compare different cleaning chemicals and CIP methods.

Yu et al.,2017[128] This study investigated the reverse osmosis(RO) membranes before and after cleaning them with acid and alkaline. The study found that the majority of the dirt had disappeared. There is a lot of calcium, aluminum, and iron in the membranes. This couldn't get rid of neutrals that were both hydrophilic and hydrophobic. Chemical washing got rid of 94% and 90% of all germs on the lead and tail membranes, but not bacteria that are resistant to it, such as Pseudomonas and Zoogloea. The results suggest that there are new areas of research that need to be done on cleaning methods and RO pretreatment techniques.

Liberman,2018 [129] The study found that forward osmosis (FO) provides a new approach to clean RO membranes without using chemicals. We tried three FO-based cleaning methods: Direct Osmosis, Osmotic Back Flushing, and Osmotic Shock Cleaning. All of the methods performed effectively to get rid of reversible fouling, but the osmotic backwash method got the maximum permeability back in just a few minutes. By reducing chemical exposure, FO-based mechanical cleaning can make membranes live longer and prevent fouling.

Fayaz et al.,2019[130] The study looks at how adding chlorine changes the oxidation-reduction potential (ORP) and silt density index (SDI) of saltwater that has been desalinated. The results show that adding chlorine to raw water changes the SDI value because of organic and biological particles. This can improve the performance of the desalination machine by changing the turbidity and ORP settings.

Al-Balushi et al.,2024[131] This study looks at three chemical methods for cleaning dirty reverse osmosis membranes. It looks at the structure and composition of groups of microbes. The results reveal that all of the strategies worked to get rid of biofilms. Cleaning A did the finest job of getting rid of germs and making the composition of the membranes like that of new ones. The study shows that RO membranes need to be cleansed in certain ways when they get dirty. Cleaning A is a good choice for better water purification technology.

Salih & Al-Alawy ,2025[132] The goal of the study is to make reverse osmosis (RO), a membrane method for getting salt out of water, better by increasing its penetration flow and NaCl rejection. This is thought to be a powerful way to make things dirty. We tested the air sparging method in a number of conditions, such as when the air flow rate, water flow rate, feed concentration, temperature, and pressure were all variable. The results showed that the rejection and penetrate fluxes have gotten a lot better.The air sparging method made rejection go up from 88.1% to 93.7% and permeate flux go up from 3.64 to 6.51 L/hr.m², which is a big improvement. The flux was highest when the airflow rate was 1.8 L/min. This value tumbled down after that. The results showed that the concentration of the permeate steadily rises over time, while the flux drops as the process continues on. The operational time of the process increased by two times through sparging until the designated flux decline threshold was achieved. The experiment showed that air sparging created higher permeate flux and delayed the process of filter fouling.

In summary, membrane fouling appears to be an inherent and unavoidable issue within membrane technology. Depending on the quality of the feed water, the conditions of the operation, and the properties of the membrane, one or more types of fouling could happen. These include biofouling, organic fouling, inorganic scaling, and colloidal fouling. Different kinds of foulants may form in different ways, but occasionally there aren't clear lines between them, and they work together or in a way that makes them stronger. Ongoing research into fouling behaviors is crucial for improving the comprehension of fouling mechanisms.Researchers have been looking into new RO materials that could help us deal with fouling better or even modify the way we do it over the past ten years.People are now using a number of different approaches to control fouling in practice. These include membrane pretreatment, membrane monitoring and cleaning, and membrane surface modification.These strategies are quite important for keeping RO from getting dirty. Statistical analysis indicated significant research interest in RO membrane fouling and its mitigation. There are still many problems to solve, but new membrane content and synthesis processes look like they can be a good way to get rid of fouling. Future studies in this field are likely to achieve useful results..

8. CONCLUSION

This research will analyze the installed model of the reverse osmosis (RO) process, as well as analysis of simulation and adaptation studies made from 1965 to 2025. The project was required to carefully look at research on the thermodynamic boundaries of the RO desalination process. The evaluation of these models clearly shows that they are becoming more complicated, which often makes it harder for model predictions to match up with data from real plants .Simulation studies in desalination have achieved considerable sophistication, mostly due to researchers' focused efforts in analyzing the interconnections among system variables. This study highlights the inherent complexity of desalination systems, particularly those treating brackish water, requiring advanced modeling tools to accurately depict and predict system performance.

A continual difficulty in membrane technology, especially in reverse osmosis (RO) desalination, is membrane fouling. Fouling continues to be a significant concern, as it can diminish water quality, hinder system functionality, and compromise membrane efficacy. Fouling types include biofouling, organic fouling, inorganic scaling, and colloidal fouling. Researchers are diligently exploring novel reverse osmosis membrane materials and improved maintenance techniques, encompassing membrane pretreatment, regular cleaning, and surface alterations. Despite significant advancements, ongoing investigation into novel membrane materials and manufacturing methods is crucial for enhancing system reliability and reducing fouling. This work has comprehensively examined optimization attempts, highlighting the necessity of identifying optimal operating parameters and process configurations within practical constraints .Continuous developments in modeling techniques and the application of effective anti-fouling tactics are essential for sustaining the development and efficacy of reverse osmosis desalination systems.

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