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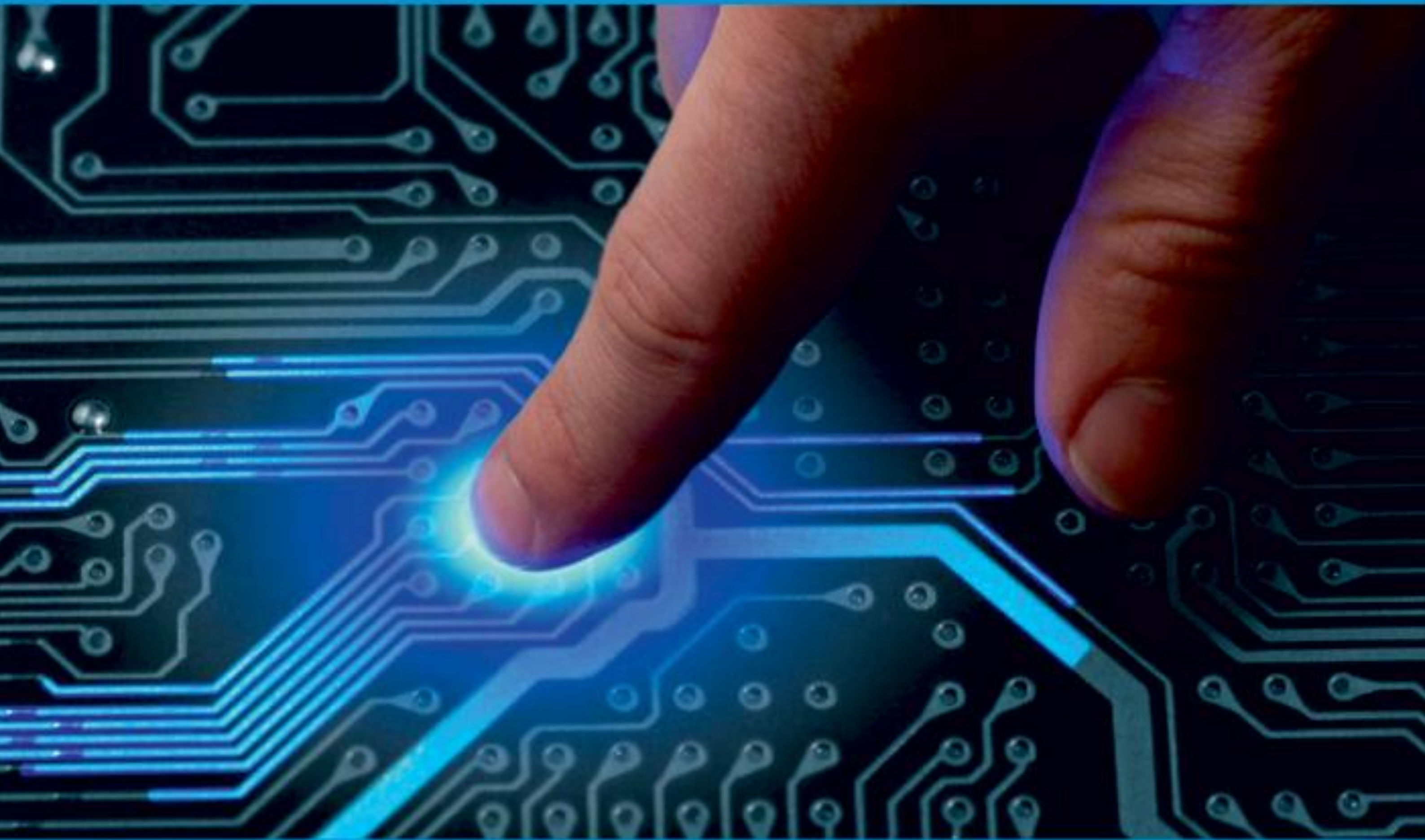

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Optimizing Hyperparameters for Advanced Deep Neural Networks to Predict Solar Still Efficiency

Halimi Soufiane[1], Benmoussa Ahmed[1], Hamidatou Taha[2], Anfal Benrezkallah[3], Soualah Mondir[4], Amira, Mohammed Toufik[1], Babahammou Hammou Ridha[5]

PHD Student, Faculty of Applied Sciences, University Kasdi Merbah of Ouargla, Ouargla, Algeria[1]

PHD Student, Faculty of Science and Technology, University of Djelfa, Djelfa, Algeria[2]

PHD Student, Faculty of Mathematics and Material Sciences, University Kasdi Merbah of Ouargla, Ouargla, Algeria[3]

PHD Student, Faculté de Technologie, Universite Saad Dahlab De Blida 1, Blida, Algeria[4]

PHD Student, Faculty of Science and Technology, University of Mentouri Brothers Constantine, Constantine, Algeria[5]

ABSTRACT: As the demand for sustainable water treatment solutions grows, passive solar distillation emerges as a promising technology for the efficient desalination of brackish water. This study explores the optimization of solar distillation systems for use in various sectors such as residential, agricultural, and industrial. The performance of these systems is influenced by several factors, including solar radiation, ambient conditions, wind speed, and the design of the system itself. By adopting cutting-edge machine learning techniques, this research presents a novel method employing Deep Neural Networks, with a focus on the Multilayer Perceptron (MLP) model, to enhance the accuracy of yield predictions. Through a detailed comparison of different hyperparameter optimization methods, the integration of Particle Swarm Optimization (PSO) with the MLP model was identified as the most effective approach. This combined PSO-MLP model, particularly when applied to a specific design of solar collectors, achieved remarkable results, highlighted by a Coefficient of Determination (COD) of 0.98167 and a Mean Squared Error (MSE) of 0.00006. The study illustrates the profound potential of advanced computational techniques in improving the efficiency of solar distillation systems, contributing valuable insights to the field of sustainable water purification.

KEYWORDS*:* Sustainable Water Treatment, Passive Solar Distillation, Deep Neural Networks, Multilayer Perceptron, Particle Swarm Optimization, Solar Distillation Efficiency, Water Purification Technology.

I. INTRODUCTION

The growing crisis of water shortage, exacerbated by climate change, population growth, and urbanization, poses a significant worldwide challenge. This problem is especially pronounced in areas where diminishing water supplies lead to higher water prices and decreased availability. The impact of this crisis is severe, leading to social conflicts, migration issues, and increased health hazards, particularly affecting children in less developed nations. Addressing this crisis requires a holistic strategy that includes conservation efforts, infrastructure upgrades, and policy changes at both the local and global levels. The United Nations' goal to achieve universal access to drinking water by 2028 highlights the critical nature of this endeavor [1].

Arid regions, such as those in the Middle East and North Africa (MENA), are especially vulnerable to water scarcity. The MENA region's water availability per person is much lower than the global average. This issue is compounded by environmental challenges, rapid demographic expansion, and suboptimal water management practices. Political turmoil also hinders the pursuit of water security in these regions.

Against this backdrop, desalination using solar power presents a viable solution. Solar stills (SSs) are at the forefront of this technology, using solar energy to convert saline or polluted water into potable water. Their simplicity, affordability, and versatility make solar stills especially suitable for small-scale and isolated settings. However, to rival other desalination methods, the productivity and efficiency of solar stills must be improved. This necessitates dedicated research and development to enhance their design and functionality [2-5].

II. RELATED WORK

Extensive studies have focused on boosting the efficiency of solar stills (SSs) through advancements in materials and designs. Research has highlighted the role of wick materials in elevating evaporation rates, thereby enhancing water yield. Notably, Essa et al. [6] identified a marked improvement in SS productivity by incorporating reflective elements and refining wick materials. Furthermore, the adoption of energy storage substances and improved insulation has been shown to elevate SS performance [7, 8]. Enhancements such as integrating Phase Change Materials (PCM) and introducing novel design elements like hollow circular fins have significantly improved SS functionality, leading to longer operational durations and higher daily water outputs [9, 10].
Progress in hybrid systems and the application of nanotechnology to SS designs have further advanced desalination efficiency and daily production rates [11, 12]. In addition, sophisticated computational models, including Deep Neural Networks (DNN) with a focus on the Multilayer Perceptron (MLP) model, have been utilized to optimize SS configurations and functions. The MLP model's capacity to analyze intricate datasets and discern patterns pertinent to SS efficiency underscores its utility in this field.

Our research employs DNN and hyperparameter tuning methods such as Particle Swarm Optimization (PSO), Grid Search (GS), and Bayesian Optimization (BO) to enhance the MLP model's predictive precision. Recent investigations affirm the effectiveness of these optimization techniques in improving DNN models' capabilities in forecasting SS productivity [13-15]. Cutting-edge design concepts, including the compact vertical water distillation tower and the incorporation of sophisticated neural network models, have demonstrated potential in forecasting and ameliorating solar distillation system efficacy [16, 17].
This backdrop frames our study's objective to harness optimized DNN strategies, especially an enhanced MLP model, to predict water production in solar stills paired with flat plate solar air collectors (CSS-FPSAC) under various operational scenarios. Our investigation not only forecasts the water output of CSS-FPSAC using DNN but also assesses the influence of diverse hyperparameter optimization strategies on the model's forecasting accuracy.

III. PROPOSED ALGORITHM

The study examined two variations of Solar Stills (SSs): a standard Conventional Solar Still (CSS) and a Modified Single Slope Solar Still coupled with a Flat Plate Solar Air Collector (CSS-FPSAC), illustrated in Figure 1. The CSS was constructed with a base size of 0.60 meters by 0.40 meters and utilized a glass cover that was 4 mm thick and set at a 16° angle. Both models of stills were equipped with steel absorber plates housed in sturdy wooden frames measuring 0.78 meters by 0.54 meters. These absorber plates were painted black to maximize solar energy absorption. The CSS-FPSAC model was slightly larger, measuring 0.90 meters by 0.58 meters, and featured a glass cover sized at 0.785 meters by 0.57 meters, positioned at a 45° angle. The added Flat Plate Solar Air Collector (FPSAC) in the CSS-FPSAC model served to reduce heat loss during the cooler months, enhancing the efficiency of the CSS throughout the year.
In February 2021, Chelgham et al. [18] conducted comprehensive experiments to gather data on these solar stills under various weather conditions. These detailed observations were taken over 10-hour spans on February 8th, 9th, and 10th, documenting critical parameters such as solar irradiance, temperature readings at different locations within the SSs, and the volume of distilled water produced.

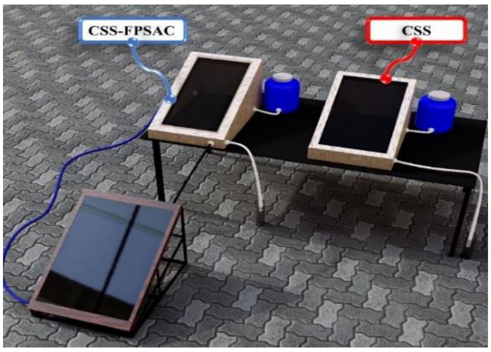

Fig.1. Experimental Configuration Illustration for Water Desalination Trials Conducted

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A. Data Preparation
Prior to analysis, the data underwent a comprehensive preparation process to enhance its quality, including cleansing, feature selection, segmentation, and normalization.

B. Cleansing the Data
The initial step involved scrutinizing the data to remove any anomalies that might affect the analysis. By employing boxplots, we evaluated the distribution of the data, ensuring no outliers were present, which indicated a consistent dataset without significant anomalies. We then examined the dataset for any missing elements, using visual checks to confirm the integrity and completeness of the data.

C. Feature Selection
A critical phase in developing our Machine Learning (ML) model was the meticulous process of selecting relevant features, driven by an analysis of correlations. This step assessed the relationships between each variable and the output of distilled water, pinpointing the most influential variables. Our findings highlighted a notable correlation between various temperature readings within the SSs and the output, underscoring their importance.

D. Data Segmentation
Following feature selection, the data was divided into separate groups for training, testing, and validation purposes. We designated 80% of the dataset for training purposes and set aside 20% for testing. Within the training segment, a subset was allocated for validation to adjust the model's parameters, aiming to enhance its precision and reliability.

E. Data Normalization
To improve the model's efficacy, Batch Normalization (BN) techniques were applied, adjusting the input data to achieve a standard zero mean and unit variance. This normalization is vital for making the learning process more stable and boosting the model's ability to generalize.

IV. MODEL DEVELOPMENT

A. Construction of the Multilayer Perceptron (MLP) Framework
The Multilayer Perceptron (MLP) represents a category of feedforward artificial neural networks characterized by several layers of nodes, interconnected in sequence. This architecture enables the sequential processing of input data through the network to produce output. Initially, the input layer receives the data, which is then processed through various hidden layers until the output layer delivers the model's predictions. The design of these hidden layers and the quantity of nodes they contain are critical factors that affect the model's capabilities. Within an MLP, each node merges incoming data with a specific set of coefficients, known as weights, incorporates a bias, and applies the outcome to an activation function. The use of nonlinear activation functions within the MLP framework permits the modeling of intricate data relationships. To improve the training process and ensure the model's consistency, normalization methods like batch normalization are applied to standardize the incoming data [18].
The MLP structure initiates with an input layer that channels data into the system, leading to several hidden layers where the data is transformed. The concluding output layer then produces the ultimate predictions of the model, which can be adapted for various applications, including regression or classification tasks. The learning efficiency of the model is enhanced through the fine-tuning of hyperparameters such as the number of hidden layers, the nodes per layer, and the choice of activation functions.

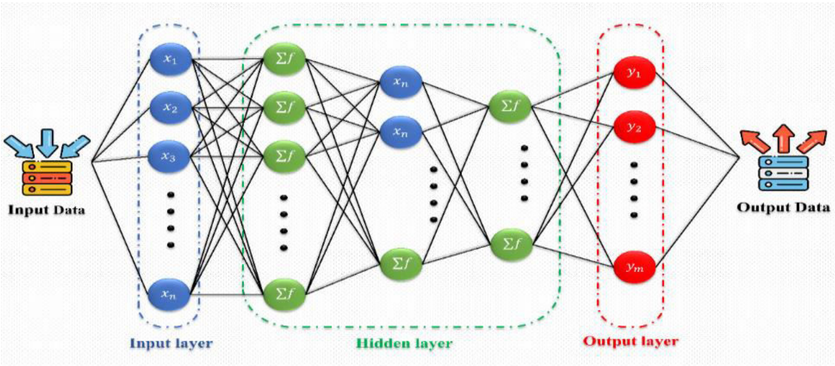

Fig.2. Schematic Diagram of an Artificial Neural Network Featuring One Hidden Layer

B. Tuning of MLP Model Hyperparameters

Fine-tuning hyperparameters is essential for maximizing the efficacy of an MLP model. This process entails determining optimal values for variables such as layer count, neurons in each layer, activation functions, and learning rates. Techniques ranging from simple random and grid searches to more advanced methods like Bayesian optimization and Particle Swarm Optimization are employed for effective hyperparameter exploration.

- Utilizing Particle Swarm Optimization (PSO) in MLP
- PSO draws inspiration from natural social behaviors, like the flocking of birds, to optimize the hyperparameter settings of an MLP model. In PSO, each particle symbolizes a potential solution with a unique set of hyperparameters. The algorithm iteratively adjusts the positions of these particles based on both personal and neighboring experiences, striving to discover the most effective solution [19-21].
- Implementing the Grid Search (GS) Technique
- GS conducts a thorough hyperparameter optimization by systematically evaluating a pre-determined array of hyperparameters to find the most effective combination. Despite its exhaustive nature and potential computational demands, GS guarantees a comprehensive assessment of all possible parameter combinations [22].
- Applying Bayesian Optimization (BO)
- BO is a strategy based on probabilistic models, typically employing a Gaussian process to predict the performance outcomes of different hyperparameter sets. This method strategically selects new hyperparameters to test by balancing the need for exploration of new areas and exploitation of known promising areas, thus optimizing the search for the best parameters efficiently [23-25].
- Leveraging the Tree-Structured Parzen Estimator (TPE)
- TPE represents a sophisticated approach to hyperparameter optimization, organizing the search space with a tree structure. It refines the hyperparameter distribution based on the outcomes of tested configurations, concentrating on more promising regions of the search landscape to improve efficiency [26-29].

C. Assessing the Performance of the MLP Model

To evaluate the performance of the MLP model, commonly used regression metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Explained Variance Score (EVS), and Coefficient of Determination (R^2) are employed. These indicators offer a clear understanding of the model's precision, where lower values of MAE and MSE denote improved accuracy, and higher values of EVS and R^2 reflect the model's enhanced ability to explain the variance in the data.

V. SIMULATION RESULTS

The effectiveness of the Multilayer Perceptron (MLP) model, enhanced through various hyperparameter optimization strategies, was thoroughly examined for its ability to predict hourly water production by a solar desalination unit, specifically the CSS-FPSAC system. This evaluation involved comparing the standard MLP model with versions improved via Particle Swarm Optimization (MLP-PSO), Grid Search (MLP-GS), Bayesian Optimization (MLP-BO), and Tree-structured Parzen Estimator (MLP-TPE). Each model variant was trained using a select group of features identified through correlation analysis to forecast the output of the CSS-FPSAC system. The dataset was normalized and divided, comprising 85 instances for training and 22 for testing, to support this comparative study.

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Among the models, the MLP-PSO stood out for its exceptional accuracy in predicting the actual hourly water outputs, as depicted in Fig. 3. The MLP-PSO model, in particular, achieved a Coefficient of Determination (R^2) of 0.981 and a Mean Squared Error (MSE) of merely 0.00006, surpassing the performance of the MLP-GS, MLP-TPE, MLP-BO, and the base MLP model. This notable performance highlights the effectiveness of PSO as a hyperparameter optimization tool in refining the predictive accuracy of the MLP model, especially for forecasting water yields from solar desalination systems.

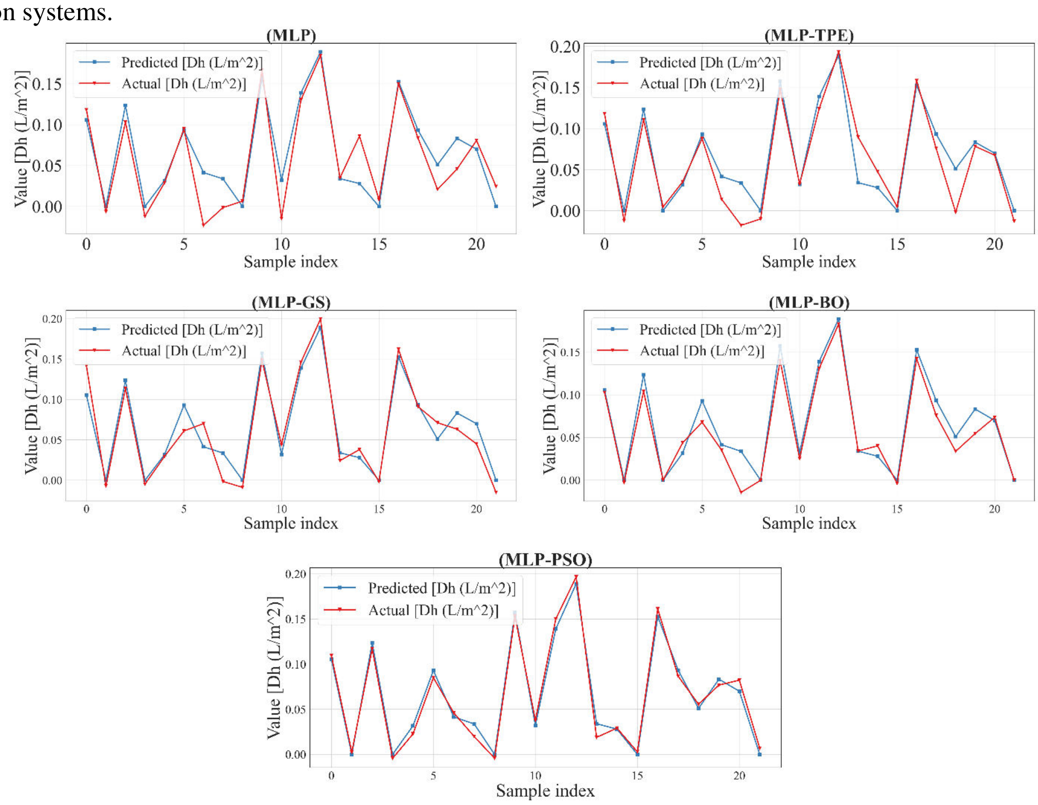

Fig.3. Comparative Visualization of Forecasted Versus Actual Hourly Water Output in CSS-FPSAC Using Various Model Approaches

Subsequent detailed analysis showed that the MLP-PSO model recorded the smallest error values, noting an MAE of 0.0068 and an RMSE of 0.0077, which were markedly less than the metrics associated with other models. These findings, illustrated in Fig. 4, underscore the superior precision of the MLP-PSO in forecasting the efficiency of the solar still.

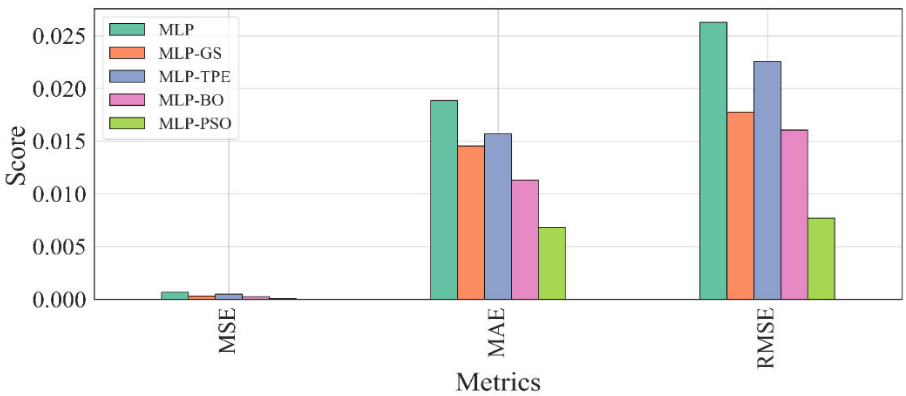

Fig.4. Assessment of Prediction Models for Hourly Water Output in CSS-FPSAC via MSE, MAE, and RMSE Indicators, Considering Both Comprehensive and Specific Feature Sets

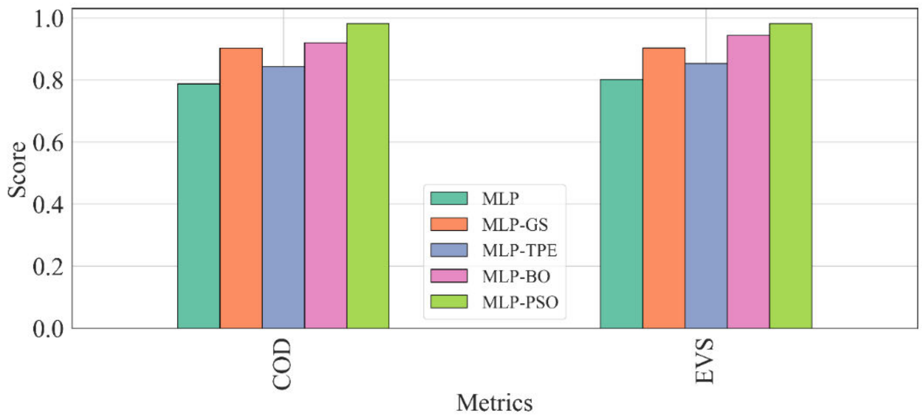

Fig.5. Evaluation of Model Forecasts for Hourly Water Yield in CSS-FPSAC Using COD and EVS Measures for Complete and Condensed Feature Collections

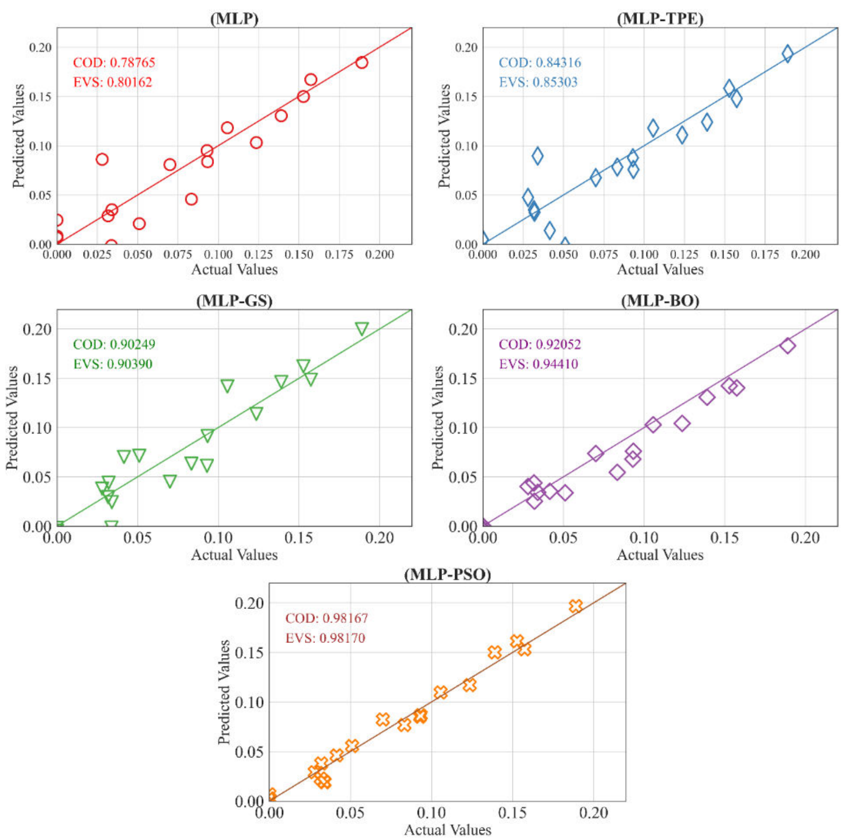

Fig.6. Quantile-Quantile Comparison Between Forecasted and Real Hourly Water Output in CSS-FPSAC Through Different MLP Enhancement Techniques

The graphical analyses in Figures 5 and 6, utilizing Q-Q plots and Taylor diagrams, respectively, further confirm the MLP-PSO model's exceptional alignment with the experimental observations. These visuals distinctly illustrate that the predictions from the MLP-PSO model align more closely with the perfect agreement line compared to those from the base MLP model, which shows greater deviation and thus lower accuracy.

Beyond these visual comparisons, detailed statistical evaluations were conducted to explore the intricacies of the models' performances. The MLP-PSO model consistently surpassed other models in all evaluated metrics, achieving

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COD and EVS scores as high as 0.981, indicating a near-perfect correlation with the actual data. These results are visually represented in Fig. 6, where the Taylor diagram demonstrates the MLP-PSO model's closeness to the ideal performance benchmarks, further validating its enhanced predictive capability.

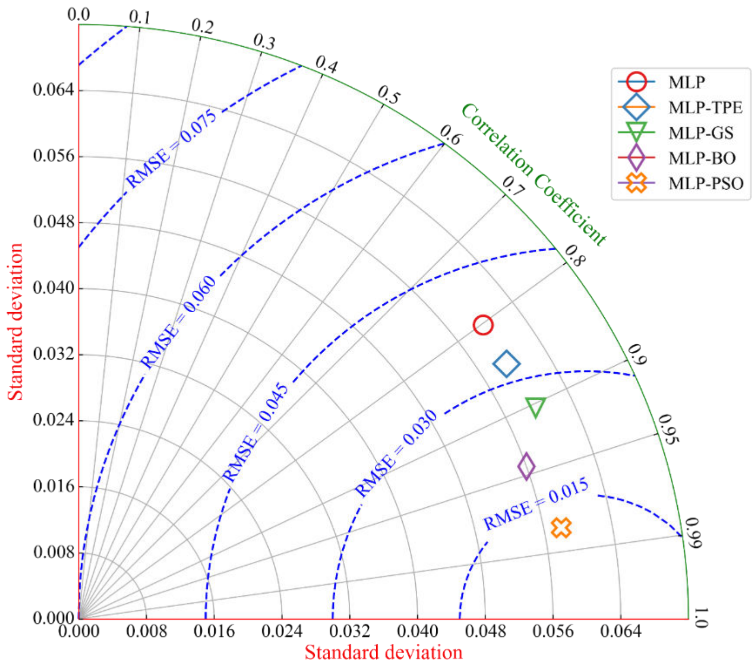

Fig.7. Taylor Diagram Depicting the Statistical Correlation Between Actual and Predicted Hourly Water Yields of CSS-FPSAC Through Various MLP Optimization Techniques

In summary, the findings detailed in this discussion, bolstered by extensive statistical evaluations and illustrated through Figures 3 to 7, definitively position the MLP-PSO model as the premier choice for accurately forecasting the hourly water output of the CSS-FPSAC system. This body of evidence highlights the significant advantages of incorporating Particle Swarm Optimization with Multilayer Perceptron models to boost prediction precision. Furthermore, these insights open new avenues for applying such enhanced models in the refinement and operational optimization of solar desalination systems, aiming to elevate their water production capabilities.

VI. CONCLUSION AND FUTURE WORK

This research highlights the effectiveness of the Multilayer Perceptron (MLP) model, particularly when enhanced with Particle Swarm Optimization (PSO) for fine-tuning hyperparameters, in accurately predicting the hourly output of water from desalination systems. The PSO integration not only bolsters the model's precision but also reinforces the alignment of its predictions with actual experimental data, marking a critical step forward in improving the operational efficacy and dependability of desalination units.

When compared to other models like MLP-GS, MLP-BO, and MLP-TPE, the MLP-PSO model emerged as the frontrunner. Its optimized configuration—consisting of three hidden layers with 64 units each, ReLU activation function, SGD optimizer, 600 epochs, a batch size of 6, and a learning rate of 0.2—demonstrated a substantial decrease in Mean Squared Error (MSE) and Mean Absolute Error (MAE) throughout the training period, culminating in a remarkably low final MSE of 0.0001. These figures underscore the model's adeptness at learning from the dataset and delivering precise forecasts.

Moreover, the MLP-PSO model surpassed other models in all evaluative metrics, recording the lowest MSE, MAE, and RMSE values, alongside the highest Coefficient of Determination (COD) and Explained Variance Score (EVS) metrics. These outcomes not only attest to the model's unmatched predictive accuracy but also its strong congruence with experimental findings, positioning the MLP-PSO model as a recommended predictive tool for CSS-FPSAC systems.

This study advocates for the fusion of PSO with MLP models as a strategy for hyperparameter optimization to elevate predictive accuracy in solar desalination endeavors. The exceptional precision and reliability of the MLP-PSO model in forecasting hourly water production earmark it as a crucial resource for optimizing CSS-FPSAC system operations.

Looking ahead, future studies might delve into alternative neural network frameworks like Convolutional Neural Networks (CNNs) for extracting spatial features, and Recurrent Neural Networks (RNNs) for capturing temporal patterns, to possibly enhance predictive precision further. Other promising research avenues include combining deep learning models with traditional machine learning methods to increase model interpretability, adapting models for real-time data processing, and extending research to encompass cost-efficiency analyses as well as durability and maintenance considerations for a comprehensive understanding of system performance. The ultimate aim is to marry predictive models with solar still control mechanisms for automated, optimized desalination operations, showcasing the vast potential for innovation in sustainable water treatment solutions.

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