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## SMARTFLOW: AI OPTIMIZATION OF DESALINATION FOR SUSTAINABLE AGRICULTURAL WATER MANAGEMENT

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### ABSTRACT

Limited access to reliable freshwater sources is a persistent barrier to agricultural productivity, particularly in coastal and arid regions where rivers, lakes, and groundwater reserves are rapidly declining. Farmers in these areas often struggle to meet irrigation demands, resulting in reduced yields and heightened vulnerability to climate variability. Although seawater desalination provides a potential alternative, conventional reverse osmosis (RO) systems are typically too energy-intensive and operationally complex to be widely adopted for agriculture. This study introduces SMARTFLOW, an AI-driven optimization framework that integrates real-time monitoring with machine learning to improve the efficiency and reliability of desalination for irrigation supply. Principal Component Analysis (PCA) revealed that feed inflow and oxidation–reduction potential are the dominant contributors to system variability, while a deep neural network (DNN) trained on 150,000 pilot-plant data points achieved high predictive accuracy for permeate flow ( $R^2 = 0.9862$ ), concentrate flow ( $R^2 = 0.9912$ ), and electrical power consumption ( $R^2 = 0.9907$ ), but showed weaker performance for permeate conductivity ( $R^2 = 0.2851$ ). Validation experiments demonstrated that SMARTFLOW reduces specific energy consumption (SEC) to 2.947 kWh/m<sup>3</sup> at design inflows, while flow-sensitivity analysis identified mid-to-high inflow operation ( $\approx 260$ – $270$  m<sup>3</sup>/h) as the most techno-economically viable regime, balancing production, energy efficiency, and quality compliance. By transforming desalination from a reactive process into an adaptive, predictive system, SMARTFLOW offers a resilient and cost-effective pathway to sustainable agricultural water management in water-scarce regions.

**Keywords:** Artificial Intelligence, Reverse Osmosis, Predictive Control, Irrigation, Energy Efficiency, Precision Agriculture.

### INTRODUCTION

Small islands face chronic freshwater scarcity due to limited aquifers, seawater intrusion, and intensifying climate variability. Because these communities are surrounded by saline water, desalination is often the only scalable way to secure reliable supplies for households and for irrigation in agriculture, where dependable watering is essential to food security and livelihoods (1). Recent assessments of Small Island Developing States (SIDS) consistently highlight constrained water resources and rising demand, making alternative sources—especially desalination and water reuse—central to resilience planning(2).

At the same time, desalination dominated today by seawater reverse osmosis (SWRO)—remains energy-intensive, so water production costs are tightly coupled to electricity use(3). Even with modern membranes, energy-recovery devices, and high-efficiency pumps, typical full-plant specific energy consumption still clusters around a few kWh per cubic meter, and energy is the largest single driver of operating cost in many SWRO plants constraints that are especially acute where island power is expensive(4). These fundamentals explain why desalinated water is often costly for broad agricultural use unless operations are tightly optimized.

Because RO membranes have operating limits (pressure, flux, stage flow balance), continuous monitoring and control are essential to prevent damage, fouling/scale build-up, and unnecessary energy draw(5). Rising differential pressure or flux beyond design can shorten membrane life and force higher feed pressure for the same output—eroding efficiency. Operating within appropriate pressure/flow envelopes and maintaining balanced stage flows therefore protects the asset and stabilizes SEC and permeate quality(6).

Given these constraints, digital technologies—especially AI/ML—are increasingly used on real plant data to (i) predict fouling and performance drift, (ii) recommend setpoints (e.g., HPP frequency/pressure and stage flow splits), and (iii) control permeate flow at target levels with lower energy(7). Open-access studies show that neural-network and model-predictive approaches trained on operating databases can forecast membrane behavior, optimize operations in pilot and full-scale RO, and reduce cleaning/energy penalties—providing a practical path for small islands to produce affordable freshwater for agriculture(8). Building on this, our work uses historical SCADA/plant data to predict and control flowrate in a real SWRO system, using AI to recommend operating windows that meet design production while minimizing pressure and energy.

## MATERIALS AND METHODS

This study was carried out using real-time operational data from a two-stage seawater reverse osmosis (SWRO) pilot plant. The database, logged from the plant's SCADA system, contained continuous measurements of permeate flowrate ( $Q$ ), feed pressure ( $P$ ), conductivity ( $C$ ), and energy usage ( $E$ ). These parameters were selected as they directly influence plant performance, water quality, and membrane stress. Data were recorded at one-minute intervals and stored in the local plant database for further analysis.

To evaluate plant efficiency, the Specific Energy Consumption (SEC) was calculated as:

$$SEC = \frac{E}{Q} \quad (1)$$

where:

SEC = Specific Energy Consumption

$E$  = Energy Usage (Kwh)

$Q$  = Flowrate (CMH)

where  $E$  is the energy consumption (kWh) and  $Q$  is the permeate production ( $m^3$ ). SEC provides a normalized measure of energy performance, making it possible to compare operating scenarios and assess optimization potential.

Prior to model development, the raw dataset was cleaned and normalized to account for sensor noise and scale differences. Principal Component Analysis (PCA) was applied to identify dominant parameters affecting energy and flow distribution. Mathematically, PCA projects the

standardized data matrix X onto orthogonal eigenvectors W:

$$Z = XW \tag{2}$$

where:

- Z = Principal component scores (new feature representation)
- X = Original dataset (flowrate, pressure, conductivity, energy usage)
- W = Eigenvectors (directions of maximum variance, used as weights)

where Z represents the transformed principal components, which retain most of the system variance while reducing dimensionality. This step ensured that the AI model focused on the most critical features driving RO performance. A Deep Neural Network (DNN) was then developed in Python (TensorFlow) to capture nonlinear relationships among the operating variables. The network architecture included:

- Input layer with four features (Q,P,C,E),
- Two hidden layers with 64 and 32 neurons using ReLU activation,
- An output layer predicting optimal flowrate reference and SEC, using linear activation.

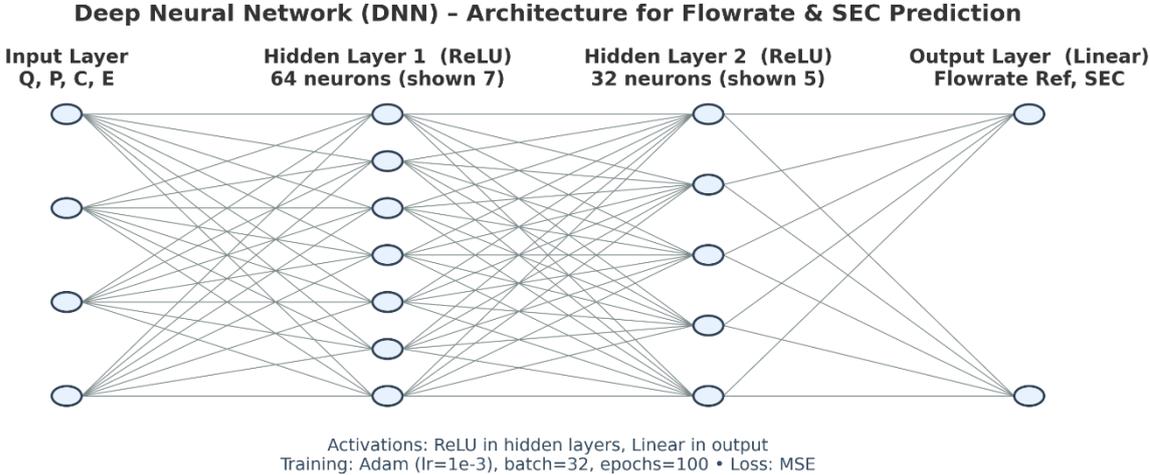


Fig.1 DNN – Architecture for Flowrate & SEC Prediction

The model was trained with the Adam optimizer (learning rate = 0.001, batch size = 32) for 100 epochs, using Mean Squared Error (MSE) as the loss function. The dataset was split into 70% training, 15% validation, and 15% testing, ensuring robust performance evaluation. Beyond prediction, the DNN was embedded in a decision-support framework. When the model detected that operating conditions could risk membrane safety (e.g., excessive flux, abnormal pressure rise, or inefficient energy use), it generated a reference adjustment recommendation. This recommendation acted as a protection layer, allowing operators to proactively adjust HPP frequency or pressure before the membrane was exposed to harmful conditions. The complete workflow is illustrated in Fig. 2, showing the process from data collection to predictive control:

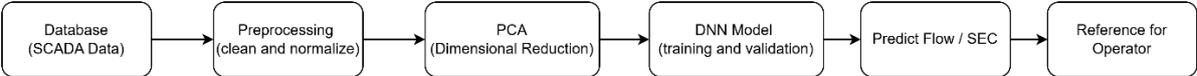


Fig.2 Place caption below each figure.

## RESULTS & DISCUSSION

### 1. Model Accuracy of the DNN

The DNN achieved excellent predictive performance for most process variables. For permeate flow ( $Q_p$ ), the  $R^2$  reached 0.9862 with an RMSE of 5.52, while concentrate flow ( $Q_c$ ) was predicted with an  $R^2$  of 0.9912 and RMSE of 7.69. The prediction of electrical power consumption ( $P_{el}$ ) was also highly accurate, with  $R^2 = 0.9907$  and RMSE = 12.50. However, permeate conductivity ( $COND_{perm}$ ) proved more difficult to capture, achieving only an  $R^2$  of 0.2851 with RMSE = 42.10, indicating a weaker correlation between input features and water quality outputs. On average, the DNN reached an  $R^2$  of 0.8133, highlighting strong overall predictive capability but with variability across parameters.

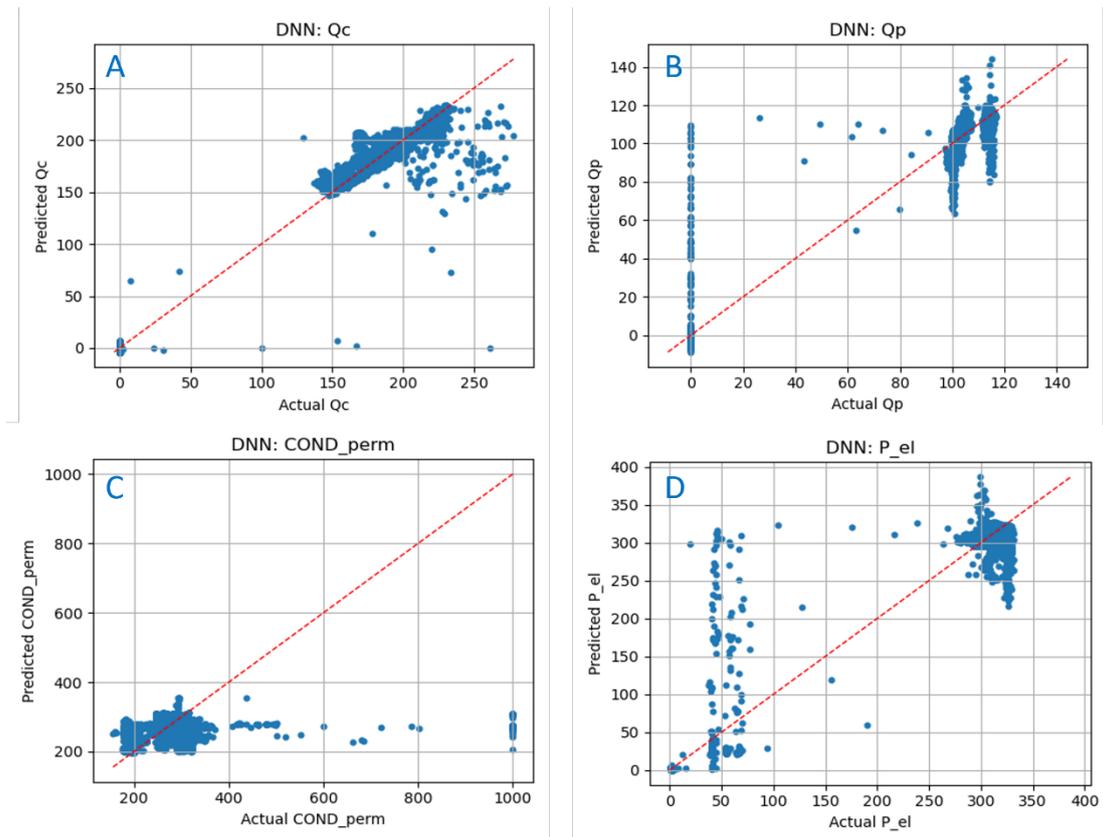


Fig.3 Performance of the DNN model for predicting (a) concentrate flow  $Q_c$ , (b) permeate flow  $Q_p$ , (c) permeate conductivity, and (d) electrical power  $P_{el}$ .

### 2. Dimensionality Reduction using PCA

PCA was used to understand the underlying structure of the inputs. The first principal component (PC1) explained 71.9% of the variance, while PC2 explained 28.1%, giving a cumulative coverage of 100%. The PCA loadings showed that feed inflow ( $Q_f$ ) and oxidation-reduction potential ( $ORP_{in}$ ) contributed equally but in opposite directions. The PCA scatter plot, colored by permeate flow, revealed distinct separation of operating states, with higher  $Q_p$  values aligned along PC1. This visualization confirms that PCA effectively distinguishes inflow and ORP conditions driving permeate production.

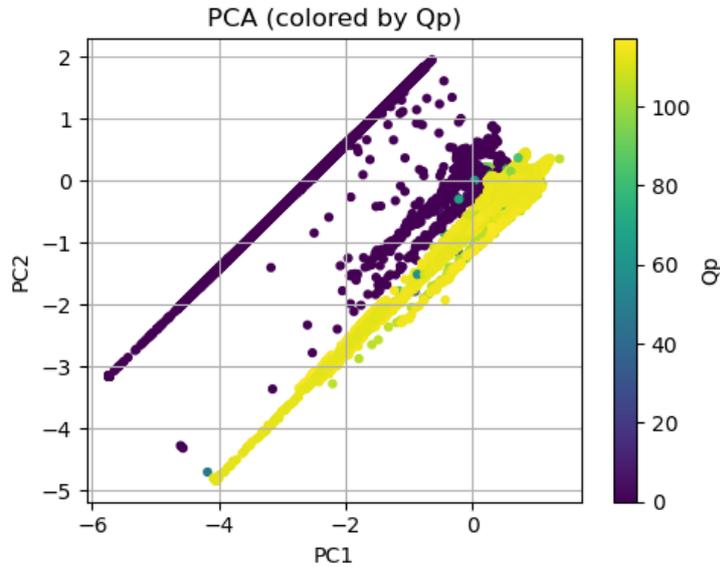


Fig. 4 PCA analysis of model inputs: (a) explained variance ratio by PC, and (b) scatter distribution colored by permeate flow ( $Q_p$ ).

### 3. Energy Efficiency and SEC Evaluation

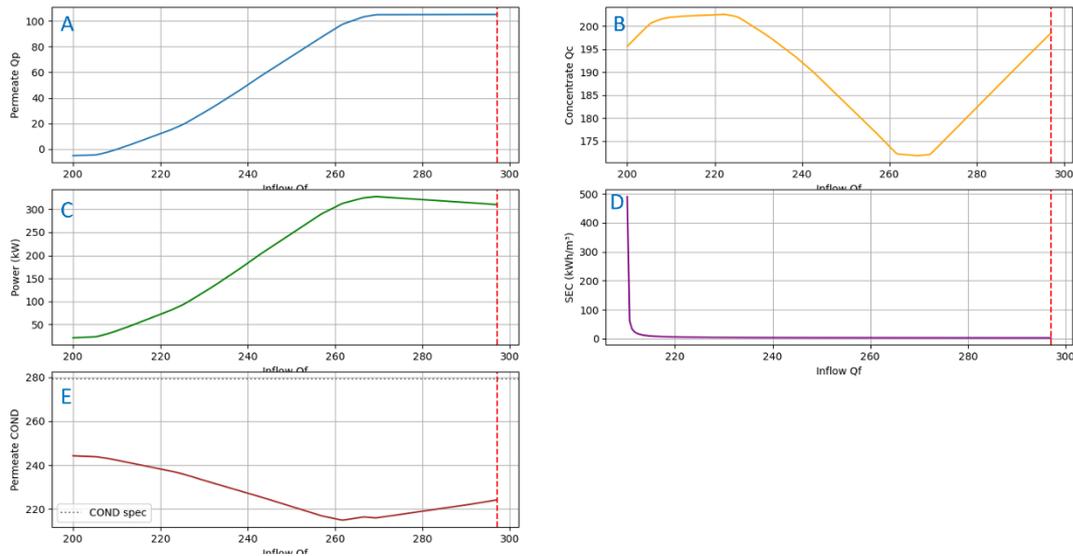
Energy analysis was conducted at the recommended operating setpoint of  $Q_f = 297$ . The DNN predicted permeate flow of  $105.14 \text{ m}^3/\text{h}$ , with recovery of  $35.40\%$ , electrical power consumption of  $309.89 \text{ kW}$ , and permeate conductivity of  $224.08 \text{ }\mu\text{S}/\text{cm}$ . The calculated SEC at this condition was  $2.947 \text{ kWh}/\text{m}^3$ , indicating that the system can meet design permeate demand while maintaining energy use within an acceptable range.

```
[Enter] to recommend, or 'q' to quit:
Min inflow: 200
Max inflow: 297
Current ORP_in: 158
Permeate demand ( $Q_p$  target): 105
(Quality gate active:  $\text{COND} \leq 279.30$ )
✅  $Q_f$ _set=297.00 →  $Q_p$ =105.14,  $Q_c$ =198.53,  $\text{RECOV}$ =35.40%,  $P_{el}$ =309.89 kW,  $\text{SEC}$ =2.947 kWh/ $\text{m}^3$ ,  $\text{COND}$ =224.08
Energy @ $Q_f$ _set → 7437.3 kWh/day, 223120.2 kWh/30d
SEC @ $Q_f$ _set → 2.947 kWh per  $\text{m}^3$ 
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Fig. 5 Energy efficiency evaluation at recommended inflow setpoints:  $\text{SEC} = 2.947 \text{ kWh}/\text{m}^3$  at  $Q_f = 297..$

### 4. Flow Sensitivity Analysis

Sensitivity analysis across the inflow range of  $200\text{--}297 \text{ m}^3/\text{h}$  revealed clear trade-offs between production, energy demand, and water quality. As inflow increased, both permeate and concentrate flows rose steadily up to  $\sim 260\text{--}270 \text{ m}^3/\text{h}$ , after which permeate plateaued while power consumption continued to rise. SEC remained relatively stable at low values in the mid-range but increased disproportionately at higher inflows. Permeate conductivity decreased initially with increasing inflow, suggesting better separation, but then began to rise again beyond  $270 \text{ m}^3/\text{h}$ , nearing the specification limit. These results indicate that operating close to maximum inflow may not be efficient, as it incurs higher energy costs and potential quality risks, whereas mid-to-high inflows provide a more balanced trade-off.



**Fig. 6** Flow sensitivity analysis showing the relationship between inflow  $Q_f$  and (a) permeate flow, (b) concentrate flow, (c) electrical power, (d) SEC, and (e) permeate conductivity.

## CONCLUSIONS

This study demonstrates the capability of deep neural networks (DNNs) to reliably capture the nonlinear dynamics of desalination processes. The model exhibited excellent predictive performance for permeate flow, concentrate flow, and electrical energy demand ( $R^2 > 0.98$ ), underscoring its robustness for operational forecasting. The weaker performance in predicting permeate conductivity ( $R^2 \approx 0.29$ ), however, reveals the complexity of water quality dynamics and highlights the necessity of incorporating additional physicochemical descriptors or hybrid modeling strategies to strengthen predictive reliability in this domain.

Principal component analysis (PCA) further revealed that feed inflow and oxidation–reduction potential are the dominant drivers of system variability, with the first two principal components capturing the entirety of input variance. The ability of PCA to distinguish operational states according to permeate production not only validates its diagnostic potential but also provides a transparent framework for feature interpretation in data-driven models. Complementary flow sensitivity analysis elucidated a nonlinear trade-off: while elevated inflows sustain production capacity, they impose disproportionate energy penalties and heighten the risk of conductivity deviation. Consequently, mid-to-high inflows ( $\approx 260$ – $270$   $\text{m}^3/\text{h}$ ) emerged as the most techno-economically viable operating regime, balancing permeate yield, energy efficiency, and compliance with quality specifications.

Overall, the integration of DNN modeling, PCA interpretation, and sensitivity analysis provides a comprehensive methodological framework for desalination system optimization. These findings reinforce the potential of advanced data-driven control to enhance the resilience, efficiency, and sustainability of next-generation water–energy infrastructures.

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