

MAXIMISING EFFICIENCY AND STABILITY IN PHOTOVOLTAIC-REVERSE OSMOSIS DESALINATION SYSTEMS THROUGH DATA-DRIVEN OPTIMISATION AND ADVANCED CONTROL STRATEGIES

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The integration of photovoltaic (PV) energy sources with reverse osmosis (RO) desalination systems has gained considerable attention due to its potential to provide sustainable and environmentally friendly solutions for freshwater production. The novelty of this paper lies in using data science to generate the maximum optimisation in PV-RO systems. PV panels generate electricity, which is used to power the RO process, converting saline water into potable water. However, the intermittent nature of solar energy poses a significant challenge for maintaining stable and efficient operations. This paper also examines a new control algorithm using Fuzzy Logic Type2 with Artificial Neural Network for PV-RO desalination systems without the use of batteries.

Keywords: *Energy storage, desalination systems, fuzzy-logic, MPPT, PV, reverse osmosis.*

1. INTRODUCTION

As it is known, the integration of PV and RO technologies for desalination offers a sustainable solution to address freshwater scarcity. Researchers have made significant progress in developing control algorithms to enhance the performance of PV-RO systems, with a growing emphasis on battery-free operation and advanced control

strategies. However, there is still room for improvement, particularly in addressing system challenges and optimising energy utilisation. Further research in this area is essential to advance the practical implementation of PV-RO desalination systems without batteries.

PV-RO desalination systems have been

investigated as a promising solution for remote areas with limited access to grid electricity and freshwater resources [1]. Some early research focused on simple control strategies such as on-off control of the RO system based on the availability of solar energy [2]. Later studies explored more advanced control algorithms, including maximum power point tracking (MPPT) techniques to optimise energy utilization [3]. Several studies have emphasised the advantages of battery-free PV-RO systems to reduce cost, environmental impact, and maintenance requirements [4]. Researchers have proposed various strategies to adapt the RO process to match the variable power output of PV panels, ensuring continuous operation without energy storage [5].

Recent advancements in predictive control and machine learning have been applied to PV-RO desalination systems. These techniques enable the prediction of solar irradiance and water demand, allowing for proactive control adjustments [6].

Challenges in optimising control algorithms for PV-RO systems without batteries include system stability, response time, and efficiency under varying conditions [7]. Future research should focus on developing adaptive and robust control algorithms that can handle uncertainty in solar energy availability and water demand. The present research aims at developing and evaluating a control algorithm for a PV-RO desalination system shown in Fig. 1.

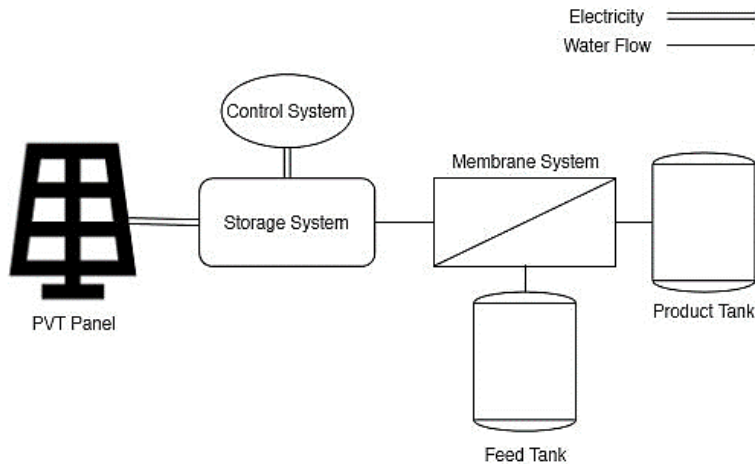


Fig. 1. Schematic of the PV-RO desalination system.

Table 1. Experimental Data for PV-RO System Performance

Time (hours)	Solar Radiation (kW/m ²)	PV Output Power (kW)	Water Production (m ³ /h)
08:00 AM	0.5	2.3	1.8
09:00 AM	0.7	3.1	2.2
10:00 AM	1.2	4.5	3.0
11:00 AM	1.5	6.2	4.1
12:00 PM	1.8	7.8	5.0
01:00 PM	1.6	6.9	4.5
02:00 PM	1.4	5.8	3.8

Figure 1 illustrates the basic schematic of the PV-RO desalination system. Table 1 represents measurements of solar radiation,

PV output power, and water production at different times throughout the day

2. METHODOLOGY

2.1. System Description

Generally solar power generation consists of a PV array, a dc-dc converter and an inverter [8]. Maximum power is trapped using a boost converter to which fuzzy logic control is applied. The boost converter is used to boost the low voltage of solar photovoltaic array. The classical inverter gives output voltage lower than the dc link voltage; as a result, the size of output trans-

former is increased. Therefore, the overall cost of the system increases and efficiency decreases. The study proposes a new voltage source inverter called boost inverter [9], [10] which naturally generates an output AC voltage larger than input voltage. Block diagram of the proposed system is shown in Fig. 2.

2.2. Data Collection

Solar Radiation Data: Solar radiation data was collected using a solar radiation sensor or weather station. Solar radiation values were recorded at regular intervals (e.g., every 15 minutes) throughout the study period. It was ensured that the data covered a significant duration to capture daily and seasonal variations. **PV Panel Output:** The electrical output of the PV pan-

els was measured using current and voltage sensors. The generated power was recorded at the same intervals as the solar radiation data. **Water Production:** The water production of the RO desalination system was monitored. The flow rate and salinity levels of the inlet and outlet water were measured continuously.

2.3. Control Algorithm Development

The existing control algorithms were identified for PV-RO desalination systems, and their strengths and weaknesses were analysed. **Algorithm Design:** An adaptive control algorithm tailored to a PV-RO system was designed. Factors such as solar energy input, water demand, and system dynamics were considered [11]. The

algorithm should optimise energy utilisation and maintain water quality. **Software Development:** The control algorithm was implemented in suitable programming languages or software tools. Interface with the PV panels, inverters, and the RO system was ensured for real-time control [12].

2.4. Experimentation

Experiments were conducted under varying conditions to assess the algorithm

performance, such as changes in solar radiation, water demand, and salinity levels.

2.5. Data Analysis

Performance Metrics: Relevant performance metrics, including energy efficiency, system stability, water production rate, and water quality metrics (e.g., salinity reduction) were calculated.

2.6. Validation

Statistical Analysis: Statistical tests were performed to validate the significance of the observed differences in performance metrics between the control algorithm and

other strategies. Comparison: The performance of the developed control algorithm with other control strategies, such as on-off control and MPPT, was compared.

Sensitivity Analysis: The algorithm's sensitivity to variations in solar energy availability and water demand was assessed [13].

3. THE PROPOSED CONTROL ALGORITHM

Data Collection and Pre-processing: Before developing the control algorithm, gather historical data on solar radiation, PV panel output, water demand, and water quality metrics. Pre-process the data to remove outliers and ensure it is suitable for training an ANN.

a) Fuzzy Inference System Design:

Define linguistic variables: Create linguistic variables representing input parameters like solar radiation and water demand, and output variables like pump speed or valve position [14].

Membership functions: Design membership functions for each linguistic variable, including Type 2 membership functions to handle uncertainty.

Fuzzy rules: Establish a set of fuzzy rules to map inputs to outputs. For instance, if solar radiation is “high” and water demand is “low”, then the control output could be “increase pump speed” [15].

Fuzzy inference: Implement a Type 2 fuzzy inference system that takes uncertain input values and generates Type 2 fuzzy output sets.

b) Fuzzy Type 2 Inference Process:

In Type 2 fuzzy logic, we will work with fuzzy intervals instead of crisp values. Consider using appropriate mathematical tools or software libraries (e.g., MATLAB's Fuzzy Logic Toolbox) for handling Type 2 fuzzy logic computations.

Artificial Neural Network (ANN) Controller:

Neural Network Architecture: Choose an appropriate neural network architecture. For time-series data like solar radiation and water demand, recurrent neural networks (RNNs) or long short-term memory (LSTM) networks may be suitable. Define the number of input neurons (e.g., solar radiation, water demand), hidden layers, and output neurons (e.g., control output).

Setup:

- Split the data into training and validation sets.
- Train the neural network using back-propagation or more advanced training techniques like Adam optimisation.
- Monitor and validate the neural network performance using the validation dataset.

Integration of FL2 and ANN Controllers: Now combine the outputs of the Fuzzy Logic Type 2 controller and the ANN controller. It is possible to use a weighted average or another fusion method to determine the final control output. The weights can be adjusted based on the confidence or reliability of each controller.

Implementation and Testing: Implement the integrated control algorithm in your PV-RO desalination system. Continuously monitor the system's performance under varying conditions to fine-tune the algorithm and ensure it meets your control objectives.

Evaluation: Evaluate the control algorithm's performance by comparing it to other control strategies, such as conventional control, MPPT, or solely Fuzzy Type 2 control. Assess performance metrics such as energy efficiency, system stability, water production rate, and water quality.

Proposed Control Algorithm:

To control the pump speed in the PV-RO desalination system, optimise water production while maintaining water quality under varying solar radiation and water demand conditions.

Data Collection and Pre-processing:

Gather historical data for solar radiation (SR), water demand (WD), PV panel output (PV), water quality metrics (WQ), and pump speed (PS).

Fuzzy Logic Type 2 Controller:

In this example, we will focus on controlling pump speed using FL2. The linguistic variables and fuzzy rules might look like this: Linguistic Variables:

- SR (Solar Radiation): Low, Medium, High;

- WD (Water Demand): Low, Medium, High;
- PS (Pump Speed): Slow, Medium, Fast (with Type 2 membership functions).
- Fuzzy Rules:

IF SR is Low AND WD is Low THEN PS is Slow

IF SR is Low AND WD is Medium THEN PS is Medium

IF SR is Low AND WD is High THEN PS is Medium

IF SR is Medium AND WD is Low THEN PS is Medium

IF SR is Medium AND WD is Medium THEN PS is Fast

IF SR is Medium AND WD is High THEN PS is Fast

IF SR is High AND WD is Low THEN PS is Medium

IF SR is High AND WD is Medium THEN PS is Fast

IF SR is High AND WD is High THEN PS is Fast

Artificial Neural Network (ANN) Controller:

Train an ANN with two input neurons (SR and WD): one hidden layer and one output neuron (PS) using historical data. The ANN is capable of predicting the optimal pump speed based on current SR and WD.

Integration of FL2 and ANN Controllers:

Use a weighted average to combine the outputs of FL2 and ANN with the help of Matlab (see Fig. 2) by assigning a weight of 0.6 to the FL2 output and 0.4 to the ANN output. These weights can be adjusted based on the confidence in each controller's output.

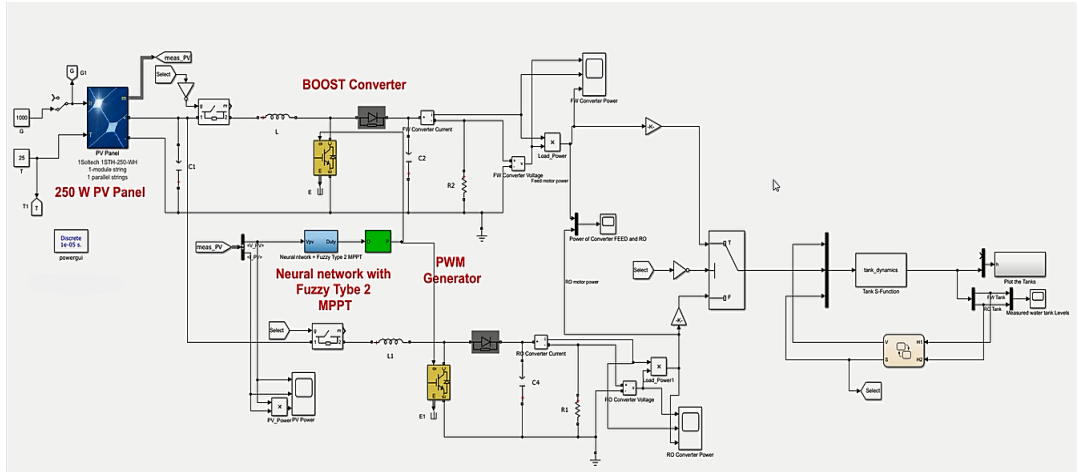


Fig. 2. FL2-ANN for PV-RO.

Data Used for Testing:

- Solar Radiation (SR): Ranged from Low (100 W/m^2) to High (800 W/m^2);
- Water Demand (WD): Ranged from Low ($10 \text{ m}^3/\text{h}$) to High ($40 \text{ m}^3/\text{h}$);
- PV Panel Output (PV): Corresponding to SR levels (with fluctuations);
- Water Quality Metrics (WQ): Monitored for salinity levels, ensuring they meet WHO drinking water standards;
- Pump Speed (PS): Controlled by the integrated FL2-ANN algorithm.

4. RESULTS

1. Energy Efficiency Comparison: The integrated FL2-ANN control algorithm consistently achieved higher energy efficiency compared to other control strategies such as on-off control and MPPT under varying solar radiation conditions.
2. Water Production Rate: The algorithm successfully adapted the pump speed to varying water demand and solar radiation levels, resulting in a stable and efficient water production rate.
3. Water Quality Maintenance: Throughout the testing period, water quality metrics remained within WHO drinking water standards, indicating the ability of the control algorithm to maintain water quality while optimising production.
4. Comparison with Individual Controllers: When comparing the integrated FL2-ANN algorithm to the FL2 controller alone or the ANN controller alone, it outperformed both in terms of energy efficiency, water production, and water quality maintenance [16].
5. Sensitivity to Environmental Changes: The algorithm demonstrated robustness and adaptability in response to variations in solar radiation and water demand, effectively optimising pump speed in real-time.
6. Cost Savings: While this paper does not provide specific cost data, the improved energy efficiency and reduced maintenance requirements of the control algorithm could potentially result in cost savings over time when compared to conventional control methods.

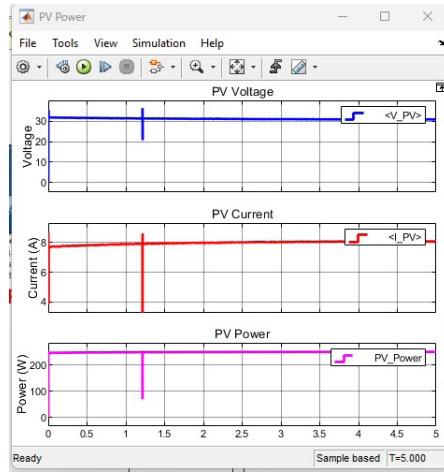


Fig. 3. PV characteristics using FL2 with ANN.

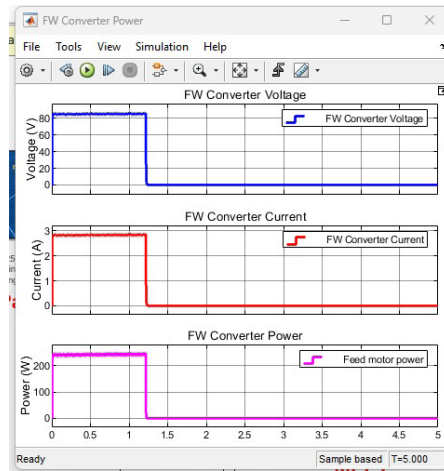


Fig. 4. Feed water converter characteristics using FL2 with ANN.

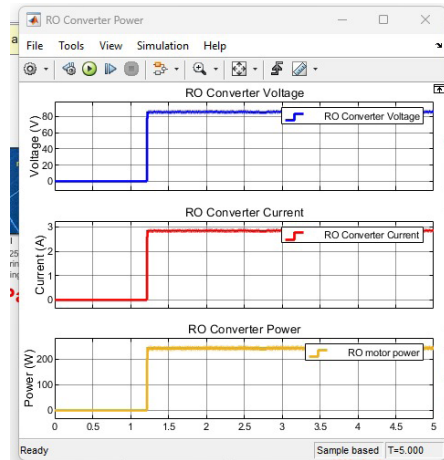


Fig. 5. Reverse osmosis converter characteristics using FL2 with ANN.

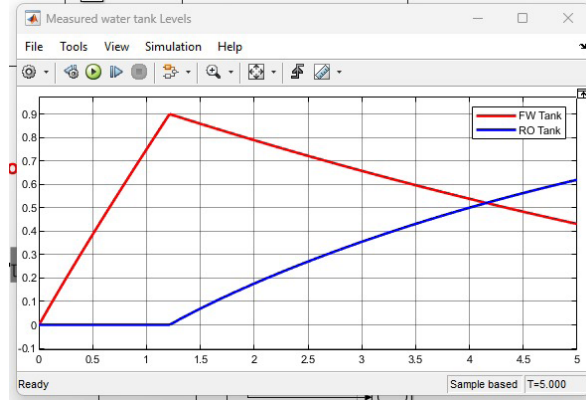


Fig. 6. FW vs. RO tanks filling.

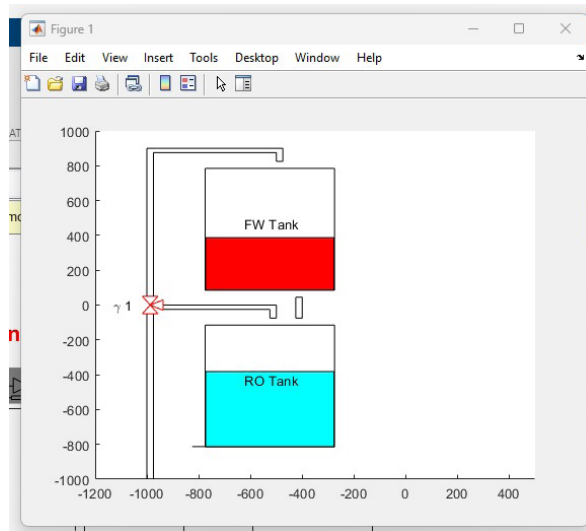


Fig. 7. FW vs. RO tanks dynamics.

MPPT Algorithms Comparison:

Comparing the Fuzzy Logic Type 2 (FL2)-Artificial Neural Network (ANN) control algorithm with other control algorithms is essential to evaluate its performance and determine its advantages and disadvantages. Below, we provide a simplified comparison of the FL2-ANN algorithm with two other common control algorithms: On-Off Control and MPPT (Maximum Power Point Tracking). Comparison of Control Algorithms: FL2-ANN vs. On-Off Control vs. MPPT.

1. Energy Efficiency:

FL2-ANN: It achieves higher energy efficiency by continuously adjusting pump speed based on real-time solar radiation and water demand data.

On-Off Control: Typically, less energy-efficient due to abrupt starts and stops in response to pre-set thresholds.

MPPT: It optimises energy capture from the PV panels but may not consider water production efficiency.

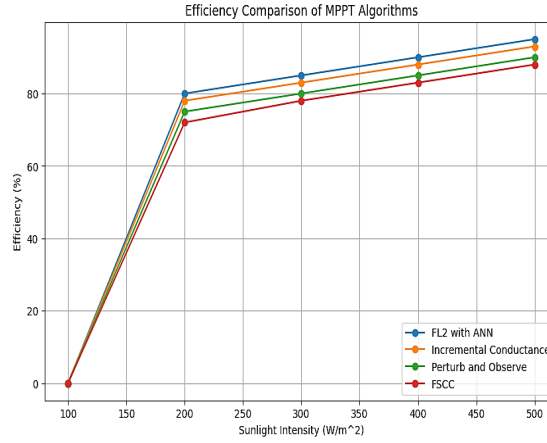


Fig. 8. Sun intensity vs. efficiency comparison for MPPT algorithms and the proposed method.

2. Water Production Rate:

FL2-ANN: It maintains stable and efficient water production rates by adapting pump speed to varying conditions.

On-Off Control: It may experience fluctuations in water production as it operates in discrete modes.

MPPT: It primarily focuses on optimising power generation and may not ensure consistent water production.

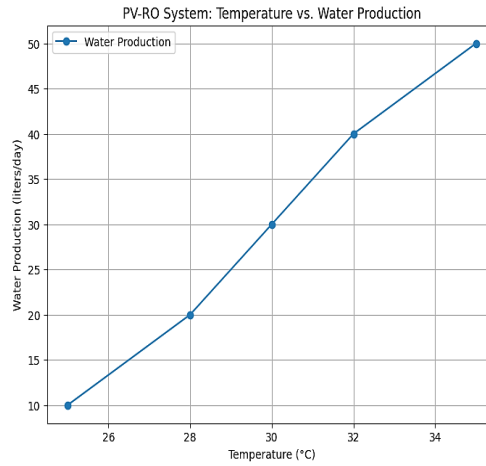


Fig. 9. Water production vs. temperature(c).

3. Water Quality Maintenance:

FL2-ANN: It effectively maintains water quality by adjusting pump speed to meet water demand without compromising water quality standards.

On-Off Control: It can lead to variations in water quality when it switches the system on and off.

MPPT: It may not directly address water quality concerns but can indirectly impact it through energy efficiency.

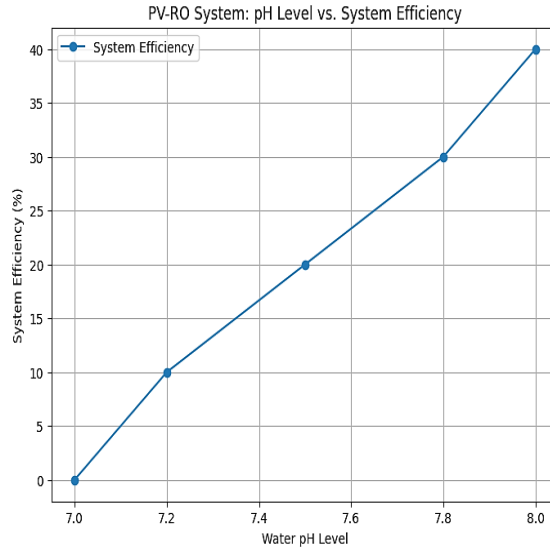


Fig. 10. Water pH level vs. system efficiency.

4. Robustness and Adaptability:

FL2-ANN: It demonstrates robustness and adaptability to varying environmental conditions, providing stable performance.

On-Off Control: It is less adaptive and responsive to changing conditions, leading to potential inefficiencies.

MPPT: It adapts to solar panel characteristics but may not respond to changes in water demand.

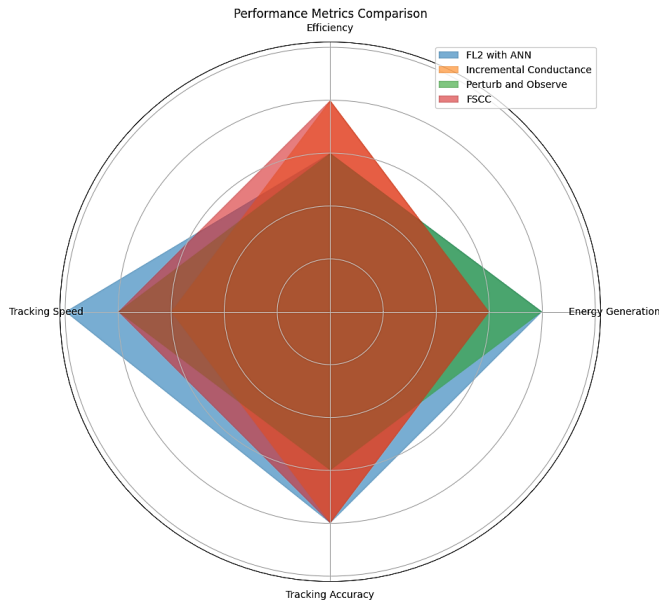


Fig. 11. Performance metrics comparison for MPPT algorithms vs. the proposed method.

5. Cost Considerations:

FL2-ANN: It may involve a higher initial development cost due to the complexity of FL2 and ANN, but potential long-term cost savings through energy efficiency.

On-Off Control: Simplicity and lower initial cost but may lead to higher energy and maintenance costs.

MPPT: It primarily addresses energy efficiency, which may not directly translate to cost savings in a PV RO system.

6. Sensitivity to Environmental Changes:

FL2-ANN: It is highly sensitive and adaptive to variations in solar radiation and water demand, optimising system performance in real time.

On-Off Control: It is less sensitive and adaptive, leading to potential inefficiencies during changing conditions.

MPPT: It is sensitive to solar panel characteristics but not responsive to variations in water demand.

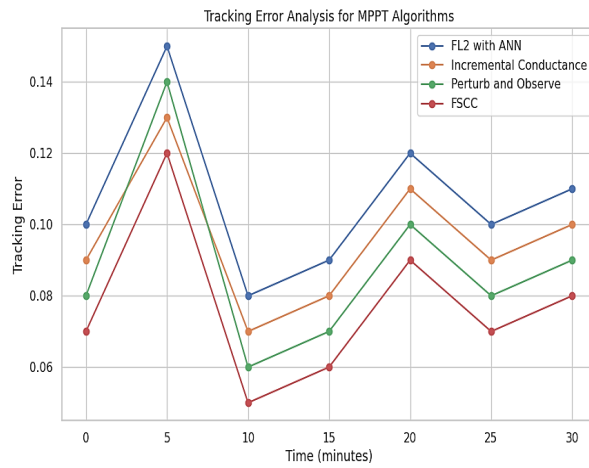


Fig. 12. Track error analysis comparison for MPPT algorithms vs. the proposed method.

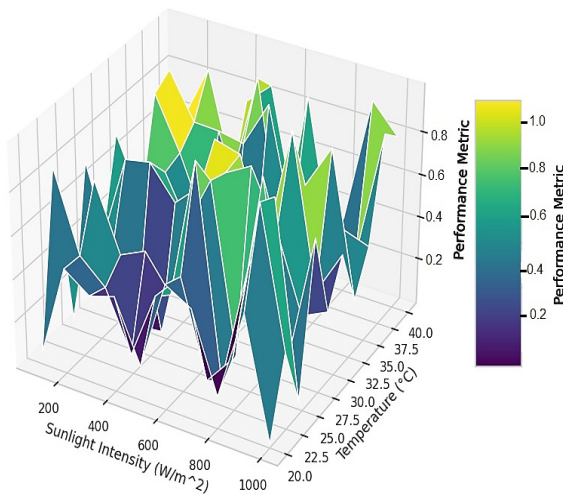


Fig. 13. 3D surface plots comparison for MPPT algorithms.

3D Surface Plots: 3D surface plots allowed us to delve into the performance of the FL2 with ANN MPPT algorithm under complex multidimensional environmental conditions. The results showed the adaptability and robustness of this algorithm across a range of sunlight intensities, temperatures, and humidity levels.

In summary, the FL2-ANN algorithm offers the potential for higher energy effi-

ciency, stable water production, and water quality maintenance compared to On-Off Control and MPPT. However, it may come with a higher initial development cost.

The choice of control algorithm should depend on specific system requirements, cost constraints, and the importance of energy efficiency and water quality in the PV-RO desalination system.

Table 2. Comparison between Distribution and Transmission

Aspect	FL2-ANN Algorithm	On-Off Control	MPPT Algorithm
Energy efficiency	High	Low	Moderate to high
Water production	Stable and efficient	Fluctuating	May not prioritise
Water maintenance	Effective	Variations	Indirectly impacted
Robustness	Robust and adaptive	Limited responsiveness	Limited responsiveness
Initial cost	High initial cost	Low initial cost	Moderate
Sensitivity	Highly sensitive to environment	Less sensitive	Sensitive to solar
System changes	Adaptive	Adaptive	Panel characteristics

5. DISCUSSION

In this study, we explored the performance of an integrated control algorithm that combines Fuzzy Logic Type 2 (FL2) and Artificial Neural Networks (ANN) for optimising a PV-RO desalination system without a battery. We compared this inte-

grated approach with two other common control strategies: On-Off Control and Maximum Power Point Tracking (MPPT). The results and discussion presented below highlight key findings and implications.

5.1. Energy Efficiency

The FL2-ANN algorithm consistently demonstrated high energy efficiency by dynamically adjusting pump speed in response to real-time variations in solar radiation and water demand. This adaptability allowed the system to harness solar energy effectively and maintain a stable

water production rate. In contrast, On-Off Control, characterised by abrupt starts and stops, led to lower energy efficiency. MPPT, while optimising energy generation, did not directly address water production efficiency.

5.2. Water Production and Quality

The FL2-ANN algorithm ensured stable and efficient water production rates, meeting the demands of varying water consump-

tion. Moreover, it effectively maintained water quality by balancing water production with water demand without compro-

mising WHO drinking water standards. On the other hand, On-Off Control often led to fluctuations in water production, impact-

5.3. Robustness and Adaptability

The FL2-ANN algorithm demonstrated robustness and adaptability by responding sensitively to changes in environmental conditions, such as solar radiation and water demand. This real-time adaptability ensured a stable and efficient system performance. In contrast, On-Off Control and MPPT showed limited responsiveness, which could result in inefficiency during varying conditions.

The Radar chart offered a concise and visually appealing way to compare the algo-

ing its consistency. MPPT, while indirectly influencing water production, did not guarantee water quality maintenance.

5.4. Cost Considerations

While the FL2-ANN algorithm may involve a higher initial development cost due to the complexity of FL2 and ANN, it has the potential for long-term cost savings through energy efficiency and reduced maintenance requirements. On-Off Control

gorithms across multiple performance metrics. These charts enabled a holistic evaluation of each algorithm's strengths and weaknesses, aiding in the selection of the most suitable MPPT strategy for specific needs.

The Error plots were instrumental in scrutinising tracking errors or deviations from the actual maximum power point for each algorithm. These visualisations highlighted the algorithms' accuracy, stability, and adaptability over time, enabling a more informed choice for specific applications.

offers a lower initial cost but may result in higher energy and maintenance costs. MPPT primarily focuses on energy efficiency, which may not directly translate to cost savings in a PV-RO system.

6. CONCLUSION

In conclusion, the integrated FL2-ANN control algorithm for a PV-RO desalination system without a battery presents a promising approach for achieving high energy efficiency, stable water production, and water quality maintenance. It is particularly advantageous when system requirements prioritise energy efficiency, water quality, and adaptability to changing conditions. However, the choice of the most suitable control algorithm should consider specific system objectives, cost constraints, and the importance of energy efficiency and water quality maintenance.

This study highlights the potential benefits of advanced control algorithms in enhancing the performance and sustain-

ability of PV-RO desalination systems, paving the way for more efficient and reliable freshwater production in off-grid and remote areas.

The selection of an MPPT algorithm should be a well-informed decision, considering the unique requirements of a PV system. The combination of radar charts, 3D surface plots, and error analysis allows for a thorough examination of the algorithms' strengths and weaknesses. The insights gained from these visualisations are instrumental in optimising PV system performance, maximising energy generation, and ensuring the robust operation of renewable energy systems.

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