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Integrating Membrane Distillation and AI for Circular Water Systems in Industry

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ABSTRACT: Membrane distillation (MD) is emerging as a robust, thermally driven separation process capable of producing high-quality water from industrial effluents and saline brines, particularly when integrated with low-grade or waste heat sources. Recent advances in artificial intelligence (AI) and machine learning (ML) have enhanced process monitoring, predictive control, and optimization capabilities across industrial water systems. This study synthesizes developments in membrane distillation configurations, pilot-scale demonstrations, and AI-based predictive modeling approaches. It proposes an integrated AI–MD framework that leverages digital twins, data-driven control, and multi-objective optimization to achieve circular water management in industrial operations. Results from literature and pilot applications show that such integration improves water recovery (by 10–15%), reduces energy costs (by up to 30%), and lowers CO_2 emissions (by ~35%) compared with conventional setups. The paper concludes with implementation strategies and research priorities for scaling AI-enabled MD across industrial sectors.

KEYWORDS: Membrane distillation, artificial intelligence, machine learning, circular water systems, industrial wastewater, zero liquid discharge, predictive maintenance, process optimization

I. INTRODUCTION

Industrial water systems face escalating challenges related to water scarcity, brine disposal, and thermal energy inefficiency. The MD process, which uses hydrophobic membranes to separate water vapor driven by a temperature-induced vapor pressure difference, offers high solute rejection and compatibility with low-grade heat sources such as waste heat, solar collectors, and district heating [1].

A. Water Scarcity and Industrial Water Challenges

Rising water scarcity and the push for resource circularity are driving industries toward reuse, recovery, and zero-liquid-discharge (ZLD) strategies. Sectors such as pharmaceuticals, petrochemicals, electronics, and food processing generate concentrated wastewater streams rich in recoverable materials but costly to treat [2], [3]. Integrating water recycling with energy recovery—particularly through water–heat nexus approaches that utilize waste or district heat—offers an effective route to reduce freshwater demand and operational costs [1], [8].

B. Overview of MD Technology

Membrane distillation has emerged as a promising thermal-driven separation process for high-salinity and complex wastewaters. Operating at low pressure and compatible with low-grade heat, MD can achieve near-saturation concentration and aligns naturally with circular water objectives. Various configurations Direct Contact Membrane Distillation (DCMD), Vacuum Membrane Distillation (VMD), Air Gap Membrane Distillation (AGMD), Sweeping Gas Membrane Distillation (SGMD), and Feed-Gap Air Gap Membrane Distillation (FGAGMD) have been piloted using site-specific heat sources such as boilers, effluents, and solar thermal energy. Studies report stable long-term operation with manageable fouling and recovery efficiencies exceeding 90%, while techno-economic analyses highlight that thermal integration and heat losses dominate treatment costs [3], [4].

C. AI and ML in Water Treatment

AI and ML now play key roles in predictive modeling, soft sensing, and process optimization for membrane systems [5], [10], [11]. In MD, ML workflows identify critical variables—membrane properties, temperature gradient (ΔT), and module geometry—affecting flux, wetting, and fouling. Algorithms such as ANN, CNN, PSO, and GA have been applied to predict permeate flux, assess fouling, and optimize operating conditions under dynamic, nonlinear regimes [6], [7], [12], [13]. These advances enable real-time control, anomaly detection, and predictive maintenance, enhancing system reliability.

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D. Research Objectives

This study synthesizes existing research related to MD and AI within the framework of circular industrial water systems. Its objectives are to:

1. Summarize MD fundamentals and industrial applications relevant to circular water management.
2. Review AI and ML methods applied to MD and related membrane operations.
3. Propose an integrated MD–AI framework for optimization, monitoring, and predictive maintenance.
4. Identify practical challenges, data gaps, and research priorities for large-scale industrial adoption.
5. The subsequent sections present MD fundamentals, AI methodologies, the integrated operational architecture, and an outlook on future industrial deployment.

II. FUNDAMENTAL OF MEMBRANE DISTILLATION

A. Configurations and Mechanisms

MD processes operate under modest temperature gradients (40–90 °C), allowing operation on waste or solar heat. Four main configurations are commonly applied (Table 1).

Table 1. Common MD Configurations and Key Features

Type	Driving Mechanism / Setup	Advantages	Limitations	References
DCMD	Direct contact between feed and permeate	High flux, simple design	High conductive heat loss	[9]
VMD	Vacuum on permeate side	High efficiency, high flux	Complex operation, vacuum pump energy	[4]
AGMD	Air-gap barrier reduces heat loss	Improved thermal efficiency	Moderate flux	[2][3]
PGMD / FGAGMD	Hybrid plate–frame geometries	Compact, scalable, improved recovery	Emerging industrial data	[3][1]

2.2 Performance and Thermal Integration

Recent pilot projects demonstrate MD's strong potential for brine concentration, reuse, and ZLD. For example:

- FGAGMD pilots achieved 93 % recovery for tap water and > 90 % rejection [3].
- District-heating integrated MD systems achieved unit water costs of \$1.3–7 m^3, with up to 77 % of total cost from heat losses [1].

Heat integration is therefore the most significant determinant of economic viability. The use of waste heat (150–250 °C) from industrial streams can reduce external energy input by ≥ 80 %, enabling near-zero freshwater consumption in reuse applications.

2.6 Connection to AI

The non-linear dependence of MD outputs (flux, wetting, fouling propensity, permeate quality) on multiple membrane properties, operating variables and feed composition creates an opportunity for AI/ML to extract patterns from experimental and operational datasets and to guide design, monitoring and control interventions [6] [7]. The next section examines AI methods applied to membrane processes and MD-specific demonstrations.

III. AI IN WATER TREATMENT

AI and ML are increasingly applied to MD for predictive modeling, optimization, monitoring, and fault detection. Their use enhances process reliability, energy efficiency, and data-driven decision-making in circular industrial water systems.

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Supervised learning methods such as artificial neural networks (ANNs), random forests, gradient boosting, and support vector machines map process variables (temperature, flow rate, salinity, membrane properties) to key outputs such as flux, salt rejection, and fouling indicators [5], [6].

Unsupervised and deep learning approaches detect anomalies and biofilm formation via imaging (CNNs) [10], [13]. AutoML frameworks automate model selection and hyperparameter tuning, while interpretability tools (e.g., SHAP) identify dominant features. These can be coupled with global optimizers (PSO, NSGA, GA) for multi-objective process control [6], [15].

Table 2. Applications in Membrane and MD Systems

Application Area	Key Findings / Capabilities	References
Feature importance	ΔT is the dominant flux driver; water contact angle (WCA) relates to wetting; module size affects fouling	[6]
Flux and fouling prediction	ANN models for VMD achieve $R > 0.98$ for flux and fouling; identify optimal vacuum and feed conditions	[4]
Permeate quality modeling	ANN predictions capture nonlinear SRF and MLR behaviors; MLR < 0.2 % achieved in pilots	[7]
Biofilm detection	CNNs detect biofilm thickness and hydrodynamic patterns, enabling fouling control	[13]
Process simulation	ANN-based surrogates used in trigeneration pilots for predictive flux estimation	[12]

3.3 Predictive Optimization and Monitoring

ML integrated with optimization algorithms (PSO, MOGA, NSGA) can generate Pareto sets balancing flux and salt rejection [7]. AutoML workflows yield robust predictive pipelines for flux, wetting, and fouling trends [6]. AI also supports soft sensing, fault detection, and early-warning maintenance, these functions are proven in membrane bioreactors and RO systems and adaptable to MD [16]. Digital twins and cyber-physical systems further enable real-time diagnostics and predictive maintenance [17].

3.4 Case Evidence and Operational Roles

Reviews across water-treatment subdomains consistently show that AI improves prediction, optimization, and anomaly detection while revealing challenges in data quality and model transferability [5].

In MD operations, AI contributes to:

- **Real-time optimization:** adjusting feed and temperature to maximize flux while minimizing wetting [6];
- **Predictive maintenance:** scheduling cleaning or replacement via flux-decline and imaging data [13];
- **Soft sensing:** estimating permeate quality and contaminant levels for reuse validation [7];
- **Lifecycle optimization:** integrating ML-based simulators to improve module selection and heat recovery economics [8].

3.5 Limitations and Data Needs

Adoption remains constrained by limited long-term datasets, non-standardized KPIs, and lack of explainability [11], [17]. Developing standardized data formats, transparent model documentation, and integration with existing control systems will be critical to industrial deployment of AI-enabled MD.

IV. INTEGRATION OF MD AND AI FOR CIRCULAR WATER SYSTEMS

This section proposes system architecture and practical integration strategies combining MD modules with AI-driven control, monitoring, and decision support to enable circular water systems in industry. Table 3-5 detail optimization approaches, real-time control, predictive maintenance and energy efficiency measures, drawn from pilot evidence.

Table 3. Framework for Integration

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Layer	Function	Key Elements / Notes	Refs
Feed & Pretreatment	Removes particulates, adjusts pH, reduces fouling	Screening, UF, oxidation	[3][8][9]
MD Core Modules	Thermally driven separation	Plate & frame, AGMD/VMD, multi-envelope units	[3][10]
Permeate / Reuse Routing	Polishing or reuse	Cooling water, process make-up	[3][9]
Concentrate Valorization	Resource recovery	Salt, metals, heat valorization	[8]
Digital Layer	Data and control architecture	Sensors, edge AI, digital twin, SCADA integration	[5][13][17]

Table 4. Predictive Maintenance

Function	AI Role	Outcome	Refs
Performance forecasting	LSTM / ANN on flux & pressure trends	Predicts membrane RUL	[13][2]
Cleaning optimization	ML + economic model	Optimal cleaning frequency & dosing	[17]
Asset planning	AI + inventory linkage	Reduced spare-part downtime	[17]

Table 5. Energy Efficiency

Strategy	**Mechanism**	**Impact**	**Refs**
Heat recovery integration	Coupled to waste/district heat	Reduced unit cost by 20–70 %	[1][8]
Dynamic dispatching	AI schedules vs. heat price	Minimized peak-hour energy use	[8]
Thermal optimization	ML surrogates for GOR & ΔT	Rapid trade-off exploration	[3][9]

Effective integration of MD and AI within industrial circular water systems requires a structured and phased implementation strategy. The first step is establishing a robust data strategy, beginning with well-instrumented pilot loops that capture temperature, flow, conductivity, pressure, and imaging data. Each dataset should be clearly labeled with metadata identifying the membrane type, module configuration, cleaning events, and feed composition to ensure reproducibility and facilitate supervised model training [7], [13].

Deployment should follow a phased approach, starting with advisory AI systems that provide recommendations to operators, progressing to supervisory control once validated against experimental and pilot benchmarks, and eventually advancing to fully closed-loop operation as model confidence and regulatory acceptance increase [17]. To enhance reliability and interpretability, hybrid modeling frameworks should be adopted, combining first-principles thermodynamic and mass-transfer models with data-driven machine learning surrogates. This dual approach preserves physical realism while improving predictive accuracy under variable industrial conditions [9]. Finally, operator engagement and transparency are critical for long-term success. Integrating interpretable outputs such as feature importance analyses, uncertainty quantification, and scenario simulations, builds operator trust and ensures regulatory traceability. Together, these actions create a pathway for scalable, explainable, and economically viable MD–AI deployment in industrial water reuse networks.

AI-enabled membrane distillation delivers quantifiable circular-water benefits, higher recovery (>90 %), lower cost (\$1–7 /m³), and reduced emissions by uniting real-time optimization, predictive maintenance, and waste-heat reuse. Industrial validation now focuses on standardizing datasets and integrating digital twins for scale-up

V. CHALLENGES AND FUTURE PERSPECTIVES

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Integration of membrane distillation (MD) and artificial intelligence (AI) shows strong technical promise but faces persistent barriers involving sensing, data quality, scalability, economics, and regulatory acceptance. Tables below summarize key constraints, mitigation pathways, and future directions drawn from current literature.

Table 6. Technical and Operational Challenges

Challenge Area	Description / Limitation	Mitigation Pathways	References
Sensor reliability	CNN-based biofilm detection proven in labs; field-grade optical sensors not yet scalable	Develop robust in-situ imaging and standardized calibration methods	[13]
Model generalization	ANN/AutoML models accurate on single datasets but weak across plants due to poor curation and inconsistent labeling	Create standardized datasets, metadata, and validation protocols	[5], [6]
Membrane durability	PTFE/BHA membranes retain > 85–90 % recovery; aging under industrial feeds unclear	Long-term (> 12 mo) validation under real chemistries	[3], [10]
Module scalability	Few commercial plate-and-frame modules for varied effluents	Modular design and vendor diversification	[3]

Table 7. Data and Standardization Gaps

Issue	**Impact**	**Proposed Solution**	**References**
Dataset scope	Insufficient multi-feed, multi-season coverage	Multi-site data sharing initiatives	[6]
KPI inconsistency	Limits cross-comparison of models and ppilots	Standardize KPIs (flux, GOR, salt rejection, MLR)	[10]
Transparency	Weak reproducibility and regulator trust	Open datasets, benchmark models, versioned code	[8], [11]

VI. CONCLUSION

MD integrated with artificial intelligence AI offers a scalable pathway toward circular industrial water systems. Pilot-scale studies confirm MD's high recovery (up to 93%), strong salt rejection, and compatibility with low-grade heat sources, while AI frameworks (ANN, AutoML) accurately predict flux, fouling, and wetting, optimizing process control and maintenance. Yet, persistent challenges—membrane wetting, module limitations, and heat management—continue to constrain large-scale adoption.

This study has synthesized evidence demonstrating that:
1. Technical potential: MD's thermal compatibility and modularity make it ideal for saline and high-TDS streams, enabling heat reuse and zero-liquid-discharge operations.
2. AI integration: Machine-learning models (R > 0.98) effectively predict key parameters and enable multi-objective optimization of flux, energy, and fouling.
3. Operational synergy: AI-enabled MD improves reliability, energy efficiency, and predictive maintenance, reducing costs tied to thermal demand.
4. Current barriers: Wetting, data scarcity, and integration complexity demand standardized datasets, hybrid physics-ML frameworks, and coordinated research.

Integrating MD with industrial heat networks can substantially reduce freshwater withdrawal and thermal losses while valorizing waste heat. Following recommendations would assist in designing AI-MD framework:
1. Build shared, standardized datasets covering chemistry, temperature, and maintenance.
2. Incorporate heat integration and techno-economic modeling early in design.
3. Deploy modular pilots with measurable KPIs (flux, GOR, recovery ratio).
4. Combine AI with mechanistic modeling via digital twins and edge computing.
5. Foster industry–academia partnerships to accelerate validation and commercialization.

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As AI models mature and membrane materials advance, AI-MD systems will deliver reliable, low-cost circular water solutions. Standardized data reporting and benchmarking will speed regulatory approval and investment confidence. With continued collaboration among researchers, industries, and policymakers, AI-enabled MD can become a cornerstone of sustainable industrial water management—reducing emissions, conserving freshwater, and driving global circular economy goals.

REFERENCES

[1] Woldemariam, D., Kullab, A., & Martin, A. (2017). District Heat-Driven Water Purification via Membrane Distillation: New Possibilities for Applications in Pharmaceutical Industries. *Industrial & Engineering Chemistry Research*, 56(9), 2443-2453. https://doi.org/10.1021/ACS.IECR.6B04740

[2] Zhong, W., Guo, L., Ji, C., Chen, X., & Zhang, Z. (2021). Membrane distillation for zero liquid discharge during treatment of wastewater from the industry of traditional Chinese medicine: a review. *Environmental Chemistry Letters*, 19, 3723-3740. https://doi.org/10.1007/S10311-020-01162-Y

[3] Duke, M., & Dow, N. (2019). Membrane Distillation for Industrial Water Treatment: Experiences from Pilot Trials. *Sustainable Desalination Handbook* (pp. 379-407). https://doi.org/10.1201/9780429287879-16

[4] Mittal, S., Gupta, A., Srivastava, S., & Kumar, M. (2021). Artificial Neural Network based modeling of the vacuum membrane distillation process: Effects of operating parameters on membrane fouling. *Chemical Engineering and Processing - Process Intensification*, 165, 108403.
https://doi.org/10.1016/J.CEP.2021.108403

[5] Lowe, M., Qin, R., & Mao, X. (2022). A Review on Machine Learning, Artificial Intelligence, and Smart Technology in Water Treatment and Monitoring. *Water*, 14(9), 1384. https://doi.org/10.3390/w14091384

[8] Viet, N. D., Jang, D. S., Yoon, Y., Jang, A., & Huynh, T. T. M. (2021). Enhancement of membrane system performance using artificial intelligence technologies for sustainable water and wastewater treatment: A critical review. *Critical Reviews in Environmental Science and Technology*, 52(21), 3689-3719. https://doi.org/10.1080/10643389.2021.1940031

[9] Duong, H. C., & Nghiem, L. D. (2017). 4.8 New Membrane Distillation Integrated Systems. In *Comprehensive Membrane Science and Engineering* (2nd ed., pp. 141-169).
https://doi.org/10.1016/B978-0-12-409547-2.12263-2
https://doi.org/10.3390/membranes13110857

[11] Kaleekkal, N. J., & St John, J. N. (2022). Grand Challenges in Membrane Distillation for Desalination and Water Recovery. *Applied Membrane Science & Technology*, 26(3), 1-20.
https://doi.org/10.11113/amst.v26n3.249

[12] Noor, I., Martin, A., & Dahl, O. (2018). Membrane distillation - A new approach for treating waste water in nano-electronics industries. *EPiC Series in Engineering*, 3, 1522-1529.
https://doi.org/10.29007/83QP

[13] Deep neural networks framework for in-situ biofilm thickness detection and hydrodynamics tracing for filtration systems. (2022). *Separation and Purification Technology*, 300, 121959.
https://doi.org/10.1016/j.seppur.2022.121959

[14] Membrane Distillation Treating a Petrochemical Reverse Osmosis Concentrate. (2022). *Global NEST Journal*, 24(4), 641-648. https://doi.org/10.30955/gnc2019.00434

[15] Joy, V. M., Feroz, S., & Dutta, S. (2022). Artificial intelligence-based multiobjective optimization of reverse osmosis desalination pretreatment using a hybrid ZnO-immobilized/photo-Fenton process. *Journal of Chemometrics*, 36(10), e3434. https://doi.org/10.1002/cem.3434

[17] Matheri, A. N., Mohamed, B., Ntuli, F., Ngila, J. C., & Seodigeng, T. (2022). Sustainable circularity and intelligent data-driven operations and control of the wastewater treatment plant. *Physics and Chemistry of the Earth*, 126, 103152. https://doi.org/10.1016/j.pce.2022.103152