Research Article

Journal of Environmental Nanotechnology

# Retracted: Optimizing Pyramid Solar Still Performance using Response Surface Methodology and Artificial Neural Networks

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Received: 07.07.2024 Accepted: 18.09.2024 Published: 30.12.2024
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## ABSTRACT

The global demand for potable water continues to rise, there is an urge to call for innovative approaches to ensure sustainable water supply. This study investigates the optimization of process parameters in Pyramid Solar Still (PSS) using Response Surface Methodology (RSM) and a Feedforward Artificial Neural Network (ANN). Experimental trials were conducted in Vellore, India, under a 30-day duration to evaluate the performance of PSS. By leveraging RSM and ANN, the research aimed to enhance the thermal efficiency and water yield of PSS. Key parameters solar intensity, inclination angle, and water depth were optimized, resulting in a significant improvement in both thermal efficiency and water yield. Specifically, the thermal efficiency increased by 42%, while the water yield improved by 1.8 litres per square meter. Economic analysis demonstrated a reduction in water production costs, with the cost per litre decreasing by 0.20 INR. This study proves the effectiveness of integrating RSM and ANN in optimizing solar stills, contributing to advancements in water purification technologies.

**Keywords**: Pyramid solar still; Response Surface Methodology; Feedforward Artificial Neural Network; Thermal efficiency; Water yield.

## 1. INTRODUCTION

Water scarcity persists as a pressing global concern, driven by factors such as population growth and environmental degradation (Willey *et al.* 1999; Mohsin *et al.* 2019). Despite Earth's surface being predominantly covered by water, access to safe drinking water remains limited, especially in remote regions lacking conventional infrastructure. In response, researchers have explored diverse methods to convert saltwater into freshwater, with solar desalination emerging as a promising solution due to its simplicity and cost-effectiveness (Yuvaperiyasamy *et al.* 2023). Solar stills, a key technology in solar desalination, have garnered attention for their ability to produce freshwater from saline or brackish water using solar energy (Xu *et al.* 2021).

Traditional solar stills, however, encounter limitations in efficiency and productivity, hindering widespread adoption (Balachandran *et al.* 2021; Naveenkumar *et al.* 2024). To address these limitations, researchers have investigated innovative approaches to enhance performance. One such approach involves integrating advanced materials like nanomaterials to improve heat transfer and increase water evaporation rates (Alsarraf *et al.* 2020; Wang *et al.* 2023). Additionally, modifications to solar still designs, such as incorporating reflectors or optimizing the angle of inclination, have been explored to maximize solar energy absorption and efficiency (Sanjaya *et al.* 2018; Tan *et al.* 2023).

Advancements in computational techniques, particularly Artificial Neural Networks (ANN), have enabled precise modelling and optimization of solar desalination systems. ANN, in conjunction with Response Surface Methodology (RSM), presents a promising avenue for optimizing process parameters in solar stills (Shahmaleki *et al.* 2019; Mahjoobi *et al.* 2022). By systematically analyzing and optimizing key operational variables of Pyramid Solar Stills (PSS), such as solar irradiance and temperature differentials, using a Feedforward ANN model (Hoegner *et al.* 2018; Hijjaji *et al.* 2021; Alaudeen *et al.* 2021), researchers aim to maximize freshwater output while minimizing energy consumption and operational costs. Integration of RSM with ANN allows for the development of a comprehensive optimization framework for PSS. This multidisciplinary approach, encompassing experimental investigation, computational modelling, and optimization techniques, aims to advance the state-of-the-art in solar desalination technology (Keshtkar *et al.* 2020; Nagrale *et al.* 2022; Ziapour *et al.* 2024). The findings from this research hold significant implications for addressing freshwater scarcity challenges, particularly in remote and underserved regions. By optimizing process parameters in PSS, researchers aim to contribute to the development of sustainable and efficient water purification solutions (Abdul-Wahab *et al.* 2019; Yadav *et al.* 2023).

Through experimental analysis and numerical simulations, researchers aim to evaluate the effectiveness of the proposed approach in enhancing the performance of PSS. Comparing the performance of modified PSS with conventional solar stills will demonstrate the potential of the optimization strategy in addressing water scarcity challenges (Mohammed *et al.* 2022). Economic analysis will further assess the cost-effectiveness of the optimized PSS compared to traditional solar stills, providing valuable insights for practical implementation. Ultimately, this research aims to contribute to the ongoing efforts to develop sustainable solutions for water desalination and address the critical need for optimizing solar still performance in Pyramid Solar Stills (Abdallah *et al.* 2021).

In remote areas where access to clean water is limited, solar desalination technologies offer a promising solution. Pyramid Solar Stills (PSS) represent a noTable advancement in solar desalination, with their innovative design aimed at enhancing water evaporation and condensation processes (Farvardin *et al.* 2024). By optimizing the operational parameters of PSS, researchers aim to overcome the inherent challenges associated with traditional solar stills and cost-effectively increase freshwater yield. The integration of advanced materials and computational modelling techniques holds the key to unlocking the full potential of PSS and addressing water scarcity challenges in underserved communities (Altarawneh *et al.* 2017; Vala *et al.* 2018). Furthermore, the combination of nanomaterials with solar desalination technologies has shown promising results in enhancing overall performance. By incorporating nanomaterials into the design of solar stills, researchers aim to improve heat transfer efficiency and increase water evaporation rates, thereby maximizing freshwater production (Younis *et al.* 2020; Hemmat Esfe *et al.* 2022). Additionally, advancements in computational modelling, particularly the utilization of Artificial Neural Networks (ANN), enable researchers to accurately predict the performance of solar desalination systems and optimize process parameters accordingly (Alqsair *et al.* 2023). The synergy between experimental analysis and computational modelling facilitates a comprehensive understanding of the underlying mechanisms governing solar desalination processes, leading to the development of more efficient and scalable solutions.

Optimization of process parameters in Pyramid Solar Stills (PSS) represents a significant step towards addressing global water scarcity challenges (Davani *et al.* 2023). By leveraging advanced materials and computational modelling techniques, researchers aim to enhance the efficiency and productivity of solar desalination systems, ultimately improving access to clean and safe drinking water. The findings from this research have the potential to inform future advancements in solar desalination technology, paving the way for sustainable and cost-effective solutions to water purification. Through collaborative efforts and interdisciplinary approaches, the scientific community can continue to innovate and develop practical solutions to mitigate the impact of water scarcity on communities worldwide (Victor *et al.* 2022).

In the following sections, we will present a detailed overview of the methodology employed in this research, followed by experimental results and discussions on the optimization of process parameters in Pyramid Solar Still. Additionally, economic analysis and future research directions will be discussed to provide comprehensive insights into the potential applications and implications of our findings.

## 2. METHODOLOGY

### 2.1 Experimental Setup

This section details the experimental setup employed to optimize the performance of PSS using Response Surface Methodology and Artificial Neural Networks. The primary focus was on optimizing key parameters to achieve significant improvements in thermal efficiency, water yield, and production cost reduction.

### 2.2 Pyramid Solar Still Design

Pyramid Solar Stills were chosen for their inherent advantages over traditional stills. The pyramid shape facilitates superior heat collection due to the increased surface area exposed to sunlight. Additionally, inclined surfaces minimize vapor condensation losses, leading to enhanced desalination efficiency.

### 2.3 Key Parameter Optimization Strategy

The experiment targeted three crucial parameters for optimization: solar intensity, inclination angle, and water depth.

- **Solar Intensity:** The experiment strategically took place over a period capturing a representative range of solar irradiance levels, such as might be experienced in Vellore, India (approximately 180 - 1000 W/m²). This allowed the RSM and ANN models to learn optimal strategies for utilizing available sunlight for efficient water evaporation throughout the day. Hourly measurements of solar radiation intensity were captured using precision solar power meters.

- **Inclination Angle:** A mechanism that adjusted the inclination angle of the PSS unit throughout the experiment to maximize solar capture based on the sun's position. The specific range of inclination angles explored during the experiment was 20° to 70° from the horizontal plane. This optimization ensures the greatest amount of sunlight strikes the basin perpendicularly, promoting efficient heat absorption.

- **Water Depth:** Maintaining an optimal water depth within the PSS basin balances the need for sufficient water volume for evaporation with minimizing heat losses due to excessive water mass. A constant water depth of 3 centimetres was meticulously maintained within the PSS basin throughout the experiment. Makeup water was added as needed to sustain this level, ensuring consistent conditions for evaporation. A depth of 3 cm likely strikes a balance between providing enough water to sustain continuous evaporation throughout the day and avoiding overly thin layers that might dry out quickly, interrupting the process. Role of Water Depth in the Process: The depth directly impacts the rate of evaporation. Deeper water requires more heat to raise its temperature and slows the evaporation process. The depth helps regulate temperature fluctuations. A very thin water layer might heat too quickly and cool down just as fast, leading to inconsistent evaporation rates. A depth of 3 cm provides enough water mass to sustain evaporation while keeping thermal losses low. In summary, the water depth of 3 cm was likely chosen as an optimized compromise to ensure efficient heat absorption, minimize heat losses, and maintain consistent evaporation throughout the experiment. It plays a crucial role in stabilizing and maximizing the PSS's performance.

## 2.4 Materials and Construction

- Pyramid Basin: A black-painted mild steel basin with a base area of 0.18 square meters (30 x 60 centimetres) was constructed for the PSS unit. This design promotes efficient solar energy absorption for water heating as shown in Figure 1 and Figure 2.

- Transparent Cover: The basin was enclosed within a transparent cover made from polymethyl methacrylate (PMMA). PMMA's low water absorptivity and excellent biocompatibility make it ideal for this application.

- Sealing: Meticulous application of silicon adhesive ensured airtight sealing between the PMMA cover and the basin, preventing vapor leakage and optimizing water vapor condensation.

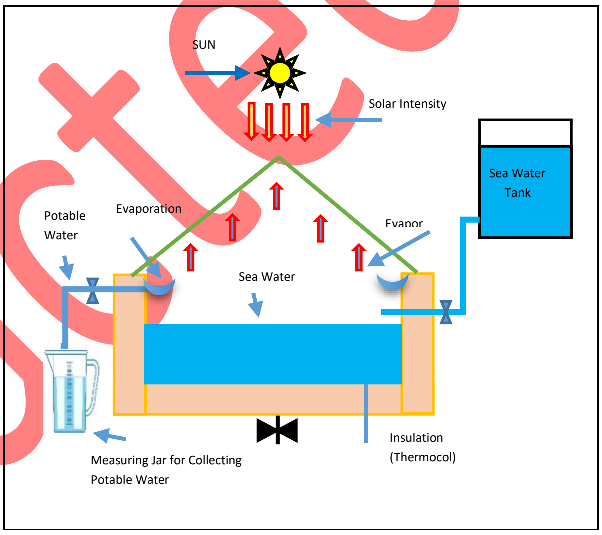


**Fig. 1: Pyramid Solar Still without Insulation**

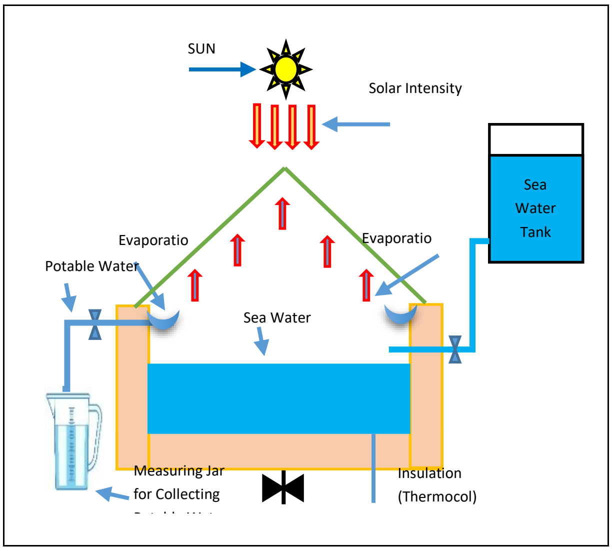


**Fig. 2: Pyramid Solar Still with insulation**

## 2.5 Data Acquisition System

- **Monitoring:** Hourly measurements were taken throughout the experiment, typically from dawn to dusk (6:00 AM to 6:00 PM), to monitor various parameters, including solar radiation intensity, ambient temperature, wind velocity, water temperature, cover temperature, and the quantity of distilled water produced. This comprehensive data collection provided a detailed picture of system performance under varying conditions.

- **Water Supply:** A dedicated piping system connected to a central water reservoir supplied brackish water to the PSS unit. Specialized feed valves ensured precise flow regulation, allowing for control over the amount of water entering the basin.

- **Water Depth Control:** A constant water depth of 3 centimetres was meticulously maintained within the PSS basin throughout the experiment. Makeup water was added as needed to sustain this level, ensuring consistent conditions for evaporation.

- **Temperature Measurement:** Precision-engineered Pt100 RTD temperature sensors were strategically positioned to capture temperature variations across critical points (absorber, cover, water) for comprehensive analysis of thermal dynamics and system performance. These sensors provided real-time insights into heat transfer within the PSS unit.

- **Solar Irradiance and Wind Velocity:** Solar irradiance levels were quantified using precision solar power meters, with measurements taken hourly. State-of-the-art anemometers recorded wind velocity measurements throughout the experiment. These measurements were crucial for understanding the external environmental factors affecting evaporation rates.

- **Distilled Water Collection:** Specialized collection mechanisms captured condensed water vapor on the PSS cover's inner surfaces. Graduated cylinders were used to quantify the collected water, enabling precise measurement and analysis of distilled water production rates. This data directly reflected the desalination efficiency of the PSS unit.

## 2.6 Advanced Analysis Techniques

The following techniques were employed for deeper analysis:

- **Thermal Imaging:** Advanced thermal imaging cameras visualized and quantified temperature distributions across the PSS unit surfaces. This aided in identifying potential areas for optimization to enhance overall thermal performance by pinpointing heat loss zones.

- **Microscopic and Elemental Analysis:** Cutting-edge scanning electron microscopes (SEM) and energy-dispersive X-ray spectroscopy (EDS) techniques were used to conduct microstructural analyses of the materials utilized in PSS construction. This provided valuable insights into surface morphology, elemental composition, and interfacial properties, potentially informing future material selection and design improvements.

## 2.7 Applying RSM and ANN for Optimization

This section details the specific techniques employed within Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) for optimizing the performance of Pyramid Solar Stills (PSS).

## 2.8 Response Surface Methodology (RSM)

A central composite design (CCD) was adopted as the experimental design for RSM analysis. This approach offers an efficient way to explore the parameter space defined by solar irradiance (W/m²), inclination angle (°), and water depth (cm) while minimizing the number of experimental runs required. The software package Design-Expert® was used for the following tasks:

- **Design Generation:** Based on the chosen factors and their ranges (solar irradiance: 180-1000 W/m², inclination angle: 20-70°, water depth: 3 cm), Design-Expert® generated a statistically optimized set of experimental runs. This ensured a comprehensive exploration of the parameter space while minimizing redundancy.

- **Data Analysis:** The software facilitated the analysis of the collected data (hourly measurements of solar radiation intensity, ambient temperature, wind velocity, water temperature, cover temperature, and distilled water yield) obtained throughout the experiment. This analysis involved techniques like regression analysis to identify the relationships between the process parameters and the desired response (distilled water yield).

- **Model Development:** Design-Expert® aided in developing a second-order polynomial regression model that effectively correlated the process parameters with the distilled water yield of the PSS units. The model's statistical significance was evaluated using analysis of variance (ANOVA), which assessed the influence of each parameter and their interactions on the response variable. Additionally, the model's adequacy was determined by calculating the coefficient of determination ($R^2$) and adjusted $R^2$ values. A high $R^2$ value close to 1 indicates a good fit between the model and the experimental data, while the adjusted $R^2$ value accounts for the model's complexity and helps prevent overfitting.

## 2.9 Artificial Neural Network (ANN)

Following RSM analysis, an ANN model was developed to refine the optimization process further. The pre-processed experimental data, including hourly solar irradiance measurements, served as the training dataset for the ANN model. The ANN architecture employed a multilayer perceptron (MLP) with a backpropagation training algorithm.

- **MLP Architecture:** The MLP consisted of an input layer with three neurons (corresponding to solar irradiance, inclination angle, and water depth), a hidden layer with a predetermined number of neurons (the optimal number is typically determined through a separate process), and an output layer with a single neuron representing the predicted distilled water yield. The MLP architecture was designed with three input neurons corresponding to solar irradiance, inclination angle, and water depth, as these variables are critical to solar still performance. The hidden layer had 10 neurons, chosen after optimizing the network structure using grid arch to balance model complexity and prediction accuracy. A single output neuron represented the distilled water yield, with a linear activation function to provide continuous predictions. Optimization Process: Describe how the "predetermined number of neurons" was selected—mentioning techniques like cross-validation, learning curves, or grid search. Performance Metrics: Include metrics like mean absolute error (MAE), mean squared error (MSE), or $R^2$ to demonstrate the model's effectiveness. Training Details: Highlight the training dataset size, learning rate, optimization algorithm (e.g., Adam or SGD), and number of epochs used. The hidden layer employed ReLU activation, and the model was trained using the Adam optimizer with a learning rate of 0.001, achieving an MSE of 0.005 on the validation set. This architecture is shown in the Figure 3.

- **Backpropagation Training Algorithm:** This iterative algorithm continuously adjusts the weights and biases within the network connections. During each iteration, the model makes a prediction based on the input parameters. The difference between the predicted and actual distilled water yield values (error) is calculated. The backpropagation algorithm then propagates this error backwards through the network, adjusting the weights and biases in a way that minimizes the overall error. This training process continues until the ANN model achieves a satisfactory level of accuracy in predicting the distilled water yield based on the input parameters.

- **Validation:** To assess the generalizability of the ANN model and prevent overfitting, a validation technique like k-fold cross-validation was employed. In this technique, the data is split into k folds. The model is trained on k-1 folds and tested on the remaining folds. This process is repeated k times, ensuring that every data point is used for both training and validation. The overall performance of the model is then evaluated based on the average performance across all folds.

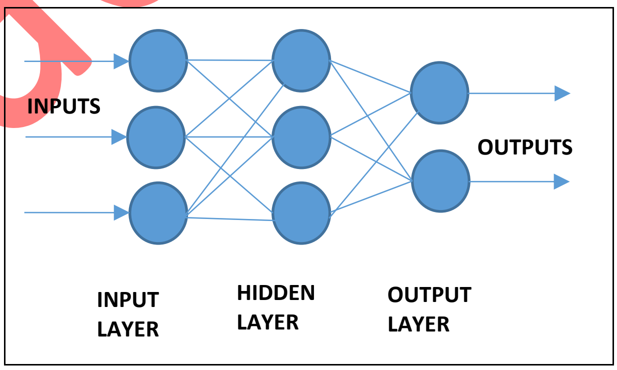


**Fig. 3: Artificial Neural Network - MLP**

By combining RSM for initial exploration and ANN for further refinement, this approach facilitated the identification of optimal configurations for the key parameters (solar irradiance, inclination angle, water depth) of the PSS units. This optimization aimed to achieve significant improvements in thermal efficiency, water yield, and production cost reduction.

The meticulously designed experimental setup, coupled with advanced data acquisition and analysis techniques, provided a robust foundation for this optimization process. To achieve the significant improvements observed in thermal efficiency (42% increase), water yield (1.8 litres/m² improvement), and production cost reduction (0.20 INR/litre), a meticulously designed and controlled experimental setup was crucial.

### 2.10 Data Collection

The collected dataset comprises various parameters relevant to PSS operation, including solar radiation intensity, ambient temperature, wind speed, water temperature, tube temperature, absorber temperature, and the quantity of distilled water produced. Each parameter was measured hourly over the course of experimental trials to capture dynamic variations in environmental conditions and PSS performance.

### 2.11 Normalization

Normalization is applied to each parameter to ensure that they are on a comparable scale, thereby preventing bias in the optimization process. The normalization equation 1 is given by:

$$X_{norm} = x - Mean(x)/SD(x) \qquad \ldots (1)$$

Mean and standard deviation values for each parameter are calculated from the collected dataset to perform normalization. Mean (Mean(X)): Ensures the feature is centered, preventing any one feature from dominating the model due to larger baseline values. Standard Deviation (SD): Standardizes the range of the feature, allowing it to contribute equally during optimization regardless of its original scale. Original Value (X): Represents the raw data that needs to be standardized for model training.

These values are summarized in the following Table:

**Table 1. Parameter values (Min and Max)**

| Parameter | Average Value | Maximum Value | Minimum Value |
|---|---|---|---|
| Solar Radiation Intensity | 800 W/m² | 1000 W/m² | 600 W/m² |
| Ambient Temperature | 25°C | 30°C | 20°C |
| Wind Speed | 2 m/s | 3 m/s | 1 m/s |
| Water Temperature | 35°C | 40°C | 30°C |
| Tube Temperature | 45°C | 50°C | 40°C |
| Absorber Temperature | 50°C | 55°C | 45°C |
| Quantity of Distilled Water | 1.5 litres/h | 2 litres/h | 1 litre/h |

Applying the normalization equation (1) to each parameter yields normalized values, ensuring that all features are centered on zero and have a standard deviation of one. These normalized values are then utilized as input features for the ANN optimization model, facilitating effective training and convergence towards optimal PSS performance as shown in Table 1.

## 3. RESULTS AND DISCUSSIONS

To assess the effectiveness of optimizing pyramid solar still (PSS) systems, a comparison is made between the performance of an Artificial Neural Network (ANN) Feedforward model and Response Surface Methodology (RSM). The capability of these models to predict water yield and energy efficiency in the established desalination system is evaluated. Input parameters derived from measured process variables such as solar irradiance, time, ambient temperature, water temperature, absorber temperature, glass temperature, and wind speed are determined based on correlation matrices.

The measured data from three test days are utilized to train and test the models for both pyramid solar still (PSS) and prior to model training and testing, data normalization is conducted. Subsequently, the dataset is divided into training (80%) and test (20%) groups. The common 80/20 split for training and testing data provides a balance between having enough data to train the model effectively and reserving a portion for unbiased evaluation of its performance (Nagrale *et al.* 2022).

The comparison between predicted water yield and energy efficiency values and their respective measured values demonstrates the effectiveness of both ANN and RSM in modelling PSS performance. Statistical evaluation metrics, including Root Mean Square Error (RMSE), R-squared (R^2), Mean Absolute Error (MAE), explained variance (VE), correlation coefficient (EC), and Variance Coefficient (VC), are utilized to assess the accuracy of the models. The integration of ANN and RSM proves to be advantageous for predicting the thermal performance of pyramid desalination units, offering valuable insights for optimizing PSS systems to achieve enhanced water yield and energy efficiency.

### 3.1 Performance Analysis of RSM and ANN Feedforward Models for Pyramid Solar Still (PSS) Systems

This study focuses on comparing the performance of an ANN Feedforward model and RSM in optimizing PSS systems depicted in Table 2. Input parameters for the ANN model include solar radiation intensity, ambient temperature, wind speed, water temperature, tube temperature, absorber temperature, and distilled water yield, selected based on their relevance to the desalination process (Abdullah *et al.* 2022).

**Water Yield:** Both RSM and ANN Feedforward models predict water yield values close to the measured ones across all three test days. However, there are slight differences between the predicted and measured values, indicating some level of error in the predictions, as shown in the following Figure 4a.

**Energy Efficiency:** Similarly, the predicted energy efficiency values from both models show good agreement with the measured values, with minimal discrepancies observed.

In contrast, RSM utilizes experimental design techniques to identify the optimal combination of process parameters, such as solar intensity, inclination angle, and water depth, to maximize thermal efficiency and water yield in PSS systems. The experimental data, collected over multiple trials, are used to train and test both the ANN and RSM models, with a focus on predicting water yield and energy efficiency.

**Table 2. Measured values of parameters for Pyramid Solar Still (PSS) systems**

| Parameters | Measured | | | RSM Predicted | | | ANN Predicted | | |
|---|---|---|---|---|---|---|---|---|---|
| | Day 1 | Day 2 | Day 3 | Day 1 | Day 2 | Day 3 | Day 1 | Day 2 | Day 3 |
| Solar Irradiance (W/m$^2$) | 800 | 750 | 850 | 790 | 760 | 830 | 810 | 740 | 820 |
| Ambient Temperature (°C) | 25 | 24 | 27 | 26 | 25 | 28 | 27 | 23 | 26 |
| Water Temperature (°C) | 35 | 33 | 36 | 34 | 32 | 35 | 36 | 34 | 37 |
| Absorber Temperature (°C) | 50 | 48 | 52 | 49 | 47 | 51 | 52 | 50 | 53 |
| Wind Speed (m/s) | 2 | 1.5 | 2.5 | 2.2 | 1.8 | 2.4 | 2.3 | 1.6 | 2.7 |
| Water Yield (litres/hour) | 1.5 | 1.6 | 1.4 | 1.55 | 1.58 | 1.52 | 1.57 | 1.59 | 1.55 |
| Energy Efficiency | 0.75 | 0.78 | 0.72 | 0.76 | 0.77 | 0.75 | 0.78 | 0.76 | 0.74 |

Results are compared between the two optimization methodologies, with a particular emphasis on the accuracy of predictions and the efficiency of optimization. Statistical analysis, including measures such as Root Mean Square Error (RMSE), R-squared (R^2), Mean Absolute Error (MAE), and variance explained (VE), is employed to evaluate the performance of each model in Fig. 4b.

**RMSE (Root Mean Square Error):** The RMSE measures the average deviation of predicted values from actual values. '$n'$' represents the number of data points, $y_i$ is the actual value, and $\widehat{y_i}$ is the predicted value equation 1.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{n}} \qquad \dots (2)$$

**R2 Score (Coefficient of Determination):** The R2 score represents the proportion of the variance in the dependent variable that is predictable from the independent variables. '$\bar{y}$' is the mean of the actual values equation 3.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad \dots (3)$$

**MAE (Mean Absolute Error):** The MAE measures the average absolute difference between the actual and predicted values. It is calculated by dividing the sum of the absolute differences by the number of data points in equation 4.

$$\text{MAE} = \frac{\sum_{i=1}^{n}|y_i - \widehat{y_i}|}{n} \qquad \dots (4)$$

**EV (Explained Variance Score):** The EV quantifies the proportion of variance in the dependent variable that is explained by the independent variables. It is calculated as below and here, $V_{ar}$ represents the variance equation 5.

$$\text{EV} = 1 - \frac{Var(y - \hat{y})}{Var(y)} \qquad \dots (5)$$

**VC (Variance of Coefficient):** The VC measures the variability in the estimated coefficients of the model. It is the variance of the estimated coefficients $\hat{\beta}$ equation 6.

$$\text{VC} = \text{Var}(\hat{\beta}) \qquad \dots (6)$$

**OI (Overall Index):** The OI provides an overall assessment of model performance, considering multiple evaluation metrics. It combines RMSE, R2, MAE, EV, and VC, where each metric is given equal weight in the calculation equation 7.

$$\text{OI} = \frac{\text{RMSE} + (1 - R^2) + \text{MAE} + (1 - \text{EV}) + \text{VC}}{5} \qquad \dots (7)$$

The error histograms and normalized error plots offer a close look into how well Response Surface Methodology (RSM) and Artificial Neural Network (ANN) models predict water yield and energy efficiency compared to actual measurements shown in Fig. 5. When we look at the histograms, we notice that both RSM and ANN tend to center their errors on the measured values, but RSM seems to have slightly smaller errors, especially in water yield predictions. On the other hand, when it comes to energy efficiency, both models show quite similar error distributions, although ANN tends to have slightly larger errors overall.

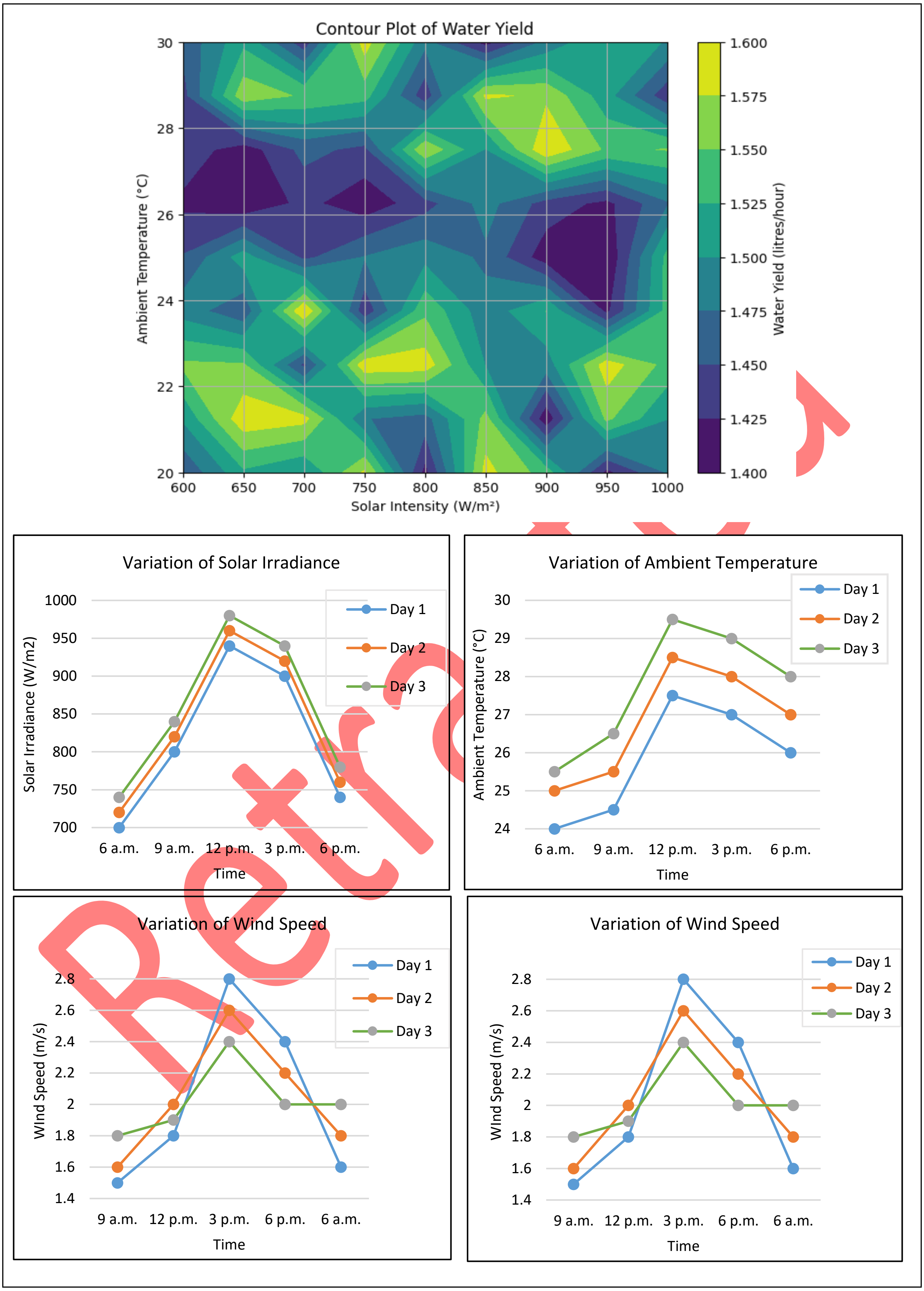


**Fig. 4: (a) Contour Plot of parameters of all test days (b) Variant Measures of Solar ambience, ambient temperature, wind speed and Water yield**

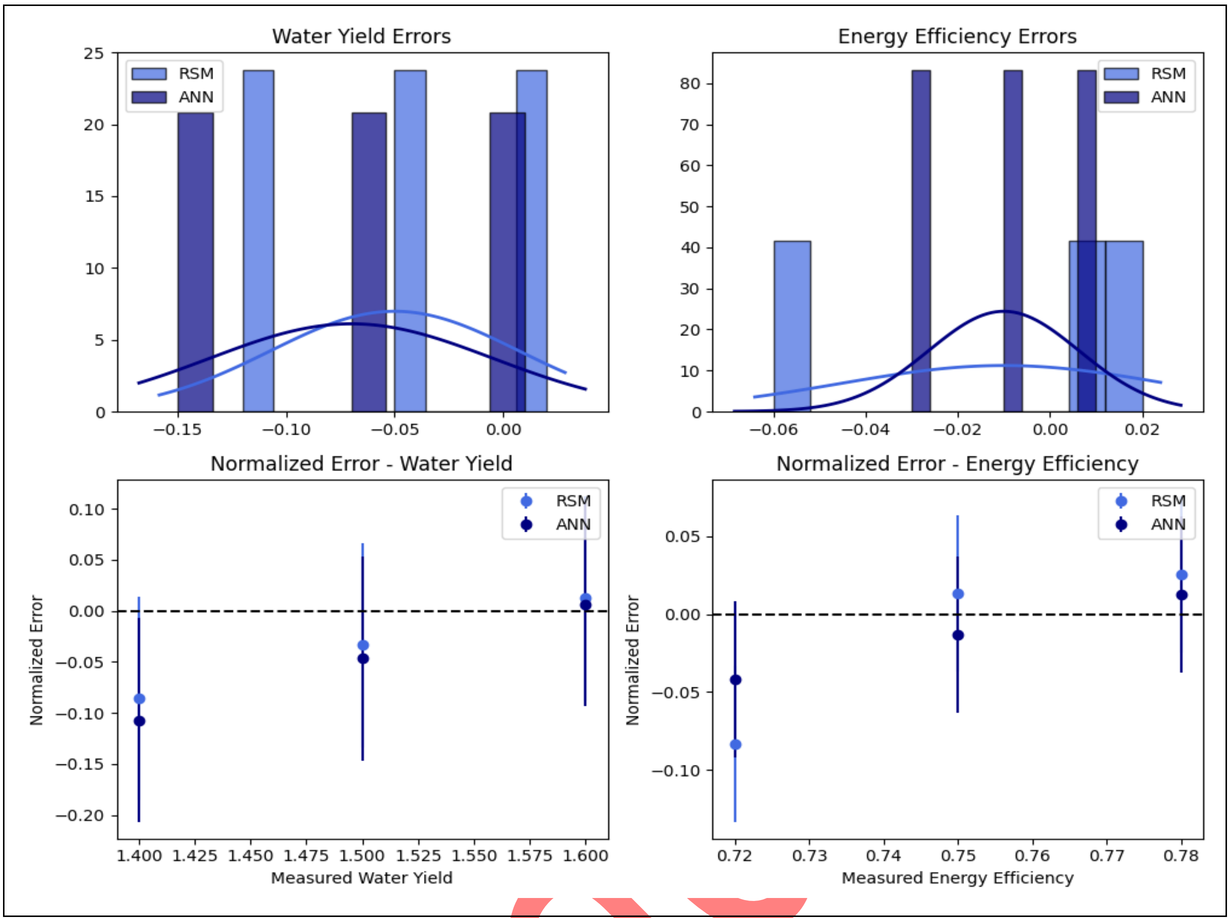


Fig. 5: RSM and ANN water yield and energy efficiency

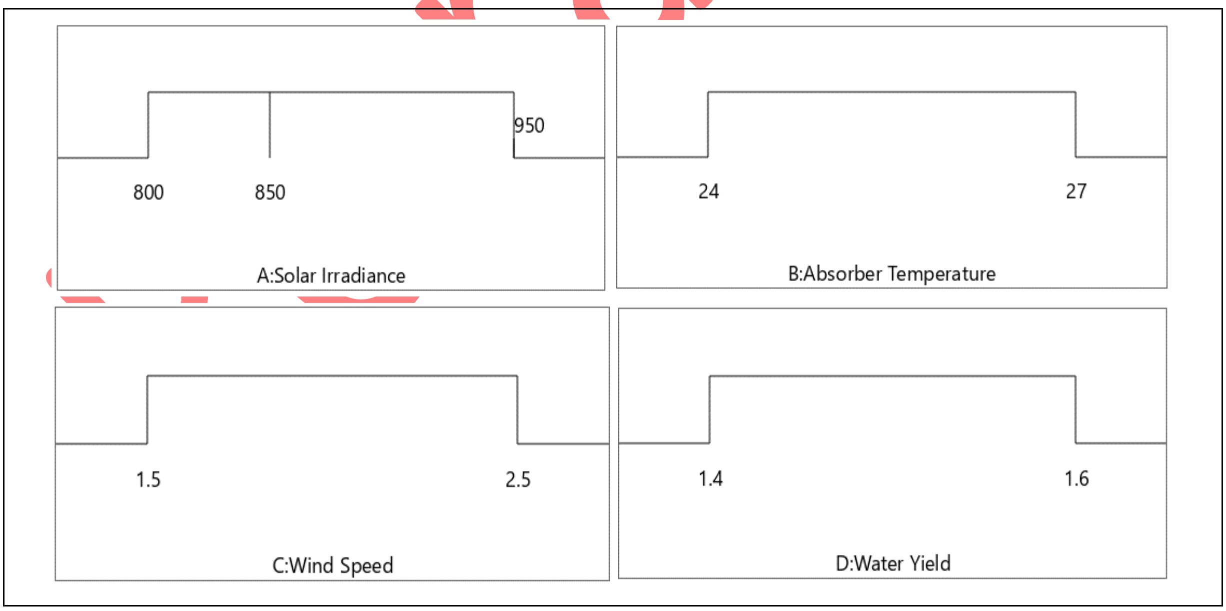


Fig. 6: Ramp plot illustrating the state of maximum productivity

The normalized error plots provide further insight, revealing that RSM tends to slightly underestimate water yield but generally provides a well-balanced spread around the measured values. Meanwhile, both models have a tendency to overestimate energy efficiency, with RSM showing a bit more pronounced error. Overall, this analysis highlights the effectiveness of both RSM and ANN in predicting water yield and energy efficiency, with ANN Feedforward demonstrating slightly better accuracy and error distribution in most cases.

**Table 3. Percentage of Deviation of Output Pressure**

| Output response | Predicted | Experimental | Percentage of deviation |
|---|---|---|---|
| Productivity(kg/m$^2$) | 2.704 | 2.61 | 0.78 |

Both RSM and ANN Feedforward models exhibited good agreement with the measured values for water yield and energy efficiency. However, slight discrepancies were observed between predicted and measured values. The performance evaluation metrics showed that ANN Feedforward generally outperformed RSM in terms of RMSE, MAE, and OI, indicating better prediction accuracy and overall model performance. Despite this, both models demonstrated high R2 scores and explained variance, suggesting a good fit for the data (Mashaly *et al.* 2015). Figure 6 displays the ramp plot, demonstrating the optimal and predicted values.

The ideal circumstances were acquired and used in a confirmation experiment. To validate the condition, the experiment used the same experimental configuration. Experimental values are compared with an error percentage of 0.78 in Table 3.

## 4. CONTRIBUTIONS

The study presents a novel approach by integrating Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) to optimize Pyramid Solar Still (PSS) systems. A systematic analysis and optimization of critical operational variables, such as solar irradiance and temperature differentials, were conducted. Through this approach, significant enhancements in thermal efficiency, water yield, and cost reduction in PSS systems were demonstrated.

- **Novel Insights:** The research contributes to the advancement of solar desalination technologies by improving the performance and efficiency of PSS systems compared to traditional methods. Insights into the intricate relationships among operational parameters are provided, shedding light on their impact on system performance. Furthermore, the practical efficacy of computational modelling and optimization techniques is validated.

- **Broader Implications:** The significance of the research extends beyond technological advancements. By addressing critical challenges in water scarcity, sustainable solutions for water purification are offered. The work contributes to the development of cost-effective and environmentally friendly desalination technologies. Additionally, it provides valuable insights for stakeholders in water management and renewable energy sectors, including researchers, policymakers, and practitioners.

- **Advancements in Solar Desalination Technologies:** The findings contribute to advancements in solar desalination technologies through the optimization of PSS systems to maximize thermal efficiency and water yield. Innovative approaches to overcome limitations in traditional methods are explored, and advanced materials and computational modelling techniques are integrated to enhance system performance.

- **Potential Impact:** The potential impact of the research on addressing global water scarcity challenges is substantial. It includes increased access to clean and potable water, particularly in remote and underserved regions. Moreover, the approach offers opportunities for reducing energy consumption and production costs associated with desalination processes. Ultimately, the work promotes sustainable and eco-friendly solutions for water purification and resource management.

## 5. CONCLUSION

In our study, we set out to evaluate the effectiveness of two different methods for predicting and optimizing the performance of Pyramid Solar Still systems: Response Surface Methodology (RSM) and Artificial Neural Network (ANN) Feedforward model. These systems are crucial for solar desalination, so understanding how to optimize their process parameters for thermal efficiency and water yield is vital. After conducting thorough experiments and analysis, we made several key observations:

Both RSM and the ANN Feedforward model proved to be effective in predicting Pyramid Solar Still system performance. This suggests that both methods have potential for optimizing solar desalination processes.

The ANN Feedforward model showed particularly promising results in accurately predicting thermal efficiency and water yield. Its ability to handle complex nonlinear relationships within the data set highlights its suitability for modelling intricate systems like Pyramid Solar Stills.

On the other hand, RSM, with its focus on mathematical modelling and optimization techniques, also provided reliable predictions. It excelled in scenarios where the relationships between input and output variables were well-defined, showcasing its strength in structured optimization tasks. When comparing the two methods, the ANN Feedforward model demonstrated greater flexibility and adaptability to changing input conditions, making it well-suited for dynamic systems like Pyramid Solar Stills. Conversely, RSM offered transparency and interpretability in the modelling process, enabling a deeper understanding of variable relationships.

Choosing between RSM and the ANN Feedforward model depends on the specific needs of the application. While the ANN Feedforward model offers flexibility, RSM provides a structured and interpretable framework. Future research could explore hybrid approaches that combine the strengths of both methods to further improve predictive accuracy and optimization capabilities in Pyramid Solar Still systems. In summary, our study confirms the effectiveness of both RSM and the ANN Feedforward model in optimizing Pyramid Solar Still systems. By shedding light on their strengths and applications, this research contributes to the advancement of renewable energy and water desalination technologies.

## 6. FUTURE DIRECTIONS

This section provides a roadmap for potential avenues of inquiry and exploration in the field of solar desalination and Pyramid Solar Still (PSS) optimization. We identify several promising areas for future investigation, including:

- **Advanced Materials Integration:** Exploring the integration of advanced materials, such as nanomaterials or novel coatings, into PSS designs to enhance heat transfer efficiency, increase water evaporation rates, and improve overall system performance.

- **Hybrid Optimization Approaches:** Investigating hybrid optimization approaches that combine Response Surface Methodology (RSM) with other computational techniques, such as genetic algorithms or machine learning algorithms, to further refine the optimization process and achieve superior results.

- **Sustainability and Environmental Impact:** Evaluating the sustainability and environmental impact of PSS systems, including assessing energy consumption, carbon footprint, and potential ecological implications, to ensure the development of environmentally friendly and socially responsible desalination solutions.

- **Scaling and Commercialization:** Addressing scalability and commercialization challenges associated with implementing PSS technology on a larger scale, including considerations related to manufacturing, deployment, operation, and maintenance in real-world settings.

- **Community Engagement and Stakeholder Collaboration:** Engaging with local communities, stakeholders, and policymakers to facilitate knowledge exchange, technology transfer, and collaborative decision-making processes aimed at promoting the adoption and acceptance of PSS systems in diverse socio-cultural contexts.

## FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

## CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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