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Application of response surface methodology and neural networks in pyramid solar still for seawater desalination: An optimization and prediction strategy

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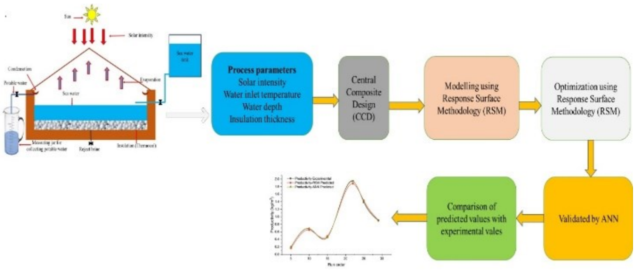
Graphical abstract



Abstract

Potable water is essential in various aspects of daily life. Converting brackish water to drinkable water using traditional methods is costly and has environmental impacts. Solar energy is preferred over fossil fuels and other energy sources due to its cost and environmental benefits. Solar stills are increasingly popular due to the growing need for drinkable water, but their performance requires improvement. The study examines the pyramid solar still (PSS) productivity using different operating parameters, such as solar intensity (350-950 W m^{-2}), water inlet temperature (30-50°C), water depth (4-8 cm), and insulation thickness (0.05-0.15m). The response surface technique (RSM) was used to examine the performance of the still under different operating conditions. The RSM approach optimized the process for maximum output and reduced testing time and effort. To verify the optimum response derived from RSM, the artificial neural networks (ANN) model was implemented. The comparative studies of the ANN and RSM models demonstrates a strong correlation with the outcomes achieved in maximizing the productivity of PSS. It found that the ideal values for solar intensity, water intake temperature, water depth, and insulation thickness are 950 W m^{-2}, 50°C, 4 cm, and 0.15 m, respectively. These parameters contribute to the production of 2.585 kg/m^2 of distillate.

Keywords: Response surface methodology, artificial neural network, productivity, insulation, pyramid solar still, analysis of variance

1. Introduction

Our needs have been met since the beginning of time and will continue to be met. Water is an important life-saving natural resource. Merely 1% of the total water supply comprises freshwater, which is acceptable for household use. Due to the exponential increase in population and industrialization, the existing freshwater supply is transitioning from a renewable source to a limited one, posing a significant threat. In order to prevent this situation and meet the needs and desires of the population, it is necessary to transform the abundant salt water into potable water via the process of desalination utilizing solar stills (Hammoodi *et al.* 2023a; yuvaperiyasamy *et al.* 2023b). In research today, the management and recreation of freshwater resources are emphasized. One significant achievement that provides us with confidence to fulfill the increasing need is the ability to produce fresh water via means other than the natural hydrological cycle. Numerous studies on transforming saltwater into freshwater are being conducted globally (Singh *et al.* 2023). Most research studies indicate that desalination technology based on solar energy is the most efficient method for producing cheap freshwater (Abdullah *et al.* 2023a). Hameed *et al* (2023) created the pyramid solar still and single slope solar still (SSSS) to compare thermal performance, productivity, and efficiency. In remote areas with limited access to electricity and other resources, the solar desalination process is the most effective means of producing freshwater from seawater. The yearly average daily productivity was determined using Dunkle relations, which was found to be 2.7 L m^{-2} per day. Annual average daily efficiencies for the PSS and SSSS are 30 and 33 percent, respectively. Arunkumar *et al*. (2012) created a PSS that was connected to the basin's parallel multi-shelf configuration. Compared to corrugated or horizontal beds, the experimental setup generated 90–95% freshwater. Another solar still designed by Taamneh and Al-Abed Allah (2020) has a concave wick evaporation surface and a collector fashioned like a tetrahedral pyramid. It produced 4.1 L of fresh water per day per m^2, which is 200 % more than what a conventional solar still could with an average daily efficiency of 30 %. For a comparison investigation, Peng and Sharshir (2023) built a passive and active pyramid solar still (PPSS and APSS). The only difference between the two stills is a little fan at the side wall of the APSS that runs at a very low power. The research found that at an 8 cm water level, the APSS produced 3.14 and 1.89 L m^{-2} in the summer and winter, respectively. Abdullah *et al*. (2023b) examined the PSS mounted at the collector surface with and without a fan. Because of the air circulation within the solar still, the PSS with a fan produced a yield that was 25% greater than the PSS without a fan. Muthukumar *et al*. (2020) examined the PSS alone, PSS in conjunction with the concentrated coupled collector (CPC), and the hemi-spherical solar still (HSS) (HSS). PSS generated 3300, 6928, and 2730 mL m^{-2} of freshwater every day, correspondingly, along with PSS - CPC and HSS. Hammoodi *et al*. (2023b) compared the PSS and SBSS and found that the PSS produced 7368 mL m^{-2} per day of fresh water, while the SBSS produced approximately 5570 mL m^{-2} per day of distillate water. Hussen *et al*. (2023) reported that since the PSS received more direct sunlight than the SSSS and DSSS, it produced a larger yield. Many improvement methods require additional components that increase costs. The solar still's thermal efficiency may be increased by optimizing its working conditions without adding to its cost (Ellappan and Madhavan., 2023; Yuvaperiyasamy *et al.*2023c). Wind speed, outside temperature, sun insolation, intake water temperature, water depth, insulation thickness, and other variables still affect solar production. There are still a number of variables that affect solar productivity, such as wind speed, surrounding temperature, sun insolation, water depth, input water temperature, insulation thickness (Tariachaicahn *et al.*2023). The primary element influencing solar still production is sun intensity. Numerous studies have examined how sun insolation affects the productivity of solar stills. Changes in sun intensity have an impact on solar still production, according to the research (Jamil *et al.* 2023; Cherraye *et al.*2020). Jathar *et al*. (2021) examined the effects of varying water depths on solar still evaporation rates in both passive and active modes. Research indicates that an increase in water brine depth causes a drop in the freshwater production of solar stills. Response Surface Methodology (RSM), a statistical and mathematical technique, is used to identify the ideal circumstances for multivariate systems. It is well known that this is a useful tool for process optimization (Chen *et al.*2022). RSM is commonly used to analyze how different operating parameters interact and optimize the response. Regression correlation between many parameters and responses is estimated using this method. RSM has been successfully used to optimize engineering systems in various applications (Chen *et al.*2021).

The main emphasis of earlier research was examining different factors that influence solar still production. However, no optimization research was conducted for the parameter that significantly affects the performance of solar stills. There has been a lack of research devoted to the development of a regression model that can forecast the daily production of a solar still using RSM. Furthermore, the research does not yet examine the effect of the factors that affect daily distilled water production on other parameters. This study aims to investigate the impact of four input factors on a pyramid solar still's daily productivity: solar intensity, water intake temperature, water depth, and insulation thickness.

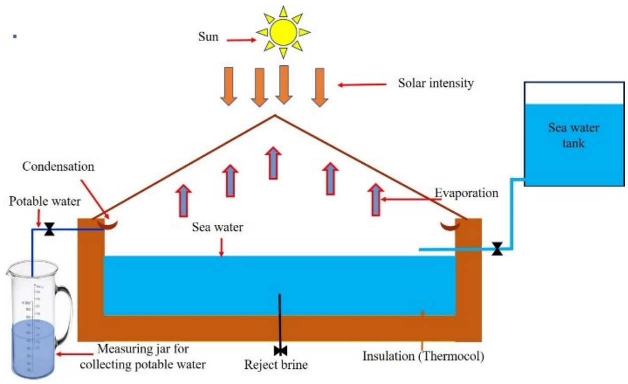


Figure 1. Pyramid solar still without insulation

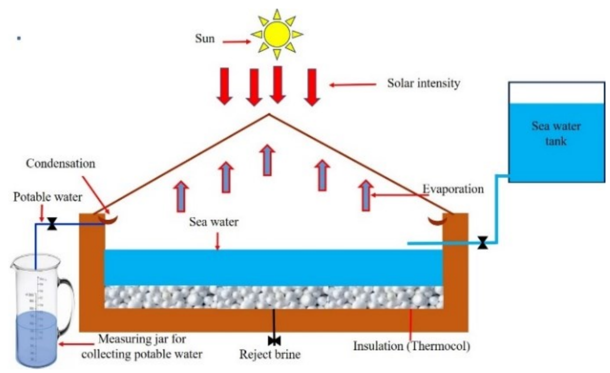


Figure 2. Pyramid solar still with insulation

2. Experimental setup and procedure

Figures 1 and 2 depict the schematic of the PSS with and without insulation, respectively. The 0.30 m^2 still basin is constructed of galvanized iron, and the collector surface is acrylic. Two percent more light passes through acrylic compared to glass. Compared to glass, it offers a stronger impact strength and clarity. The experiment examines the productivity using different operating input process parameters such as solar intensity, water inlet temperature, water depth, and thickness of the insulation. For the purpose of reducing heat loss from the solar still to the atmosphere, insulating thermocol was used. The properties of thermocol used in the experiment is given in Table 1. The duration of the experiments was from 9:00 am to 5:00 pm. A little glass barrier situated on the inside surface of the collector is used by the PSS to gather freshwater. Transporting condensed water to a measuring jar is accomplished by a flexible hose connection. Basin, water, glass, and environmental temperatures are all measured via thermocouples. An anemometer is used to determine wind speed, whereas a solar power meter is employed to quantify solar intensity. The instrument types and percentages of error are detailed in Table 2 (Yuvaperiyasamy *et al.* 2023a).

3. Response surface methodology (RSM)

A statistical and mathematical method called Response Surface Methodology (RSM) is used to help with process creation, optimization, and improvement. In the context of solar stills, RSM aids in identifying the optimal combination of operating conditions, such as solar intensity, water inlet temperature, water depth and insulation thickness by creating a mathematical model from experimental data. This efficient approach reduces the number of experiments needed, saves resources, and allows for pinpointing conditions that yield maximum distillate output. RSM's significance lies in its ability to streamline exploration of operating conditions, identify optimal parameters, and provide insights for efficient solar still design and performance enhancement. RSM is useful for creating an accurate model that demonstrates a link between the response variable and the independent variables by using the analysis of variance (ANOVA) approach (Tgarguifa *et al.*2017). The correlation between the response and independent variables is often unknown in the majority of RSM scenarios (Weremfo *et al.* 2022). The first step in Response Surface Methodology is to determine an approximation that faithfully captures the functional relationship between the independent variable "x" and the output response variable "y." (RSM). Generally, one applies a low-degree polynomial to a particular collection of independent variables. When a linear function of the independent variables accurately describes the response, the first-order model is used as the approximation function (Ahmed *et al.* 2023).

Table 1. Properties of thermocol

S. No	Properties	Range
1	Density	14-29 kg m^{-3}
2	Tensile strength	2.5-7 kg cm^{-2}
3	Compressive strength	0.7-1.5 kg cm^{-2}
4	Thermal conductivity	0.033 W m^{-1} k^{-1}

Table 2. Measuring instruments and % of Error (Yuvaperiyasamy *et al.* 2023a)

S.No	Instruments	Accuracy	Range	% of Error
1	Thermocouple	± 0.1 °C	0–100 °C	0.357
2	Solar power meter	±1 W m^{-2}	0–2500 W m^{-2}	3.33
3	Anemometer	±0.1 m s^{-1}	0–15 m s^{-1}	10
4	Measuring jar	±10 mL	0–1000 mL	10

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \qquad (1)$$

In the presence of system curvature, employing a higher-degree polynomial model, such as the second-order model, is necessary. The quadratic polynomial regression model is used (Ahmed *et al.* 2022).

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i<j} \sum \beta_{ij} x_i x_j + \varepsilon \qquad (2)$$

The method of least squares is employed for parameter estimation in approximating polynomials. The fitted surface is used to perform response surface analysis. An examination of the fitted surface will provide outcomes comparable to those obtained from an analysis of the real system, if it precisely reflects the response function. Optimal estimation of model response relies on using appropriate experimental designs for data collection (Khayet *et al.*2010). In the construction of response surfaces, the designs used are referred to as response surface designs. RSM is a step-by-step procedure that is used to identify a system's ideal operating circumstances or to define a region of the factor space where the essential operational requirements are met (Mahadeva *et al.* 2023). Analysis of various replies is typically necessary for response surface problems. To consider several responses at once, one must first build response surface models for every response and then identify the operating parameters that maximize all responses or keep them within the appropriate ranges. Figure 3 shows the design, modeling, and optimization pattern of distillate water production in RSM.

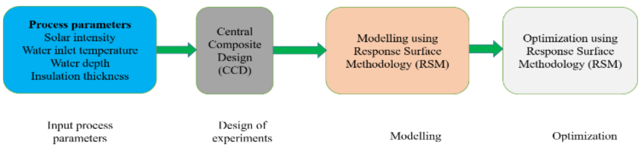


Figure 3. The suggested system's design, modelling, and optimization in RSM

This analysis examines four input parameters: solar intensity, water inlet temperature, depth, and insulation thickness. The chosen low-level and high-level values of these parameters are shown in Table 3 (Liu *et al.* 2021).

The study employs Central Composite Design (CCD) in RSM to systematically vary input parameters like solar intensity, water inlet temperature, water depth and insulation thickness. CCD involves a factorial design at different levels, allowing for the estimation of quadratic effects and interactions. This design facilitates the construction of a response surface model to optimize the pyramid solar still's productivity. The resulting mathematical model aids in predicting optimal conditions for maximum productivity. The study evaluates the impacts of process parameters using the central composite design (CCD) in the traditional response surface methodology (RSM) design. The Central Composite Design is often a 2^k factorial design with n_F runs, 2^k axial or star runs, and n_c center runs (CCD). The face-centered central composite design, often known as the face-centered cube, is a useful variation of the central composite design with α = 1. This design identifies the star or axial points at the cube's face centers. More center runs in the RSM face-centered cube design may be employed with the same input parameters to estimate experimental error. This improves resilience against outliers or missing numbers and aids in evaluating internal error (Al-Balushi *et al.* 2023). This is also valuable for constructing an accurate prediction model.

Table 3. Lists the levels of the input process parameters

Process parameters	Notation	Levels		
		-1	0	+1`
Solar intensity (W m^{-2})	S	350	650	950
Water inlet temperature (°C)	T	30	40	50
Water depth (cm)	D	4	6	8
Insulation thickness(m)	W	0.05	0.10	0.15

Table 4. Design of experiments with input and output response

Run	Solar intensity (W m^{-2})	Water inlet temperature (°C)	Water depth (cm)	Insulation thickness (m)	Productivity (kg m^{-2})
1	650	40	6	0.1	0.68997
2	350	50	4	0.05	0.42184
3	650	40	6	0.1	0.67997
4	350	30	4	0.05	0.70184
5	350	40	6	0.1	0.19334
6	950	50	8	0.15	1.98861
7	350	50	8	0.05	0.35066
8	350	50	4	0.15	0.80856
9	350	30	4	0.15	0.99856
10	650	40	6	0.1	0.67997
11	350	30	8	0.15	0.50539
12	950	50	8	0.05	1.70021
13	650	40	6	0.1	0.87997
14	650	40	8	0.1	0.63761
15	950	30	8	0.15	0.4545
16	650	30	6	0.1	0.33108
17	650	40	6	0.1	0.67997
18	650	50	6	0.1	0.67997
19	950	50	4	0.05	2.53021
20	950	30	4	0.05	1.99855
21	650	40	6	0.15	0.68244
22	950	30	4	0.15	1.94854
23	950	40	6	0.1	1.07184
24	650	40	6	0.05	0.67413
25	650	40	4	0.1	1.38863
26	950	50	4	0.15	2.58573
27	950	30	8	0.05	0.45005
28	350	30	8	0.05	0.17523
29	350	50	8	0.15	0.89856
30	650	40	6	0.1	0.67997

4. Artificial Neural Network (ANN)

A neural network (ANN) is a model of statistics that tries to replicate the functions of neural networks (Mahadeva *et al.* 2023). One target neuron and three input neurons were used to make a multilayer perceptron (MLP). Experiments that look into important neurons in the hidden layer make predictions less accurate based on the results of the experiments. Using easily accessible data, the new model was built with at least 10 neurons, and the addition of more neurons investigated the potential for over-modelling. The research results were used for modelling 90% of the time, and the rest of the results were properly divided up for model approvals and testing. A neural network is required to identify fitness concerns in order to ensure that target and input neurons are firing at the same time. Figure 4 shows the neural network design (Mahadeva *et al.* 2021).

The Artificial Neural Network (ANN) in this study serves to model and predict the complex relationships within the pyramid solar still system, capturing non-linearity's. It complements Response Surface Methodology (RSM) by addressing intricate interactions and providing a more comprehensive understanding of the system's behaviour. While RSM is effective for analysing quadratic effects, ANN excels in capturing intricate patterns, enhancing the study's ability to optimize productivity under diverse and dynamic conditions.

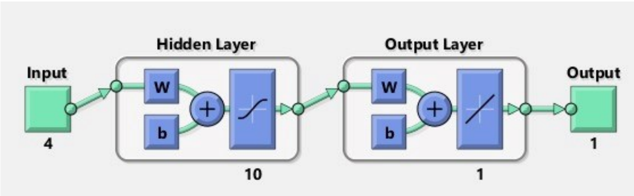


Figure 4. Artificial neural network designs

5. Results and discussion

Table 4 displays the experimental design using a face-centered central composite design (CCD). It demonstrates conclusively that input process variables like insulation thickness, solar intensity, and water intake temperature have a favourable effect on the fresh water productivity of PSS. Water depth, on the other hand, has an adverse influence on production of distilled water (Abdullah *et al.* 2023a).

ANOVA studies determine if advanced models are appropriate for establishing a relationship between input and response parameters. Table 5 displays the ANOVA results for productivity. All process factors are relevant, according to the data in Table 5, with solar intensity being the most important input process parameter for the productivity of PSS. The model's significance is substantiated by the F-value (74.83). The probability of obtaining an elevated number due to noise is very little, namely 0.01 percent. The model was considered statistically significant when the P-value was below 0.05 (Ahmed *et al.* 2022). The R^2 values that were predicted and adjusted are 0.9453 and 0.9727, respectively. The R^2 values show a substantial degree of concordance, with a deviation of no more than 0.2. A precision of 31.7657 is sufficient for design space navigation.

Table 5. Analysis of variance (ANOVA) for productivity (kg/m^2)

Source	Sum of squares	df	Mean square	F-value	p-value	
Model	12.59	14	0.8996	74.83	< 0.0001	Significant
S	5.20	1	5.20	432.52	< 0.0001	
T	1.08	1	1.08	89.50	< 0.0001	
D	2.15	1	2.15	178.89	< 0.0001	
W	0.1939	1	0.1939	16.13	0.0011	
S*T	0.9286	1	0.9286	77.24	< 0.0001	
S*D	0.7520	1	0.7520	62.55	< 0.0001	
S*W	0.0997	1	0.0997	8.30	0.0114	
T*D	0.4402	1	0.4402	36.62	< 0.0001	
T*W	0.0304	1	0.0304	2.53	0.1327	
D*W	0.0145	1	0.0145	1.21	0.2891	
S^2	0.0066	1	0.0066	0.5455	0.4716	
T^2	0.0153	1	0.0153	1.27	0.2775	
D^2	0.4809	1	0.4809	40.01	< 0.0001	
W^2	0.0239	1	0.0239	1.99	0.1791	
Residual	0.1803	15	0.0120			
Lack of Fit	0.1476	10	0.0148	2.25	0.1915	Not significant
Pure Error	0.0328	5	0.0066			
Cor Total	12.77	29				
			Std. Dev.	0.1096	R^2	0.9859
			Mean	0.9489	Adjusted R^2	0.9727
			C.V. %	11.56	Predicted R^2	0.9453
					Adeq Precision	31.7657

The second-order regression model that was created throughout the investigation is shown in Eq. (3).

$$\mathit{Productivity}\left(\frac{kg}{m^2}\right) = +5.46170 + 0.000547\ S - 0.024822\ T - 1.59236\ D - 7.47703\ W + 0.000080\ S*T - 0.000361\ S*W - 0.005263\ S*D + 0.008294\ T*D + 0.087152\ T*W + 0.301225\ D*W + 5.58990E{-07}\ S^2 - 0.000768\ T^2 + 0.107710\ D^2 + 38.40165\ W^2 \quad (3)$$

Figure 5 displays the diagnostic plot acquired during the analysis of productivity. The residuals' normal probability plots show that they follow a linear pattern, indicating that the raw data doesn't need to be transformed in order to build the model. The residual versus run plot suggests that the process is under control since the residuals lie within the upper and lower control boundaries (Veza *et al.* 2023). The plot comparing predicted and actual values indicates that experimental values are comparatively near to the expected values, roughly following 45° line. The perturbation figure demonstrates that higher values of solar intensity, water inlet temperature, and insulation thickness correspond to increased rates of freshwater productivity. Additionally, the plot suggests that increasing water depth hurts water productivity. According to the research, the following factors have the most effects on the production of fresh water: solar intensity>water depth>water inlet temperature> insulation thickness.

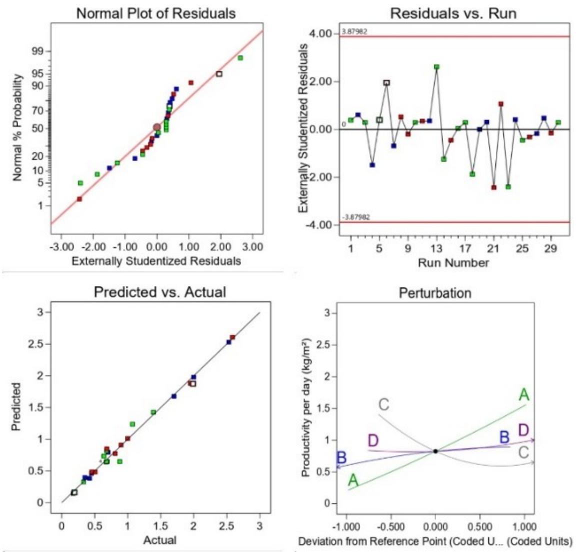


Figure 5. Diagnostic plots for productivity

Figure 6 illustrates the relationship between solar intensity, water inlet temperature and water depth, insulation thickness of PSS. The solar intensity ranges from 350 to 950 W m^{-2}, while the water inlet temperature varies between 30°C and 50°C. The remaining parameters, including insulation thickness and water depth, are set at 0.10 m and 6 cm, respectively. The solar intensity has a more major influence on the productivity of PSS compared to water inlet temperature (Al-Mezeini *et al.* 2023). The productivity increases from 0.482 to 2.472 kg m^{-2} as the solar intensity increases from 350 to 950 W m^{-2}, while maintaining a fixed water inlet temperature of 50°C. The water in the basin becomes warmer due to the increased solar intensity. The rate of evaporation is positively impacted by raising the water's temperature, leading to an increase in the yield of distilled water (ahanpanah *et al.*2021).

Furthermore, with a solar intensity value of 950 W m^{-2}, an increase in the water input temperature from 30 to 50°C results in a 2.472 kg m^{-2} increase in the distillate water productivity rate from 1.833 kg m^{-2}. In contrast, higher water inlet temperature reduces heat losses in solar collectors. As a result, there is a temperature increase between the brine in the basin and the condensing glass cover, which increases the amount of distilled water produced. The insulation thickness is increased from 0.05 to 0.15 m, while water depth is raised from 4 to 8 cm and remaining factors, water inlet temperature and solar intensity are fixed at 40°C and 650 W m^{-2} respectively. The water depth significantly influences solar still efficiency more than insulation thickness (Abdullah *et al.* 2023). The productivity decreases from 0.969 to 0.772 kg m^{-2} as the water depth increases from 4 to 8 cm. while keeping the insulation thickness fixed at 0.15 m. The temperature of the salty water in the basin decreases as the volumetric heat capacity increases when the temperature differential between the water and the glass cover is reduced. As a result, the convective heat transfer coefficient rates between the salinized water and the glass cover decrease, which in turn leads to a decline in freshwater production. In the context of a constant input of solar energy, a decrease in water depth induces higher evaporation rates. In addition, it was found that when the insulation thickness increased from 0.05 to 0.15 m at a water depth of 4 cm, the distillate water productivity rate improved slightly from 0.664 to 0.969 kg m^{-2}. Increasing insulation thickness reduces back heat losses, leading to higher water temperatures and increased productivity of distilled water.

5.1. Confirmation of test

The main objective of the current research is to ascertain the parameter values that result in the highest level of production. Figure 7 displays the ramp plot, illustrating the optimal and predicted values. The ideal circumstances were acquired and used in a confirmation experiment. In order to validate the condition, the experiment used the same experimental configuration. The results of this experiment are presented in Table 6. Experimental values are compared with an error percentage of 0.80.

5.2. Artificial Neural Network

The trainer's confidence in attaining retention serves as the model's motivation. The trainer provides a clear response for the individual parameters during the modelling process. The neural model developed in this study can function without a trainer due to its self-association capabilities. For tackling technological problems, the neural model diagram is mainly used (Chan *et al.*2023 & Khazaai *et al.* 2023). The model includes comprehensive information about to the hidden neurons, their output characteristics, and input parameters. This method is a novel and comprehensive model that can be evaluated by monitoring the layers and neurons in a map (Khayet & Cajocaru,2013). In artificial neural network models, the learning rate, momentum coefficient, and training algorithm are crucial parameters influencing the training process. The learning rate determines the step size for weight updates, impacting the convergence speed; a too high rate may cause overshooting, while a too low one can lead to slow convergence. Momentum introduces a historical gradient term to accelerate optimization, aiding in navigating through flat regions of the loss landscape and enhancing convergence efficiency. The momentum coefficient, typically set between 0.8 and 0.9, requires careful tuning to balance acceleration without causing overshooting or instability. The training algorithm, such as stochastic gradient descent (SGD) or Adam, plays a pivotal role in weight updates based on the loss gradient.

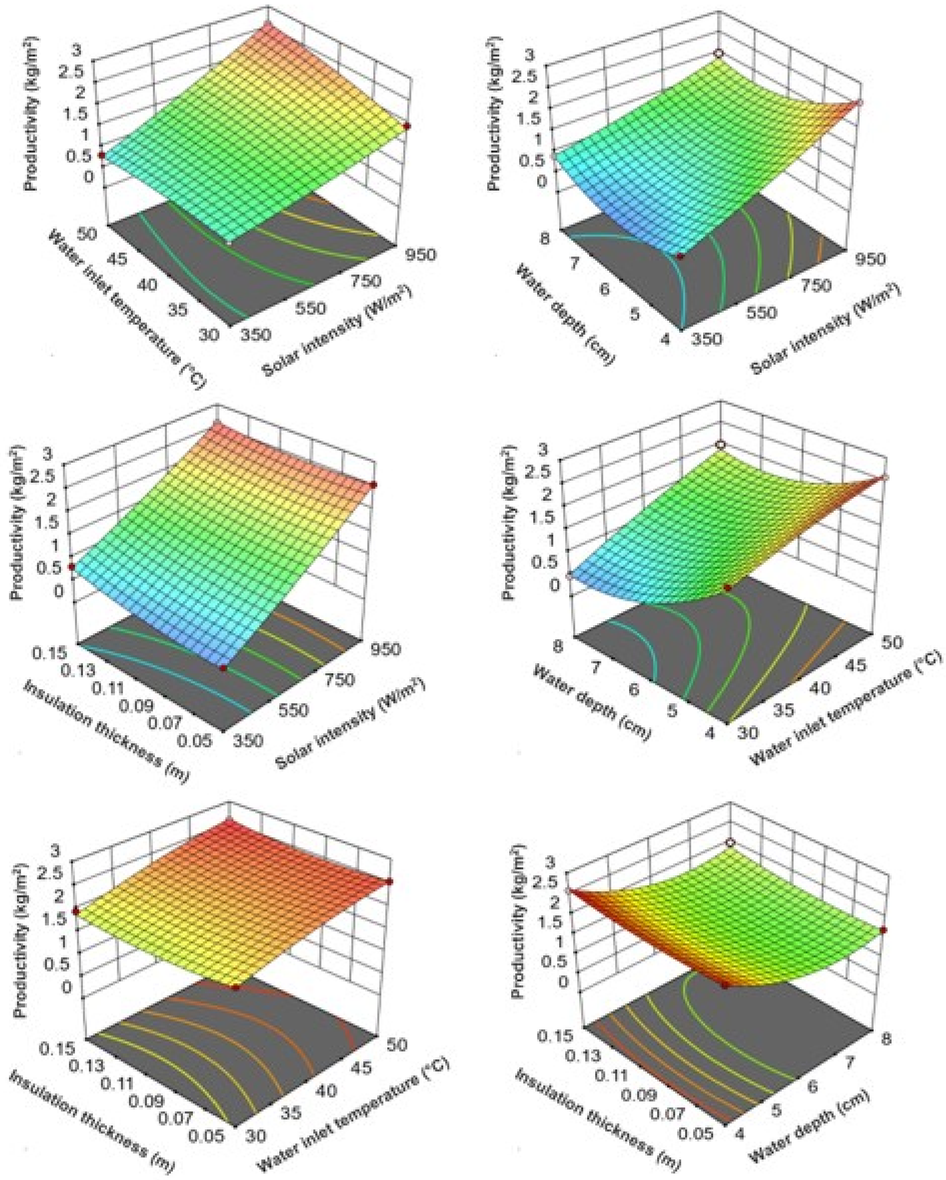


Figure 6. Surface plots show the effect of input process parameters on productivity

The choice of algorithm influences convergence speed and the ability to escape local minima, demanding experimentation to find the most effective approach tailored to the specific problem and dataset. Table 7 displays the results obtained from the ANN model. The average squared difference between the response and the target is measured by the Mean Squared Error, or MSE. Small estimations are quite precise, and the zero is perfect. The level of correlation between the terms and the output is shown by the regression values (R). R has a value of 1, which denotes a positive link, while 0 denotes an unequal correlation. The limitations of mean squared error (MSE) and R are zero and sequential. It is recommended to ensure precise control over the installation of the curve. The network model was designed to have a balanced structure, and its introduction was carefully planned to accommodate any necessary modifications for the training exercise. The histogram inaccuracy of the neural model created for this investigation is shown in Figure 8.

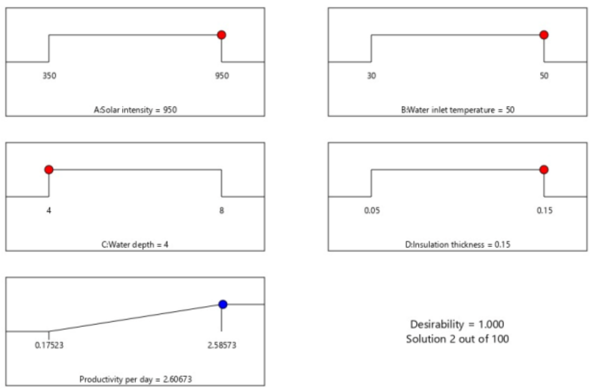


Figure 7. A ramp plot illustrating the state of maximum productivity

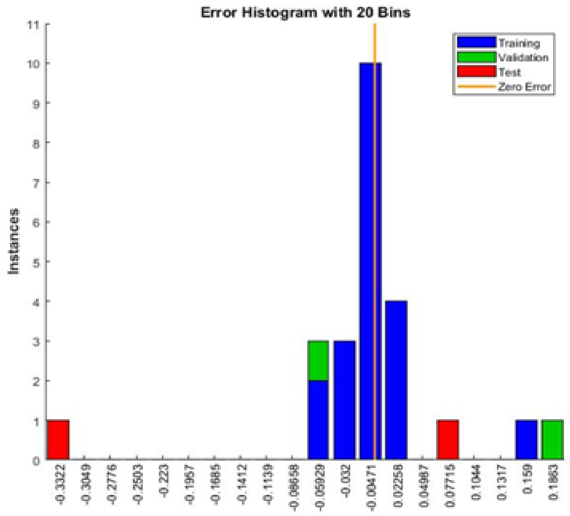


Figure 8. Error histogram chart

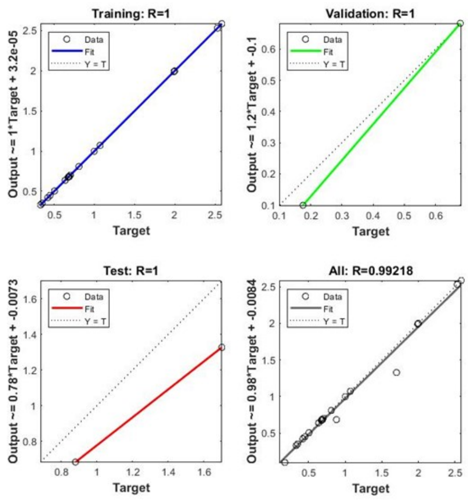


Figure 9. Regression graph for productivity

Table 6. Comparison of experimental and predicted results

Output response	Predicted	Experimental	% Deviation
Productivity(kg/m^2)	2.60673	2.58573	0.80

Table 7. MSE and R values

	Sample	MAP	R
Training	16	1.82379e-2	9.83360e-1
Validation	4	2.68588e-2	9.93866e-1
Testing	4	2.86397e-1	9.93429e-1

Table 8. Experimental and ANN predicted values

Run order	Solar Intensity(W/m^2)	Water Inlet Temperature (°C)	Water Depth (cm)	Insulation Thickness (m)	Productivity experimental (kg m^{-2})	Productivity ANN Predicted (kg m^{-2})
5	350	40	6	0.1	0.19334	0.1963
10	650	40	6	0.1	0.67997	0.6862
15	950	30	8	0.15	0.4545	0.4578
22	950	30	4	0.15	1.94854	1.9392
25	650	40	4	0.1	1.38863	1.4064
29	350	50	8	0.15	0.89856	0.9085

Figure 9 displays the regression plot for the combined training, validation, and test runs of the artificial neural (ANN) network. The obtained regression value of 0.99218 is highly satisfactory. The trend line in the artificial neural network (ANN) model connects the data points during training to provide the best fit for the training data. Validation data is utilized for parameter tuning, while test data is employed for performance assessment. The regression graphs obtained during training demonstrate that the ANN model produces favourable outcomes (Salem *et al.* 2022). Table 8 presents the predicted productivity values obtained using Artificial Neural Networks (ANN) alongside the corresponding experimental values determined for the test conditions. Figure 10 compares the productivity of experimental values with productivity predicted by ANN and RSM models. The predicted values closely align with the experimentally determined values, indicating a reliable model for predicting the productivity of pyramid solar stills (Park *et al.* 2017).

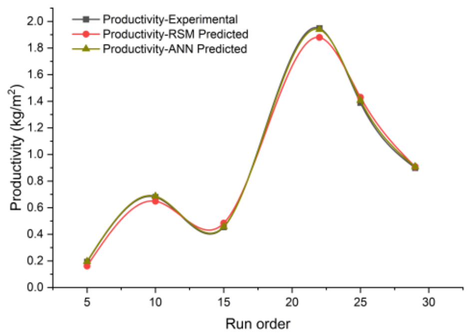


Figure 10. Comparing the productivity values predicted by RSM and ANN with experimental data

6. Validation

The divergence of the outcomes from the RSM and ANN was evaluated by a comparative study. Table 9 displays the data's comparative analysis. Based on the RSM-based desirability method, the difference between the expected and actual productivity was 0.80%. The testing using RSM-based methodology has effectively determined the ideal combination of parameters to maximise the production of the PSS, as shown by the minimal variance. To verify the correctness of the RSM-based optimum parametric configuration, the ANN model was created. The best parametric parameters for the ANN model were used to perform the experiment. The findings show that 2.602 kg m^{-2} was the estimated productivity by ANN. There was a 0.65 percent difference between the predicted and real values. The little divergence shows that the created model is accurate and that it is in good accord with the productivity of the pyramid solar still that has been observed. The study found a strong correlation between the outcomes obtained from Response surface methodology (RSM) and Artificial neural network (ANN) models. Both approaches exhibited similar predictive accuracy in optimizing input parameters for maximizing the pyramid solar still (PSS) performance, emphasizing the reliability of both RSM and ANN in achieving optimal conditions for distillate productivity.

Table 9. Comparative analysis of optimum values

Methodology	Process parameters	Productivity (kg m^{-2}) (Predicted)	Productivity (kg m^{-2}) (Actual)	Deviation (%)
RSM	Solar intensity (950 W m^{-2}) , water inlet temperature(50°C), water depth (4cm) and insulation thickness (0.15m)	2.606	2.585	0.80
ANN		2.602		0.65

7. Conclusion

The following findings were drawn from the carried out experiments and the validation that followed:

- Input process parameters like solar intensity, water intake temperature, and insulation thickness improve the productivity of pyramid solar stills (PSS). Water depth negatively affects the pyramid solar still's output.
- Using a statistical response surface methodology (RSM) model, the interactions and cumulative impacts of the parameters on the daily production of distilled water are investigated. The predicted R^2 and Adjusted R^2 values are 0.9453 and 0.9727, respectively. The polynomial model yields precise prediction outcomes with excellent fit.
- The influences on daily distilled water production are ranked in order of significance: solar intensity, water depth, water intake temperature, and insulation thickness.
- The polynomial statistical model enables calculating and optimizing daily production from a solar still by using four input variables.
- The research found that the optimal combination of factors for reaching the highest production level in a pyramid solar still consists of a solar intensity of 950 W m^{-2}, a water input temperature of 50°C, a water depth of 4 cm, and an insulation thickness of 0.15m. The experimental, RSM optimization and ANN model yielded distillate production rates of 2.585, 2.606 and 2.602 kg m^{-2}, respectively.
- The neural network was created using MATLAB, resulting in a divergence of 5.78% compared to the findings obtained using RSM-based design.
- The research discovered that using an artificial neural network (ANN) model may efficiently provide optimum results in the productivity of pyramid solar stills.
- Pyramid solar stills are effective in arid and remote areas, providing decentralized water solutions and Coastal regions with brackish water.

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