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Original Article

Optimizing Water Productivity in a Passive Solar Still via Advanced Deep Neural Networks Technique

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Abstract: *In the quest for sustainable water purification methods, passive solar distillation systems stand out for their ability to desalinate brackish water efficiently. This research focuses on enhancing the efficacy of such systems across varied sectors, including residential, agricultural, and industrial domains. Key variables such as solar radiation, ambient conditions, wind velocity, and design parameters play pivotal roles in the operational efficiency of solar stills. Leveraging advanced machine learning methodologies, the study introduces an innovative approach using Deep Neural Networks, particularly focusing on the Multilayer Perceptron (MLP) architecture, to refine predictions of system yield. A comparative analysis of various hyperparameter tuning strategies reveals the superior performance of the Particle Swarm Optimization (PSO) technique in conjunction with the MLP model. This synergistic PSO-MLP framework, especially when integrated with a specific solar collector design, demonstrated notable achievements, evidenced by a Coefficient of Determination (COD) of 0.98167 and a Mean Squared Error (MSE) of 0.00006. The findings underscore the significant impact of employing advanced computational strategies to predict and enhance the functionality of solar distillation systems, setting a benchmark for future research in sustainable water purification technologies.*

Keywords: *Deep Neural Networks (DNN), Multilayer Perceptron (MLP), Particle Swarm Optimization, Solar Distillation, WaterPurification.*

I. INTRODUCTION

The escalating crisis of water scarcity, intensified by climate change, demographic expansion, and urban growth, presents a significant global challenge. This issue is particularly acute in various regions where water resources are diminishing, leading to increased water costs and reduced accessibility. The ramifications of this crisis are profound, manifesting in social strife, migration pressures, and heightened health risks, notably in underdeveloped countries where children are disproportionately affected. A comprehensive approach, integrating conservation, infrastructure enhancement, and policy reform at both local and international levels, is vital to mitigate this issue. The United Nations' commitment to ensuring global access to potable water by 2028 [1] underscores the urgency of this mission.

Particularly affected are arid regions, such as the Middle East and North Africa (MENA), where water scarcity is starkly evident. The per capita water availability in the MENA region, significantly lower than the global average, coupled with environmental challenges, rapid population growth, and inefficient water use, exacerbates the situation. Political instability further complicates efforts towards achieving water security in these areas.

In this context, desalination, particularly through solar energy, emerges as a promising solution. Solar stills (SSs) represent a pivotal technology in this domain, utilizing solar energy to purify saline or contaminated water. Their simplicity, cost-effectiveness, and adaptability make SSs particularly appealing for small-scale and remote applications. Despite their potential, the efficiency and output of SSs need enhancement to compete with other desalination technologies, necessitating innovative research and development efforts aimed at improving their design and performance [2, 3, 4, 5].

Significant research has been dedicated to enhancing SS efficiency through material and design innovations. Studies have shown the effectiveness of wick materials in improving evaporation rates and, consequently, water production. For example, Essa et al. [6] demonstrated a significant increase in productivity with the use of reflective surfaces and optimized wick materials. Similarly, innovative approaches involving energy storage materials and thermal insulation have proven to increase the output of SSs [7, 8]. The integration of Phase Change Materials (PCM) and design modifications like hollow circular fins have further augmented the performance of SSs, extending their operational hours and increasing daily water production

[9, 10].

The exploration of hybrid systems and the application of nanotechnology in SS design have also yielded positive results, enhancing desalination efficiency and daily water output [11, 12]. Moreover, advanced mathematical modeling techniques, particularly Deep Neural Networks (DNN) and specifically the Multilayer Perceptron (MLP) model, have been employed to optimize SS design and performance. The MLP model's ability to process complex data sets and identify patterns relevant to SS efficiency has made it a valuable tool in this research domain.

This study leverages DNN and hyperparameter optimization techniques such as Particle Swarm Optimization (PSO), Grid Search (GS), and Bayesian Optimization (BO) to refine the MLP model's predictive accuracy. Recent studies have demonstrated the efficacy of these optimization methods in enhancing the performance of DNN models in predicting SS output [13, 14, 15]. Innovative design approaches, such as the compact vertical water distillation tower and the integration of advanced neural network models, have shown promising results in predicting and improving the performance of solar distillation systems [16, 17].

This introduction sets the stage for presenting our research, which aims to apply DNN techniques, particularly an optimized MLP model, to forecast the water productivity of solar stills integrated with flat plate solar air collectors (CSS-FPSAC) under various conditions. This study not only predicts CSS-FPSAC water output using DNN but also evaluates the impact of different hyper parameter optimization methods on the predictive model's performance.

II. MATERIAL AND METHODOLOGIES

The data pertained to two distinct types of Solar Stills (SSs): a Conventional Solar Still (CSS) and a Single Slope Solar Still integrated with a Flat Plate Solar Air Collector (CSS-FPSAC) as shown in Fig. 1. The CSS featured a base measuring 0.60 m by 0.40 m, with a 4 mm thick glass cover inclined at 16°. Both stills contained steel absorber plates within robust wooden enclosures (0.78 m x 0.54 m). To optimize solar absorption, the internal surfaces of these plates were coated in black. The CSS-FPSAC was larger, with dimensions of 0.90 m by 0.58 m, and utilized a glass cover of 0.785 m by 0.57 m, inclined at 45°. The FPSAC component was designed to mitigate heat loss in colder seasons by warming the CSS's surroundings, thereby maintaining its efficiency throughout the year.

In February 2021, detailed experiments conducted by Chelgham et al. [18] provided a rich dataset under varying meteorological conditions. Measurements were meticulously recorded over 10-hour periods on the 8th, 9th, and 10th of February, capturing key variables such as solar irradiance, temperatures at various points within the SSs, and distilled water output.

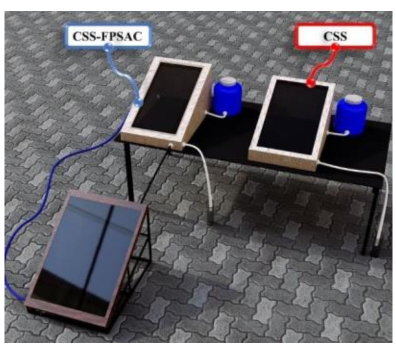

Figure 1: Experimental Setup Display for the Conducted Water Desalination Tests

A. Data Processing

Before analysis, the dataset underwent a rigorous preprocessing regimen to ensure its quality. This process involved cleaning, selecting relevant features, partitioning the data, and normalizing the batches.

B. Cleaning the Data

Initial data cleaning steps focused on identifying and excluding any aberrant data points that could skew the analysis. Utilizing boxplots, we assessed the data distribution and confirmed the absence of outliers, indicating a robust dataset devoid of extreme deviations. Following this, we addressed any potential gaps in the dataset, confirming through visual inspection that no data points were missing, thus ensuring the dataset's completeness and reliability.

C. Selecting Features

The cornerstone of our Machine Learning (ML) model development was an in-depth feature selection process, guided by correlation analysis. This involved evaluating the interrelationships between each variable and the distilled water output, thereby identifying the most impactful features. Notably, our analysis revealed significant correlations among various temperatures measurements within the SSs, affirming their relevance to the distilled water output.

D. Partitioning the Data

The dataset was then divided into distinct subsets for training, testing, and validation. We allocated 80% of the data for model training, with the remaining 20% reserved for testing. A portion of the training set was further designated for validation to fine-tune the model's parameters, ensuring its accuracy and robustness.

E. Normalizing the Data

To enhance the model's performance, we employed Batch Normalization (BN) techniques, standardizing the input data to have zero mean and unit variance. This step is crucial for stabilizing the learning process and improving the model's generalization capabilities.

III. MODEL DEVELOPMENT

A. Development of Multilayer Perceptron (MLP) Model

The Multilayer Perceptron (MLP) is a class of feedforward artificial neural network that includes multiple layers of nodes, each linked to subsequent layers. The structure of MLP allows for the forward propagation of input through the network to generate output. The initial layer receives input data, and the final layer provides the model's predictions. The configuration of hidden layers and the number of nodes within these layers are crucial decisions that influence the model's capacity. In an MLP, each node combines input with a set of coefficients, or weights, adds a bias, and passes the result through an activation function. The incorporation of nonlinear activation functions allows MLP to model complex relationships in the data. Normalization techniques, such as batch normalization, are employed to standardize input data, enhancing model training efficiency and stability [19].

The MLP model begins with an input layer that introduces the data into the network, leading to one or more hidden layers where data undergoes transformations. The output layer then generates the final model predictions, tailored to the specific problem at hand, such as regression or classification tasks. The model's ability to learn from data is refined through the optimization of hyperparameters, including the number of layers, the number of nodes in each layer, and the type of activation functions used.

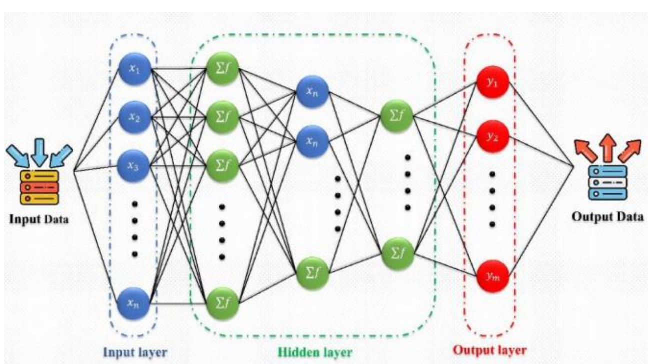

Figure 2: Schematic Representation of an Artificial Neural Network with a Single Hidden Layer

B. Optimization of MLP Hyper Parameters

Optimizing hyperparameters is critical in enhancing an MLP model's performance. This involves selecting the best values for parameters like the number of layers, neurons per layer, activation functions, and learning parameters. Various strategies, including random search, grid search (GS), and more sophisticated methods like Bayesian optimization (BO) and Particle Swarm Optimization (PSO), are utilized to navigate the hyperparameter space effectively.

a) Particle Swarm Optimization (PSO) for MLP

PSO is inspired by social behaviors observed in nature, such as bird flocking, and is used to explore the hyperparameter space of an MLP model. Each particle in the PSO algorithm represents a potential solution, characterized by a set of hyperparameters. The algorithm iteratively updates the particles' positions based on their own experience and that of their neighbors, aiming to find the optimal solution [20, 21, 22].

b) Grid Search (GS) Methodology

GS is a systematic approach to hyperparameter tuning that evaluates a predefined set of hyperparameters to identify the best combination. Although GS is exhaustive and can be computationally intensive, it ensures that every combination is evaluated,providing a thorough exploration of the parameter space [23].

c) Bayesian Optimization (BO) Approach

BO is a probabilistic model-based optimization technique that uses a surrogate model, typically a Gaussian process, to estimate the performance of various hyperparameter sets. BO iteratively selects the most promising hyperparameters to evaluate, balancing exploration and exploitation to efficiently identify optimal settings [24, 25, 26].

d) Tree-Structured Parzen Estimator (TPE)

TPE is another advanced method for hyperparameter optimization, modeling the search space using a tree structure. It updates the distribution of hyperparameters based on the performance of evaluated configurations, focusing on promising areas of the search space [27, 28, 29, 30].

C. Evaluation of MLP Model Performance

The efficacy of the MLP model is gauged using standard regression metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Explained Variance Score (EVS), and Coefficient of Determination (COD). These metrics provide insights into the model's accuracy, with lower MAE and MSE values indicating better performance, and higher EVS and COD values suggesting greater explanatory power of the model.

IV. RESULTS AND DISCUSSION

The predictive performance of the Multilayer Perceptron (MLP) model, augmented with hyperparameter optimization techniques, was rigorously evaluated in the context of forecasting the hourly distilled water output from a solar desalination system, namely CSS-FPSAC. The assessment encompassed a comparative analysis of a baseline MLP model against variants optimized with Particle Swarm Optimization (MLP-PSO), Grid Search (MLP-GS), Bayesian Optimization (MLP-BO), and Tree-structured Parzen Estimator (MLP-TPE). These models were trained on a carefully curated feature set, derived from a correlation matrix, to predict the water yield of the CSS-FPSAC system. The dataset, normalized and split into 85 training instances and 22 test instances, facilitated this analysis.

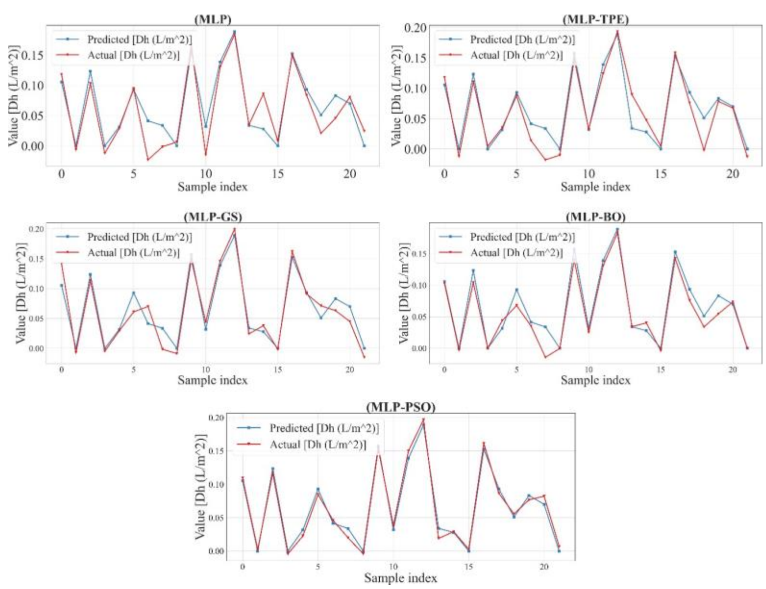

Figure 3: Comparative Graph of Predicted vs. Observed Hourly Water Production in CSS-FPSAC across Multiple Models

The MLP-PSO model demonstrated remarkable predictive accuracy, closely mirroring the actual hourly water yields, as evidenced in Fig. 3. Specifically, the MLP-PSO variant exhibited a Coefficient of Determination (COD) value of 0.981 and a Mean Squared Error (MSE) of just 0.00006, outperforming the MLP-GS, MLP-TPE, MLP-BO, and the standalone MLP model. This superior alignment with experimental data underscores the efficacy of PSO in optimizing MLP's predictive capabilities, particularly in the context of solar still water yield forecasting.

Further quantitative analysis revealed that the MLP-PSO model achieved the lowest error metrics, with an MAE of 0.0068 and an RMSE of 0.0077, significantly lower than those recorded by other models. These results, presented in Fig. 4, highlight the enhanced accuracy of MLP-PSO in predicting the solar still's performance.

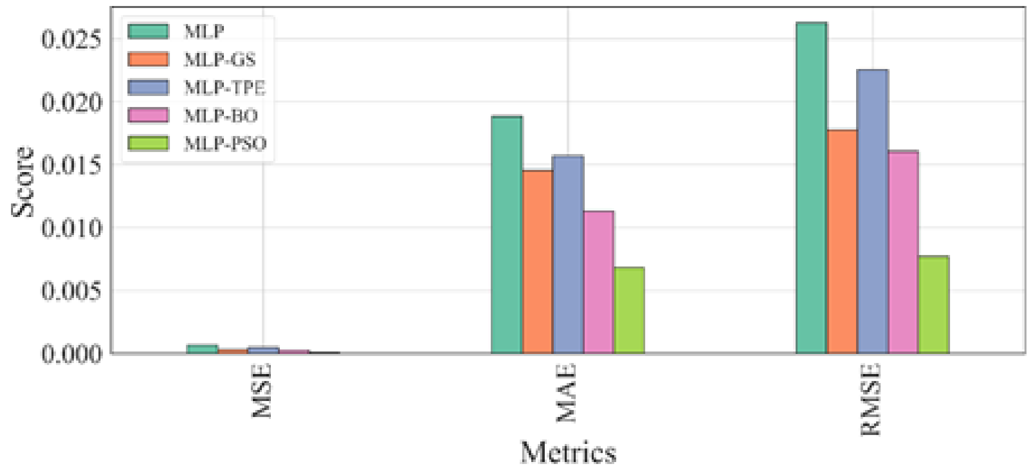

Figure 4: Evaluation of Predictive Models for Hourly Water Production in CSS-FPSAC Using MSE, MAE, andRMSE Metrics for Comprehensive and Subset Features

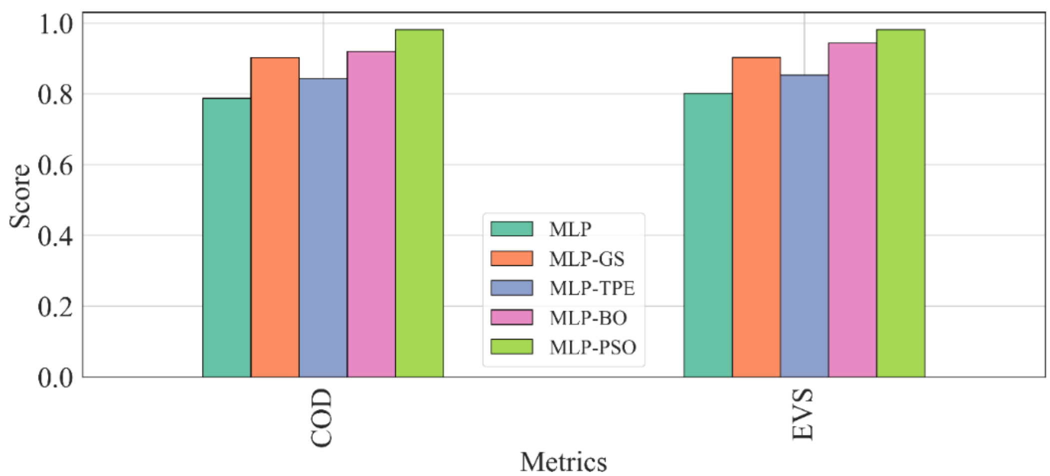

Figure 5: Assessment of Model Predictions for Hourly Water Production in CSS-FPSAC Based on COD and EVSMetrics across Full and Reduced Feature Sets

Visual comparisons in Fig. 5 and Fig. 6, through Q-Q plots and Taylor diagrams respectively, further corroborate the superior correlation of the MLP-PSO model with experimental data. The plots distinctly show the MLP-PSO model's predictions closely hugging the line of perfect agreement, unlike the standalone MLP model which deviates significantly, indicating lesser accuracy.

In addition to these comparative analyses, specific statistical measures were employed to delve deeper into the models' performance nuances. The MLP-PSO model consistently outshined its counterparts across all metrics, with COD and EVS values reaching up to 0.981, signifying an almost perfect match with the experimental outcomes. These findings are visually summarized in Fig. 6, where the Taylor diagram illustrates the MLP-PSO model's proximity to ideal model performance markers, further attesting to its superior predictive power.

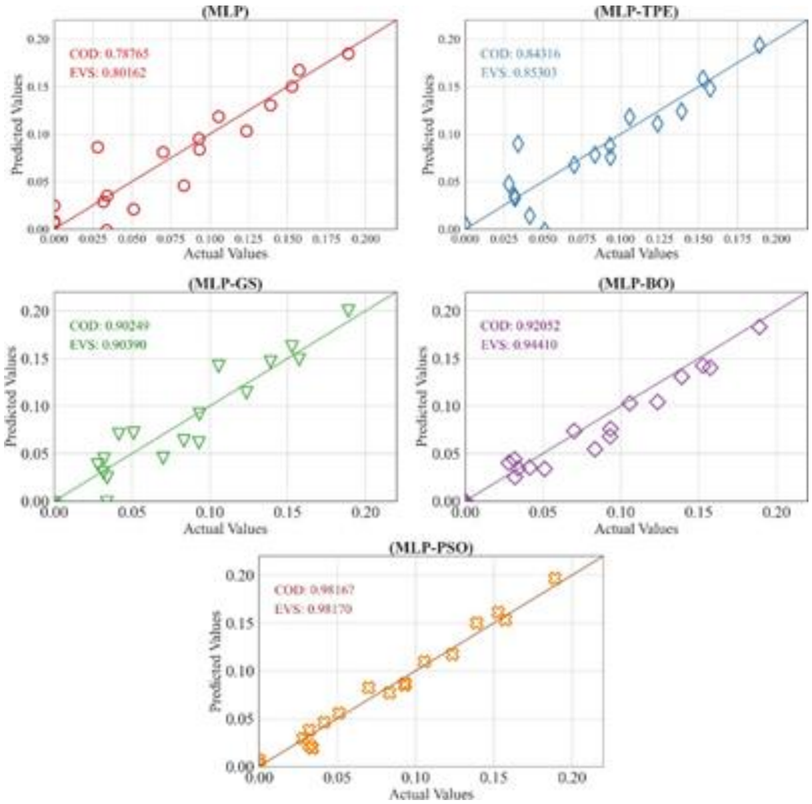

Figure 6: Quantile-Quantile Analysis of Predicted and Actual Hourly Water Production in CSS-FPSAC byVarious MLP Optimizations

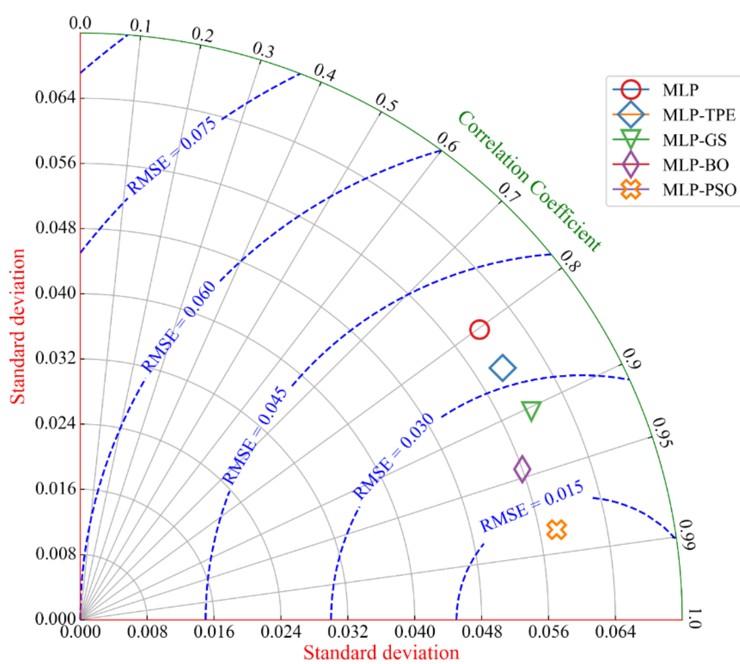

Figure 7: Taylor Diagram Illustrating the Statistical Relationship between Observed and Forecasted HourlyOutputs of CSS-FPSAC via Different MLP Enhancements

In conclusion, the empirical evidence presented herein, supported by comprehensive statistical analysis and visual aids (Fig. 3 through Fig. 7), firmly establishes the MLP-PSO model as the most accurate and reliable tool for predicting the hourly water yield of the CSS-FPSAC system. These insights not only underscore the value of integrating PSO with MLP models in enhancing predictive accuracy but also pave the way for their application in optimizing the design and operation of solar desalination systems for improved water production efficiency.

V. CONCLUSION

This study has demonstrated the efficacy of the Multilayer Perceptron (MLP) model, especially when augmented with Particle Swarm Optimization (PSO) for hyperparameter optimization, in forecasting the hourly water yield of desalination systems with notable precision. The integration of PSO not only improves the accuracy but also strengthens the correlation between the model's predictions and the actual experimental outcomes. Such advancements are pivotal for enhancing the efficiency and reliability of desalination systems.

A comparative evaluation with alternative models, including MLP-GS, MLP-BO, and MLP-TPE, established the superior performance of the MLP-PSO model. This model, characterized by optimized hyperparameters—three hidden layers with 64 units each, ReLU activation, SGD optimizer, 600 epochs, a batch size of 6, and a learning rate of 0.2—showed a significant reduction in Mean Squared Error (MSE) and Mean Absolute Error (MAE) during the training phase, culminating in a final MSE of 0.0001. Such metrics underscore the model's capacity to learn effectively from the data and to make accurate predictions.

Further, the MLP-PSO model outshines its counterparts across all evaluation metrics, achieving the lowest MSE, MAE, and RMSE scores, and the highest Coefficient of Determination (COD) and Explained Variance Score (EVS) values. These results not only confirm the model's superior predictive accuracy but also indicate a strong alignment with experimental data, making MLP-PSO a recommended tool for forecasting water yield in CSS-FPSAC systems.

Given these findings, the study advocates for the integration of PSO with MLP models as a hyperparameter optimization approach to enhance predictive performance in solar desalination applications. The notable precision and reliability of the MLP-PSO model in predicting hourly water yield positions it as a valuable asset for optimizing the operations of CSS-FPSAC systems.

Future research directions include exploring other neural network architectures, such as Convolutional Neural Networks (CNNs) for spatial feature extraction and Recurrent Neural Networks (RNNs) for modeling temporal dependencies, to potentially improve predictive accuracy further. Investigating the integration of deep learning models with traditional machine learning techniques, enhancing model interpretability, and adapting models to real-time data are other promising areas. Additionally, extending the scope to include cost-effectiveness analysis and exploring the durability and maintenance aspects of solar stills could provide a more holistic view of the system's performance. The ultimate goal is to integrate predictive models with solar still control systems for automated and optimized desalination processes, highlighting the potential for significant advancements in thefield of sustainable water purification.

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