Development of AI-Based Energy Management Strategy in Seawater Desalination Plant Based on Physical Modeling

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ABSTRACT

Global water scarcity is becoming increasingly severe, and seawater reverse osmosis (SWRO) has become a major technology for freshwater production due to its high efficiency. However, membrane fouling during long-term operation increases transmembrane pressure, reduces flux, and raises energy demand, ultimately lowering efficiency and shortening membrane lifetime. Traditional control and prediction methods struggle with the nonlinear and dynamic nature of these processes. To address this, we propose an intelligent management framework that integrates an adaptive control algorithm (ACA) with Extreme Gradient Boosting (XGBoost), based on real operational data from a desalination plant in Taiwan. The ACA performs real-time optimization of feed pressure, recovery rate, and specific energy consumption (SEC), while XGBoost learns nonlinear patterns from historical data to predict key system behaviors. Experimental results demonstrate strong performance: feed pressure prediction achieved RMSE = 0.2395 and MAPE = 0.3217%; flow resistance trends were captured with MAPE = 1.1956%; and SEC predictions reached high precision (MAPE = 0.2616%) with errors within ±0.04 kWh/m³.

Keywords: Seawater Reverse Osmosis (SWRO), Artificial Intelligence (AI), Energy Management, Seawater Desalination Plant

INTRODUCTION

Global water scarcity, intensified by population growth and climate change, has made seawater desalination an essential solution [1–2]. Membrane filtration, especially pressure-driven processes such as MF, UF, NF, and RO, is widely used due to its efficiency and flexibility [1–4]. However, membrane fouling remains the main challenge, causing pressure increase, flux decline, and higher energy consumption, which shorten membrane life and reduce overall efficiency [5–8].

Conventional fouling models rely on mathematical simplifications and often fail to capture nonlinear interactions or adapt to dynamic plant conditions, limiting their predictive accuracy [9–12]. In contrast, artificial intelligence (AI) methods have shown superior capability in modeling nonlinear behavior and handling complex datasets, offering improved prediction

performance [13–15].

This study proposes an intelligent management framework integrating an adaptive control algorithm (ACA) with Extreme Gradient Boosting (XGBoost). The ACA performs real-time optimization of key operating parameters—including feed pressure, recovery rate, and specific energy consumption (SEC)—while XGBoost learns from historical data to forecast system behavior. This combination enhances prediction accuracy, enables early fouling detection, and supports more efficient SWRO operation.

MATERIALS AND METHODS

Intelligent Control Framework

The integrated intelligent control system connects real-time plant operations with computational modules through a Programmable Logic Controller (PLC)–Supervisory Control and Data Acquisition (SCADA) environment. As illustrated in Fig. 1, the PLC gathers signals from sensors and actuators and stores them in a database. The Adaptive Control Algorithm (ACA), implemented in MATLAB/Simulink, performs parameter estimation and optimization, while Extreme Gradient Boosting (XGBoost) analyzes historical and real-time data to provide predictive insights. The Human–Machine Interface (HMI) displays results for operator reference, and optimized parameters are sent back to the PLC for immediate adjustment. This architecture enables monitoring, autonomous control, and predictive analytics within a unified system.
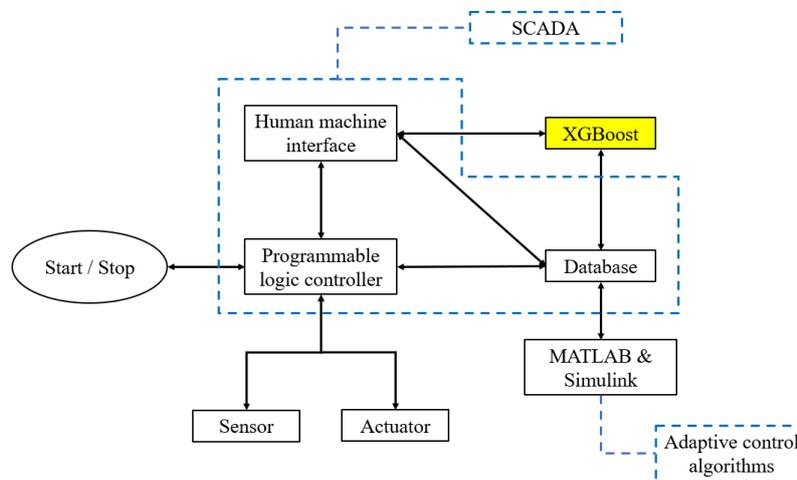

Fig. 1 Architecture of Integrated Intelligent Control System

Predictive Model

A multi-target XGBoost regression model was constructed to predict feed pressure, flow resistance, and SEC. Outliers in both input features and target variables were detected using the Interquartile Range (IQR) method; values outside 1.5 × IQR were treated as anomalies and replaced with the corresponding median to improve data stability. The cleaned dataset was divided into training and testing subsets before being introduced into the XGBoost framework. The algorithm generates an ensemble of decision trees through iterative boosting, with regularization terms included to prevent overfitting and enhance generalization. The

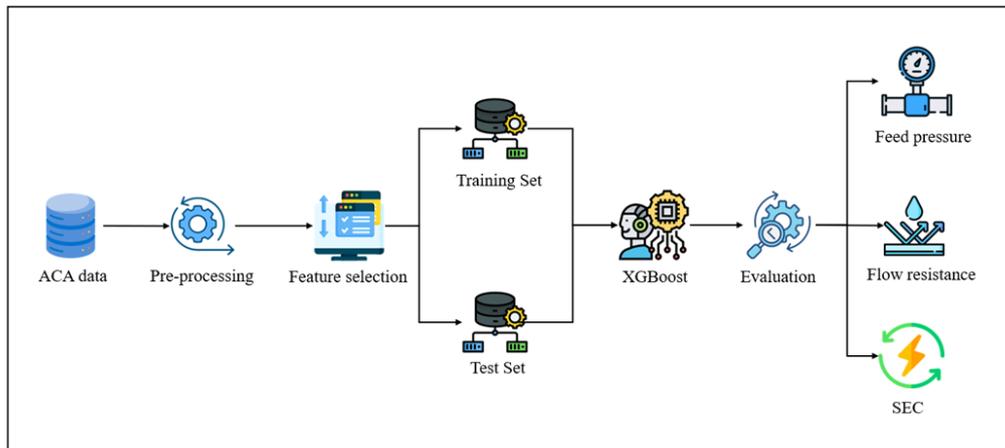simplified framework of the predictive model is shown in Fig. 2

Fig. 2 XGBoost Model Prediction Framework

RESULTS & DISCUSSION

The prediction results of feed pressure, flow resistance, and SEC on the test set are shown in Fig. 3, with corresponding error metrics summarized in Table 1. The XGBoost model achieved high accuracy in feed pressure prediction (RMSE = 0.2395, MAE = 0.2054, MSE = 0.0574, MAPE = 0.321%), with trends closely matching ACA values and most errors remaining small. In contrast, flow resistance exhibited relatively lower accuracy (RMSE = 5.02×10^9, MAE = 4.55×10^9, MSE = 2.52×10^{19}, MAPE = 1.20%), where the model captured the general trend but underestimated under higher resistance conditions, likely due to complex fouling dynamics and water quality fluctuations. For SEC, the best performance was obtained (RMSE = 0.0171, MAE = 0.0134, MSE = 0.0003, MAPE = 0.262%), with prediction trends almost overlapping ACA outputs, demonstrating the model's strong ability to capture nonlinear interactions among variables.
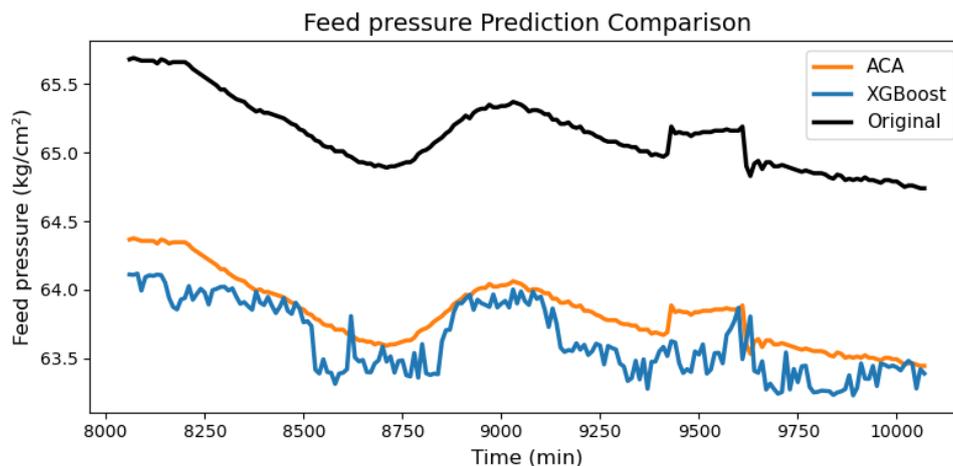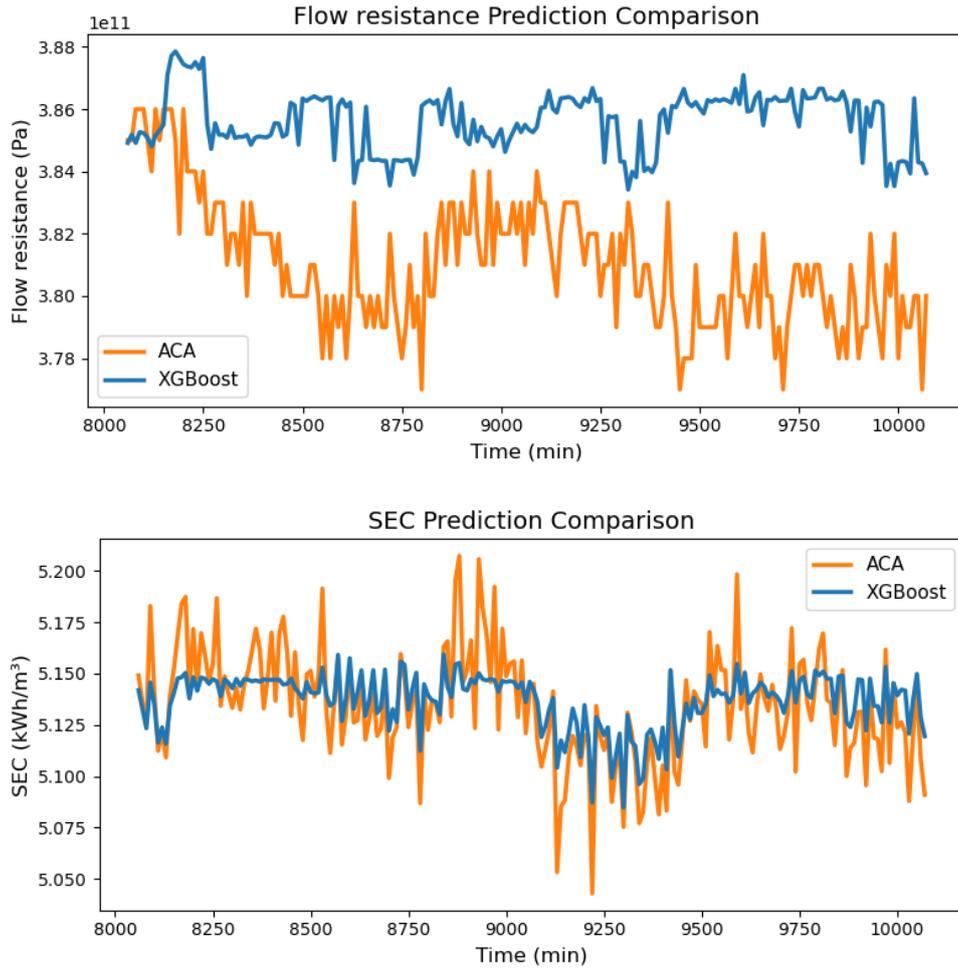
Fig. 3 Comparison of Predicted and Actual Values for Feed Pressure, Flow Resistance, and SEC

Table 1. Evaluation Metrics of XGBoost Model on the Test Set

Target	RMSE	MAE	MSE	MAPE(%)
Feed pressure	0.2395	0.2054	0.0574	0.3217
Flow resistance	5.0202×10^9	4.5454×10^9	2.5202×10^{19}	1.1956
SEC	0.0171	0.0134	0.0003	0.2616

CONCLUSIONS

This study proposed an intelligent energy management framework integrating the ACA with XGBoost for seawater reverse osmosis systems. The ACA ensures real-time regulation of feed pressure, recovery rate, and SEC to maintain stable and energy-efficient operation, while XGBoost enhances long-term forecasting by learning nonlinear parameter relationships. Experimental results confirm strong predictive performance, with feed pressure (RMSE = 0.2395, MAPE = 0.322%) and SEC (MAPE = 0.262%) showing high consistency with ACA outputs. Although flow resistance was more difficult to predict (MAPE = 1.20%), its overall trends were effectively captured. The integrated ACA–XGBoost framework therefore demonstrates both reliable control and accurate prediction, enabling real-time optimization and improved management of fouling and energy consumption in SWRO plants.

REFERENCES

[1] Macedonio, F., Drioli, E., Gusev, A. A., Bardow, A., Semiat, R., & Kurihara, M. (2012). Efficient technologies for worldwide clean water supply. Chemical Engineering and Processing: Process Intensification, 51, 2–17. https://doi.org/10.1016/j.cep.2011.09.011

[2] Cairone, S., Hasan, S. W., Choo, K.-H., Li, C.-W., Zarra, T., Belgiorno, V., & Naddeo, V. (2024). Integrating artificial intelligence modeling and membrane technologies for advanced wastewater treatment: Research progress and future perspectives. Science of the Total Environment, 944, 173999. https://doi.org/10.1016/j.scitotenv.2024.173999

[3] Abdellah, R., Ilyes, M., Nabil, K., & Abdelkrim, A. (2021). A Review on Membrane Fouling Prediction Using Artificial Neural Networks (ANNs). Membranes, 11(10), 745. https://doi.org/10.3390/membranes11100745

[4] Drioli, E., Curcio, E., & Criscuoli, A. (2009). Membrane Technologies for Water Treatment and Chemical Production. In: Comprehensive Membrane Science and Engineering (Vol. 2, pp. 59–108). Elsevier. https://doi.org/10.1016/B978-044453178-00006-7

[5] Khan, I. A., Lee, Y. S., & Kim, J.-O. (2023). Chemically enhanced pretreatment (CEPT) to reduce irreversible fouling during the clean-in-place process for membranes operating under constant flux and constant pressure filtration. Desalination, 549, 116313. https://doi.org/10.1016/j.desal.2022.116313

[6] Jiang, S., Li, Y., & Ladewig, B. P. (2017). A review of novel polymeric membranes for desalination. Journal of Industrial and Engineering Chemistry, 41, 1–22. https://doi.org/10.1016/j.jiec.2016.08.030

[7] Khan, I. A., Lee, Y. S., & Kim, J. O. (2019). Identification of scaling during clean-in-place (CIP) in membrane water treatment process. Chemosphere, 237, 124398. https://doi.org/10.1016/j.chemosphere.2019.124398

[8] Zhang, Y., Yu, W., & Graham, N. (2023). Fouling in reverse osmosis membranes: Characterization, modeling and mitigation. Environmental Technology & Innovation, 32, 103176. https://doi.org/10.1016/j.eti.2023.103176

[9] Wang, Y., Zhang, Y., Yu, W., & Graham, N. (2023). Artificial intelligence-incorporated membrane fouling prediction for membrane-based processes in the past 20 years: A critical review. Journal of Membrane Science, 678, 121810. https://doi.org/10.1016/j.memsci.2023.121810

[10] Malaeb, L., & Ayoub, G. M. (2019). Can machine language and artificial intelligence revolutionize process automation for water treatment and desalination? Desalination, 458, 84–96. https://doi.org/10.1016/j.desal.2019.01.024

[11] Lu, D., Guo, W., Ngo, H. H., Wang, X. C., Wang, J., & Ni, B.-J. (2022). The intelligent prediction of membrane fouling during membrane filtration by mathematical models and artificial intelligence models: A review. Science of The Total Environment, 806, 150621. https://doi.org/10.1016/j.scitotenv.2021.150621

[12] Ali, S., Lu, X., Farah, H., & Liu, Y. (2023). Toward sustainable wastewater treatment: Transformer ensembles and multi-task learning for energy consumption and quality management. Applied Energy, 355, 121998. https://doi.org/10.1016/j.apenergy.2023.121998

[13] Alhaj, S., Al-Ghamdi, S. G., & Amin, M. T. (2020). Artificial neural networks applied to manage the variable operation of a simple seawater reverse osmosis plant. Desalination, 476, 114188. https://doi.org/10.1016/j.desal.2019.114188

[14] Mohtar, M., Abdul Raman, A. A., Mohd Arifin, K., & Yusoff, M. S. (2023). Enhancement of membrane system performance using artificial intelligence technologies for sustainable water and wastewater treatment: A critical review. Journal of Water Process Engineering, 55, 103995. https://doi.org/10.1016/j.jwpe.2023.103995

[15] Mahamad, M. K., Abdul Raman, A. A., & Mohd Arifin, K. (2021). Artificial neural network modeling of wastewater treatment and desalination using membrane processes: A review. Journal of Water Process Engineering, 44, 102440. https://doi.org/10.1016/j.jwpe.2021.102440Stratmeyer, H. A. 1965. Chapter 3: The goal

of effective systems design. In *Systems Design: Principles and Practices*, 87-109. W. H. Pierre, ed. Chicago, Ill.: Graphics Publishing.