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Enhancing Solar Forecasting Accuracy: A Comprehensive Evaluation of Artificial Neural Networks for Global Horizontal Irradiance Prediction

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Abstract – Solar energy plays a pivotal role in the global transition toward sustainable energy systems, providing a clean and renewable power source. However, the inherent variability of solar irradiance presents significant challenges for energy management and grid stability. Accurate forecasting of Global Horizontal Irradiance (GHI) is crucial for optimizing photovoltaic (PV) power generation and ensuring a reliable energy supply. GHI prediction is particularly complex due to its dependence on dynamic meteorological factors, including cloud cover, atmospheric aerosols, temperature, and humidity. Traditional statistical and physical models often struggle to capture these nonlinear patterns, whereas artificial intelligence (AI)-based approaches, particularly artificial neural networks (ANNs), have demonstrated significant potential in improving forecasting accuracy. This study examines GHI prediction in Dakhla City, Morocco, utilizing two AI-based models: the Multilayer Perceptron (MLP) and the Nonlinear Autoregressive Model with Exogenous Inputs (NARX). The objective is to enhance forecasting accuracy to facilitate more efficient solar energy integration. A performance evaluation based on statistical metrics reveals that the NARX model significantly outperforms the MLP model, achieving a regression coefficient (R) of 0.999 and a root mean square error (RMSE) of 8.722. This superior performance is attributed to the NARX model's capacity to capture nonlinear dependencies and incorporate past values alongside exogenous inputs. These findings underscore the effectiveness of AI-driven models in solar energy forecasting. Enhanced GHI predictions can contribute to improved grid stability, optimized solar energy utilization, and the advancement of Morocco's renewable energy objectives. As such, AI-based forecasting emerges as a critical tool for sustainable energy management.

Keywords – Solar *Energy, Artificial Neural Networks, Global Horizontal Irradiance Forecasting, MLP, NARX.*

I. INTRODUCTION

The escalating global energy demand, driven by industrial expansion and shifts in investment patterns, has contributed to a significant rise in crude oil prices[1]. However, the depletion of fossil fuel reserves, coupled with growing environmental concerns, underscores the unsustainability of continued reliance on conventional energy sources[2]. The transition to sustainable energy sources is both imperative and unavoidable for long-term sustainability[3]. Beyond mitigating global warming, renewable energy fosters economic growth and enhances quality of life by mitigating greenhouse gas emissions and minimizing the environmental impacts associated with fossil fuel consumption[4].

Solar energy is a prominent renewable energy source due to its abundant availability, scalability, and diverse applications[5]. It provides a sustainable and environmentally responsible alternative to fossil fuels, as it does not produce greenhouse gas emissions during operation. Advances in photovoltaic and concentrated solar power technologies have improved efficiency, making solar energy suitable for residential, commercial, and large-scale power generation. Its applications extend to grid integration, water desalination, agriculture, and space technology[6], [7].

Solar energy generation is inherently intermittent and highly dependent on weather conditions, leading to power fluctuations that can affect grid stability. To mitigate these challenges, advances in energy storage, grid modernization, and predictive modeling are essential for improving reliability[8], [9]. Solar irradiance is classified into four main components: Direct Normal Irradiance (DNI), Global Horizontal Irradiance (GHI), Diffuse Horizontal Irradiance (DHI), and Ground Reflected Irradiance (GRI). Among these, GHI is the primary metric for evaluating photovoltaic (PV) system performance, though its accurate estimation remains challenging due to complex atmospheric processes and meteorological variability[10]. Traditional physical models struggle to capture these nonlinear dependencies, highlighting the need for advanced methodologies to enhance GHI forecasting and support the seamless integration of solar energy into modern power systems[11].

Machine learning (ML) and deep learning (DL) have emerged as pivotal methodologies in solar energy forecasting due to their capability to analyze large, complex datasets and capture intricate, nonlinear relationships between meteorological variables and energy outputs[12]. These advanced computational models have demonstrated superior accuracy, efficiency, and robustness compared to traditional forecasting approaches, thereby enhancing the reliability of solar energy predictions. Their integration into energy management systems contributes to improved grid stability and optimized resource allocation. The increasing adoption of ML and DL underscores their transformative potential in renewable energy forecasting, positioning them as critical tools in facilitating the global transition toward sustainable energy systems[13].

The research literature encompasses numerous published studies that employ various methodologies for forecasting solar irradiation. For example, [14] assessed the performance of five machine learning algorithms: random tree, random forest, decision stump, multilinear regression, and linear regression, for forecasting solar radiation in three South African locations with diverse radiation patterns. The results demonstrated high prediction accuracy, with R^2 values varying from 53.7% to 98.6% and RMSE values between 47.1923 and 83.0989, depending on the location. Strong forecasting performance was observed in Pretoria and Vuwani, especially on cloudy days. Bloemfontein achieved the best overall results, with RMSE values nearing zero across all algorithms. [13] proposed a dual-branch deep learning model for hourly GHI forecasting, incorporating global and local temporal extractors with attention mechanisms to enhance feature representation. To improve robustness, an autoregressive linear model is integrated to compensate for nonlinear outputs. Experimental validation on public datasets shows a 41.76% improvement in forecasting accuracy over baseline models, surpassing state-of-the-art approaches. Zina and Octavian [15] conducted a study on predicting daily direct solar radiation utilizing the NARX model and found that it yielded robust results throughout periodic training. Similarly, M. A. Hamdan and E. Abdelhafez [16] forecasted hourly solar radiation using three different neural network models: NARX, Feedforward, and Elman. Their study demonstrated that the NARX model outperformed other models, yielding the most accurate results in both the training and validation phases of solar radiation prediction. In an analysis of solar radiation in Mutah, Yazeed and Khaled [17] developed seven different NARX network models by varying input variables, number of neurons, and time delays. Their findings indicated that the model incorporating three key factors temperature, humidity, and wind speed was the most effective for estimating solar radiation. Likewise, [18] used the NARX network to forecast hourly solar radiation in Amman. To assess the performance of the NARX model, they maintained a fixed model structure while varying the training algorithms: LM (Levenberg-Marquardt), RP (Resilient Backpropagation), SCG (Scaled Conjugate Gradient), CGP (Conjugate Gradient with Polak-Ribiére updates), CGF (Conjugate Gradient with Fletcher-Reeves updates), CGB (Conjugate Gradient with Powell-Beale restarts), and OSS (One-Step Secant Backpropagation). They concluded that the LM algorithm provided the most successful results.

This study aims to forecast Global Horizontal Irradiance (GHI) in Dakhla city using hourly meteorological data from the years 2019 to 2022. To tackle this regression problem, supervised learning techniques are applied using two distinct types of neural networks. The first model is the MLP, which consists of multiple layers where information flows from the input to the output layer through a feedforward process. The second model the NARX model. This model incorporates feedback loops that allow the network to store information from previous inputs, making it well-suited for time series forecasting. By comparing the performance of the MLP and NARX networks, the study aims to identify the most effective approach for GHI forecasting in Dakhla city. This research contributes to the field of renewable energy by providing valuable insights into how advanced neural network models can improve the accuracy of GHI predictions.

II. MATERIALS AND METHOD

This research employs a data-driven approach that integrates environmental variables specific to Dakhla, Morocco (23.684°N, 15.957°W), to predict short-term hourly temperature variations critical for optimizing solar energy systems. Various neural network algorithms are applied to determine the most effective model for ambient temperature forecasting, enhancing the operational efficiency of renewable energy systems. The study follows a structured methodology, beginning with data collection from the National Renewable Energy Laboratory (NREL) and subsequent preprocessing, including data cleaning, normalization, and partitioning. Two artificial intelligence models, the Multilayer Perceptron (MLP) and the Nonlinear Autoregressive Model with Exogenous Inputs (NARX-SP), are selected for comparison and trained using climatic input data to predict Global Horizontal Irradiance (GHI). Their performance is assessed using statistical metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2), with a focus on minimizing errors. A comparative analysis identifies the most accurate model, supporting improved solar power forecasting and grid stability.

A. Artificial Neural Networks

Artificial Neural Networks (ANNs) are computational models that replicate the structure and function of biological neural networks, enabling them to solve complex problems across a wide range of applications. Typically, ANNs are composed of three layers: an input layer, one or more hidden layers, and an output layer. The key advantages of ANNs include their speed, simplicity, and ability to learn from historical data to generate accurate predictions. ANNs are widely used in tasks such as pattern recognition, optimization, clustering, regression, and forecasting.

The process of developing an ANN model involves three key steps: First, the input data and corresponding desired outputs are provided to the network. Second, the network is trained to approximate the output through iterative learning. Finally, during the testing phase, the trained network predicts outputs using previously unseen input data[19].

B. MLP Model

MLP is a type of artificial neural network characterized by its layered design, which includes an input layer, one or more hidden layers, and a final output layer. It functions as a feedforward network, allowing data to flow in a forward direction, progressing from the input layer through the hidden layers to the final output layer[20].

The Multi-Layer Perceptron (MLP) consists of three primary components[21]:

Input Layer: Functions as the initial point of data entry, where each neuron represents a distinct feature of the input dataset.

Hidden Layers: These layers transform the input data by applying weights, biases, and nonlinear activation functions to enable learning and model expressiveness.
Output Layer: Generates the final predictions, with the number of neurons determined by the task (e.g., binary classification, multi-class classification, or regression).
The hierarchical structure of the MLP allows it to approximate complex functions and identify intricate patterns in data, making it a core model in DL and ML applications. The mathematical model of an MLP is represented by the equation[22]:

$$y = f(s) = f(\sum w_{ij}\, x_j + b_i) \qquad (1)$$

where s is the summation function, x_j are the inputs, w_{ij} are the connection weights, b_i is the bias, and f is the hyperbolic tangent activation function. Figure 2 illustrates an example of a multilayer perceptron comprising a hidden layer and an output layer.

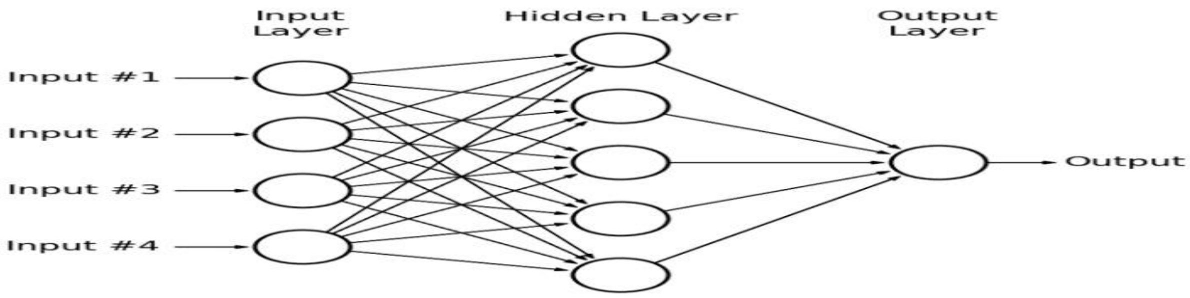
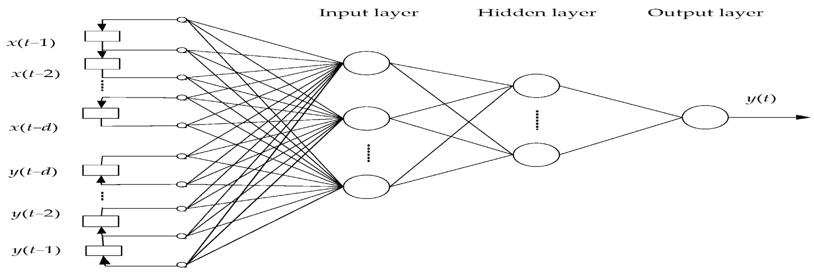


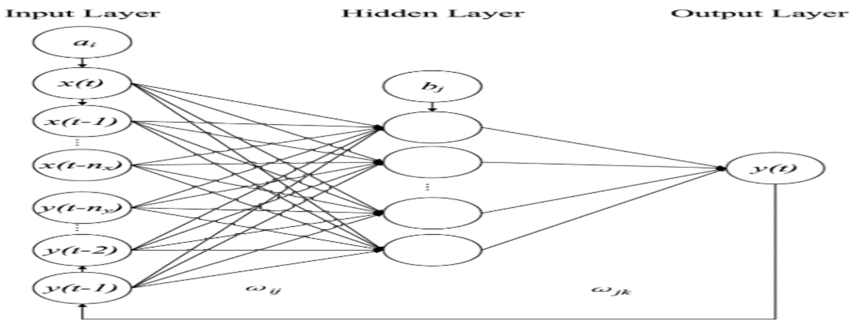
Fig. 2 Architecture of multilayer artificial neural network[19]

C. NARX Model

The NARX model is a variant of ANN that employs training methodologies akin to those used in traditional networks, utilizing the gradient backpropagation algorithm[23]. A key distinguishing feature of NARX is its capacity to effectively analyze nonlinear time series, particularly in dynamic systems. Moreover, the gradient descent algorithm within the NARX framework exhibits faster convergence compared to alternative neural network models. The model can be deployed in both closed-loop and open-loop configurations, as illustrated in Figures 3(a) and 3(b), enhancing its flexibility and effectiveness in forecasting complex temporal patterns.



(a)



(b)

Fig. 3 The NARX architectures in (a) an Open Loop Arrangement and (b) in a Closed Loop Arrangement[24], [25]

D. Evaluation Metrics

Mean Square Error (MSE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2) were employed to assess the accuracy and performance of the prediction models. MSE and RMSE quantify the discrepancy between actual and predicted values, with lower values indicating higher predictive accuracy[1]. The R^2 value measures the proportion of variance in the dependent variable that is explained by the model, with values approaching 1 signifying a better fit. An optimal model is characterized by minimal MSE and RMSE, alongside a high R^2 value, indicating strong predictive capability[26].

The formulas for MAE, RMSE, and R^2 are as follows[26]:

$$MAE = \frac{1}{N}\sum|\hat{y}_i - y_i| \qquad (2)$$

$$RMSE = \sqrt{\sum\frac{(\hat{y}_i - y_i)^2}{N}} \qquad (3)$$

$$R^2 = 1 - \frac{\sum(\hat{y}_i - y_i)^2}{\sum y_i - \bar{y}} \qquad (4)$$

Where, y represents the actual value, $\hat{y}$ is the predicted value, N is the number of samples, and $\bar{y}$ is the mean of the actual values.

III. RESULTS

E. Correlation Analysis

The relationship between the input features and the target variable is analyzed using correlation analysis. Specifically, Pearson’s correlation coefficient is computed, and the resulting correlation matrix is presented in Fig. 5. The analysis reveals that GHI exhibits a strong positive correlation with clearsky GHI, clearsky DNI, and DNI, while demonstrating strong negative correlations with solar zenith angle, and relative humidity. Conversely, surface albedo and pressure show minimal correlation with GHI. Consequently, these two features are excluded from further analysis to enhance model efficiency and reduce dimensionality.

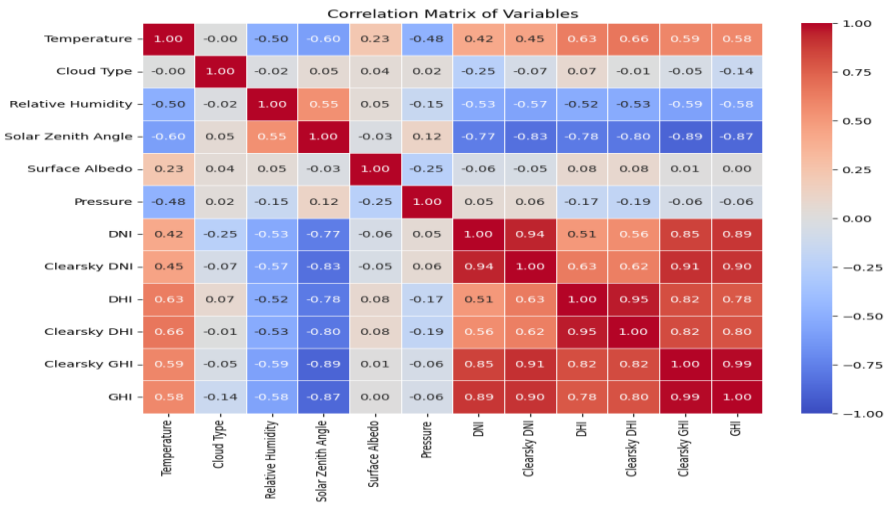


Fig. 4 Heatmap of the correlation between GHI and climatic variables

F. GHI Forecasting

The plot represents the performance of the MLP model in predicting GHI. The blue dots indicate the actual GHI values, while the orange crosses represent the predicted values. The model follows the general trend of the true GHI values, capturing the peaks and fluctuations in solar irradiance. However, there are some deviations, particularly in certain peaks where the predictions slightly underestimate or overestimate the actual values. The model effectively learns the pattern of GHI variation but may struggle with sudden changes, indicating potential improvements with more advanced architectures or additional temporal features.

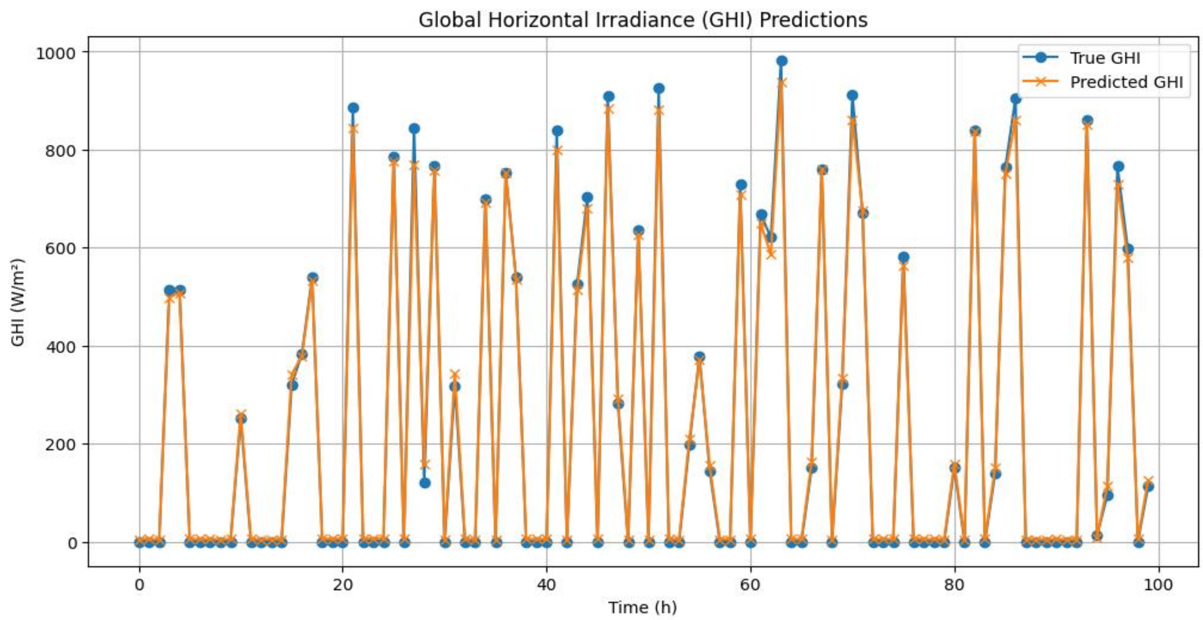


Fig. 5 The forecasting of GHI using the MLP model

Figure 6 illustrates the performance of the NARX-SP model in predicting GHI. Compared to the MLP model, the NARX-SP model appears to achieve a closer alignment between true (blue dots) and predicted (orange crosses) values. The predictions effectively capture both the peaks and fluctuations in GHI, indicating that the model leverages past GHI values and external meteorological factors efficiently. There are fewer noticeable deviations, suggesting an improvement in capturing temporal dependencies and sudden changes. This implies that incorporating autoregressive components enhances the model's ability to learn the dynamic patterns of solar irradiance.

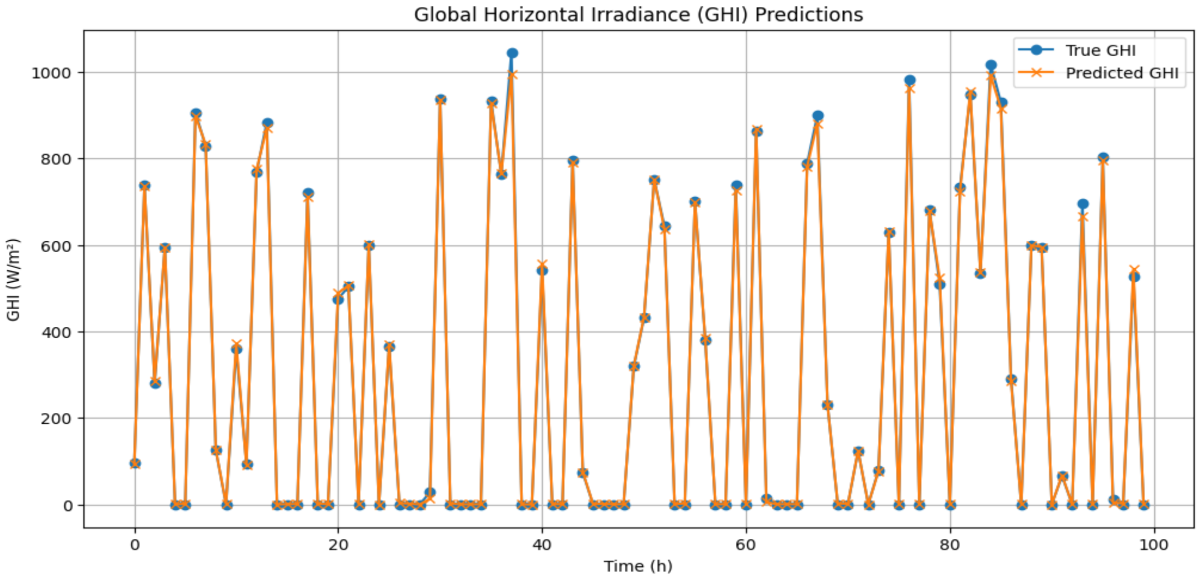


Fig. 6 The forecasting of GHI using the NARX model

Table 1 indicates that the NARX-SP model outperforms the MLP model in terms of prediction accuracy. With an MAE of 4.498 compared to 11.891 for MLP, NARX-SP demonstrates a significantly smaller average deviation from the actual values. Similarly, the RMSE is nearly half that of MLP (8.722 vs. 16.851), suggesting that NARX-SP makes fewer large errors. Additionally, both models exhibit high R^2 values (0.999 for NARX-SP and 0.997 for MLP), indicating that they explain almost all the variance in the data. However, the slightly higher R^2 of NARX-SP suggests a marginally better fit. Overall, NARX-SP proves to be the superior model, offering higher accuracy and better generalization compared to MLP.

Table 1. Performance metrics for MLP, and NARX-SP Models

Performance metrics	**MLP**	**NARX-SP**
MAE	11.891	4.498
RMSE	16.851	8.722
R^2	0.997	0.999

IV. DISCUSSION

The comparison between the MLP and NARX-SP models for GHI forecasting highlights the superior performance of the NARX-SP model. While both models exhibit a strong ability to predict GHI values, key differences emerge in their ability to capture fluctuations and sudden variations in solar irradiance. The MLP model, despite following the general trend, struggles with rapid changes, occasionally underestimating or overestimating peak values. This limitation suggests that it lacks an effective mechanism to account for temporal dependencies, making it less reliable in capturing dynamic variations in GHI. On the other hand, the NARX-SP model demonstrates a much closer alignment between actual and predicted GHI values. By leveraging past GHI data and external meteorological factors, it effectively captures both trends and sudden fluctuations, resulting in a more accurate forecast. The reduced deviation in predictions suggests that the model benefits from its autoregressive structure, allowing it to better understand the inherent patterns of solar irradiance. This improvement is further supported by the error metrics, where the NARX-SP model achieves significantly lower MAE and RMSE compared to the MLP model. In numerical terms, the performance gap is evident. The MAE of the NARX-SP model is 4.498, which is less than half of the MLP model's 11.891, indicating that its predictions are much closer to the true values. Similarly, the RMSE of NARX-SP (8.722) is nearly half that of MLP (16.851), reinforcing its ability to minimize large errors. Although both models achieve high R^2 values, the NARX-SP model (0.999) slightly outperforms the MLP model (0.997), indicating a marginally better fit and improved variance explanation.

V. CONCLUSION

In this study, two distinct neural networks (MLP and NARX) were employed to forecast Global Horizontal Irradiance (GHI) in Dakhla, Morocco, using hourly meteorological data from 2019 to 2022. The findings indicate that the NARX-SP model demonstrates superior reliability for GHI forecasting, particularly in environments characterized by sudden fluctuations in solar irradiance. These results underscore the critical role of incorporating temporal dependencies in predictive models, as evidenced by the enhanced performance of NARX-SP. Future research could focus on further advancements, such as hybrid models that integrate deep learning architectures like GRU-LSTM-TCN, which may offer improved accuracy and adaptability in solar energy forecasting.

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