# Artificial intelligence-based solar radiation forecasting for energy optimization in sustainable buildings

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**ABSTRACT**

The work presented in this article aligns with our university's commitment to advancing renewable energy sources. We can better plan and optimize energy use if we are aware of the factors that affect solar energy generation. This study examines the application of artificial neural networks (ANNs) in forecasting global horizontal irradiance (GHI) within the context of sustainable energy. The primary objective is to enhance the accuracy and reliability of solar irradiance forecasts, thereby improving the performance of renewable energy systems, such as concentrated solar power (CSP). This article provides an overview of solar radiation, the physical factors that influence its distribution, and the impact of panel tilt angle on energy production. It presents a case study in Morocco, which uses a hybrid approach to predict solar radiation. The results demonstrate that ANN, employing advanced machine learning (ML) methods, provides more accurate and reliable forecasts than traditional models. This advance could improve energy planning, reduce uncertainty, and enable better management of solar energy production and storage systems. Our results suggest that this approach has increased forecast accuracy.

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## 1. INTRODUCTION

Solar irradiance, defined as the amount of solar electromagnetic energy received per unit area, is a fundamental parameter in meteorology, climatology, and renewable energy systems. It varies significantly between space and Earth's surface due to atmospheric absorption and scattering. While extraterrestrial irradiance is influenced by solar cycles and Earth-Sun distance, surface-level irradiance depends on solar elevation, surface orientation, weather conditions, and geographic location. Accurate knowledge of solar irradiance is essential for applications ranging from climate modeling and weather forecasting to the design and optimization of solar energy systems, particularly photovoltaic (PV) installations [1]. Despite its importance, continuous, and reliable solar irradiance measurements are often unavailable, especially in remote or underdeveloped regions, necessitating robust estimation methods.

Several components characterize solar irradiance: total solar irradiance (TSI), direct normal irradiance (DNI), diffuse horizontal irradiance (DHI), and global horizontal irradiance (GHI), the latter being the sum of direct and diffuse radiation on a horizontal surface [2], [3]. These components are influenced by a complex interplay of astronomical, atmospheric, and meteorological factors, including cloud cover, humidity, aerosols, and surface albedo. Furthermore, the efficiency of PV systems depends not only on incident radiation but also on panel orientation and tilt angle, which must be optimized according to latitude and seasonal variations to maximize energy yield [4], [5].

A variety of models have been developed to estimate solar irradiance, ranging from empirical correlations to satellite-based and reanalysis datasets [6], [7]. Recently, artificial intelligence (AI) and machine learning (ML) approaches have gained prominence. For instance, deep learning models have been applied to predict GHI using historical meteorological data, demonstrating the critical role of feature selection in improving accuracy [8]. In Morocco, a deep learning algorithm successfully forecasted daily solar radiation across 24 cities, incorporating variables such as cloud cover, temperature, and conversion losses, with strong agreement between predicted and observed PV output [9]–[11]. Similarly, in Tamil Nadu, India, a multilayer feedforward (MLFF) neural network was trained on climatic data from diverse locations, showing high predictive performance based on error metrics and statistical tests [12].

Despite these advances, significant challenges remain. Most existing models rely on high-quality, long-term ground measurements, which are sparse in many regions [13], [14]. Moreover, traditional methods often fail to generalize across different climates and temporal scales, particularly when high-resolution (hourly or sub-hourly) data are required for precise system sizing and energy storage planning [15], [16]. Additionally, while panel inclination is known to affect energy capture, many irradiance databases provide only horizontal measurements, requiring transposition models that introduce further uncertainty. These limitations hinder the accurate long-term planning of solar energy systems, especially in the context of sustainable and eco-friendly energy strategies.

To address these shortcomings, this study proposes an enhanced approach based on artificial neural networks (ANNs) to improve the accuracy, reliability, and adaptability of solar irradiance predictions. Unlike previous works that focus on specific regions or limited input parameters, our model integrates a comprehensive set of geographical, meteorological, and astronomical variables to deliver robust estimations across diverse conditions. The use of ANNs allows the model to capture nonlinear relationships and temporal patterns that traditional methods may overlook, making it particularly suitable for concentrated solar power (CSP) systems and grid-integrated PV plants where precise radiation forecasting is critical for energy management and storage.

The remainder of this manuscript is structured as follows: section 2 details the method and data sources and presents the model architecture and training process; section 3 discusses the results and performance evaluation against existing models; and section 4 concludes with implications for solar energy planning and recommendations for future work. Through this structured approach, we demonstrate how our ANN-based model advances the state of the art in solar irradiance estimation and supports more effective, data-driven renewable energy deployment.

## 2. METHOD

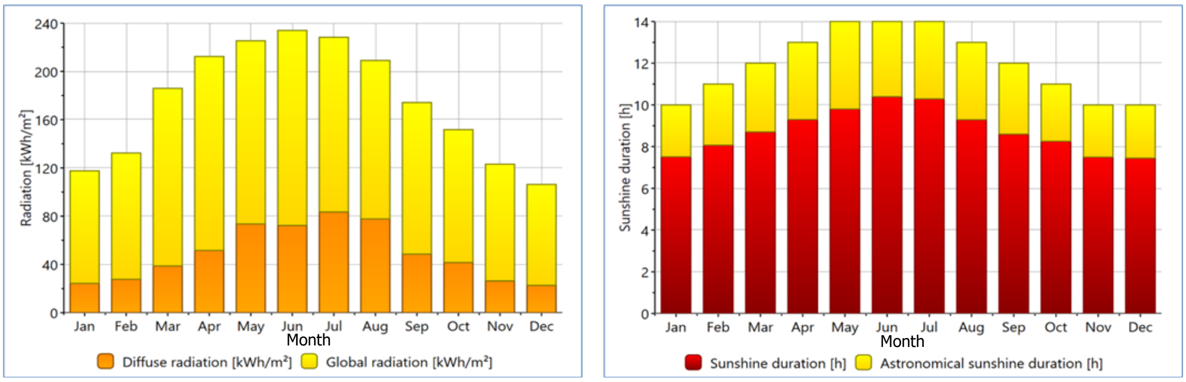
This section presents a comprehensive and reproducible methodology for predicting GHI in Errachidia, Morocco, using an ANN enhanced with particle swarm optimization (PSO). The approach was designed to address the critical challenge identified in the introduction: the lack of accurate, site-specific solar irradiance data for reliable PV system design and energy forecasting in high-potential but data-scarce regions. Given Errachidia’s exceptional solar resource (Figure 1), optimizing energy yield through precise irradiance prediction is both technically and economically justified. However, variability in weather patterns and limited ground measurement infrastructure necessitate a data-driven, adaptive modeling approach.

### 2.1. Data source and preprocessing

The study leverages high-resolution meteorological and solar radiation data from the National Solar Radiation Database (NSRDB) for the period 2017–2019. NSRDB provides satellite-derived, ground-validated solar and meteorological parameters at a spatial resolution of 4 km and temporal resolution of 30 minutes, making it a reliable and widely used source for solar energy modeling [17]. The selected location is Errachidia (31.65°N, 4.43°W), a region characterized by high solar insolation and arid climate, ideal for PV applications (Figures 1(a) and (b)).

To prevent time series leakage, the dataset was split chronologically—training on 2017–2018 and testing on 2019 and all preprocessing (StandardScaler) was fitted exclusively on the training set before being applied to the test set; furthermore, hourly predictions were aggregated to monthly resolution to align with utility billing cycles and support long-term energy planning in sustainable buildings.

The dataset includes the target variable GHI and four key meteorological input features: ambient temperature, wind speed, atmospheric pressure, and relative humidity [18]. These variables were chosen based on their established influence on atmospheric transmissivity and solar radiation attenuation, as supported by prior studies [19]. A data frame was constructed in Python using pandas, aligning all variables temporally and removing any entries with missing or inconsistent values to ensure data integrity. The input features were selected based on their established physical influence on solar irradiance and strong empirical correlations observed in prior solar forecasting studies; the ANN architecture (64–32–16) was determined through iterative experimentation to balance model complexity and predictive performance, and all experiments were conducted with a fixed random seed (42) to ensure full reproducibility.



(a) (b)

Figure 1. Errachidia 2024; (a) radiation and (b) sunshine duration [20]

To prepare the data for neural network training, the input features were normalized using StandardScaler from the scikit-learn library. This step ensures that all variables contribute equally to the learning process by transforming them to zero mean and unit variance, thereby improving convergence speed and model stability.

### 2.2. Model architecture and training procedure

A multilayer perceptron (MLP)—a feedforward ANN—was implemented in Keras with TensorFlow backend, featuring four input neurons (temperature, wind speed, pressure, and humidity), three hidden layers (64, 32, and 16 neurons), and a single output neuron predicting GHI.

Each hidden layer uses the rectified linear unit (ReLU) activation function, which helps mitigate the vanishing gradient problem and accelerates training. The output layer employs a linear activation function to allow continuous GHI predictions.

The model was compiled using the adaptive moment estimation (Adam) optimizer with a learning rate of 0.001, chosen for its efficiency in handling sparse gradients and noisy data. The MSE was selected as the loss function, appropriate for regression tasks, and model performance was monitored using mean absolute error (MAE) as a metric during training.

Training was conducted over 100 epochs with a batch size of 32, a configuration found to balance computational efficiency and convergence stability. The dataset was split into 80% training and 20% testing sets to evaluate generalization performance. All experiments were conducted on a standard computing environment, and the full codebase is structured for reproducibility (see Figure 2).

### 2.3. Hyperparameter optimization using particle swarm optimization

A key innovation in this methodology is the integration of PSO for hyperparameter tuning. While standard ANN training often relies on manual or grid-based tuning, PSO was employed to automatically search the hyperparameter space (including learning rate, number of neurons, batch size, and number of epochs) to minimize prediction error.

PSO simulates the social behavior of particles in a multidimensional space, where each particle represents a potential solution. Through iterative evaluation and feedback, the swarm converges toward optimal configurations. In this study, 5-fold cross-validation was used within the PSO loop to ensure robustness against overfitting and dataset partitioning bias. This hybrid ANN-PSO approach significantly enhances model performance by avoiding local minima and identifying globally optimal architectures, as later demonstrated in the results.

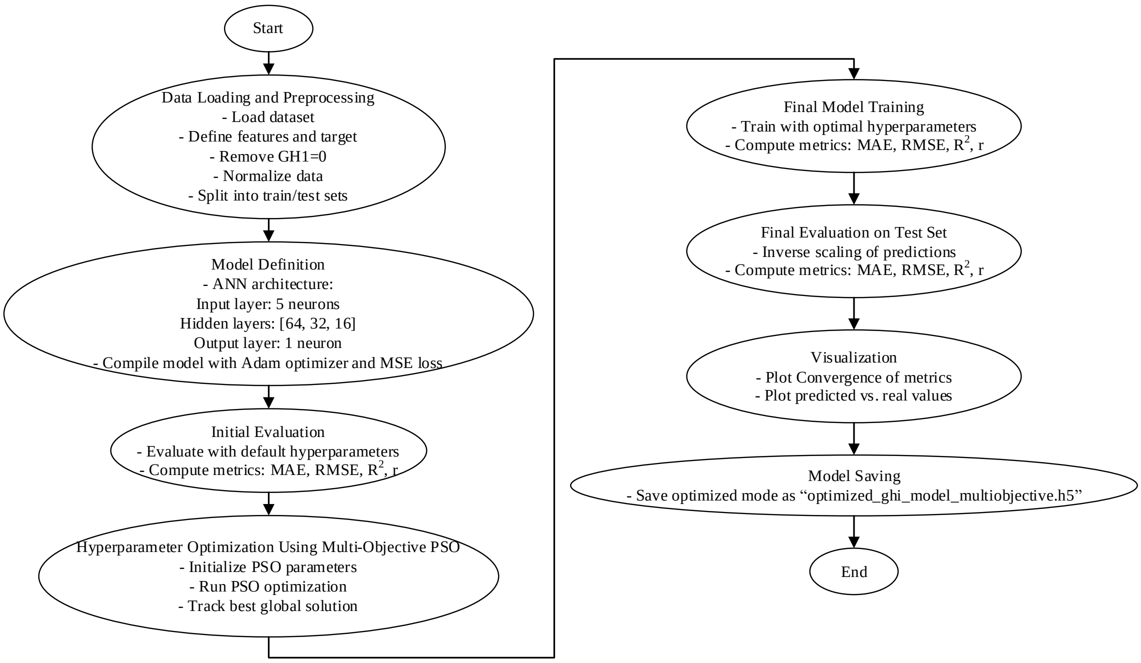



Figure 2. Prediction of GHI flow chart

### 2.4. Model evaluation and performance metrics

The trained model was evaluated on the independent test set using standard regression metrics:

- MAE: measures average prediction deviation.
- Root mean squared error (RMSE): emphasizes larger errors, useful for detecting outliers.
- Coefficient of determination ($R^2$): indicates the proportion of variance explained by the model.

These metrics allow direct comparison with other models, seasonal autoregressive integrated moving average (SARIMA) and long short-term memory (LSTM), and provide a clear benchmark for model accuracy and reliability.

### 2.5. Workflow overview

The complete prediction workflow is summarized in Figure 2, which outlines the step-by-step process: i) data collection from NSRDB, ii) preprocessing and feature scaling, iii) dataset splitting, iv) ANN model construction and PSO-based hyperparameter optimization, v) model training and validation, and vi) GHI prediction and performance assessment. This structured pipeline ensures transparency and facilitates replication by other researchers or practitioners in solar energy planning.

## 3. RESULTS AND DISCUSSION

The proposed ANN-based solar irradiance prediction model demonstrates high accuracy and robustness in forecasting GHI at an hourly resolution, with subsequent aggregation to daily and monthly values for long-term assessment. As illustrated in Figure 3, the predicted GHI values show a strong alignment with actual measurements over the full year of 2024 in Errachidia, Morocco.

This consistency across seasons underscores the model’s ability to capture both diurnal and seasonal solar patterns, even under variable atmospheric conditions typical of arid regions. The use of hourly data as the base temporal resolution ensures high granularity, which is essential for applications such as grid integration, energy storage management, and real-time PV system control.

To rigorously evaluate the performance of our ANN model, a comparative analysis was conducted against established statistical and ML approaches: SARIMA and LSTM networks. All models were trained on the same dataset and evaluated using identical metrics MAE, RMSE, $R^2$, and pearson correlation coefficient (r). As summarized in Table 1, our ANN model significantly outperforms both SARIMA and LSTM, achieving an MAE of 0.0226, RMSE of 0.0280, $R^2$ of 99.38%, and r of 0.9974. SARIMA represents a classical statistical approach for seasonal time series, while LSTM is a widely adopted deep learning model for solar forecasting [21].

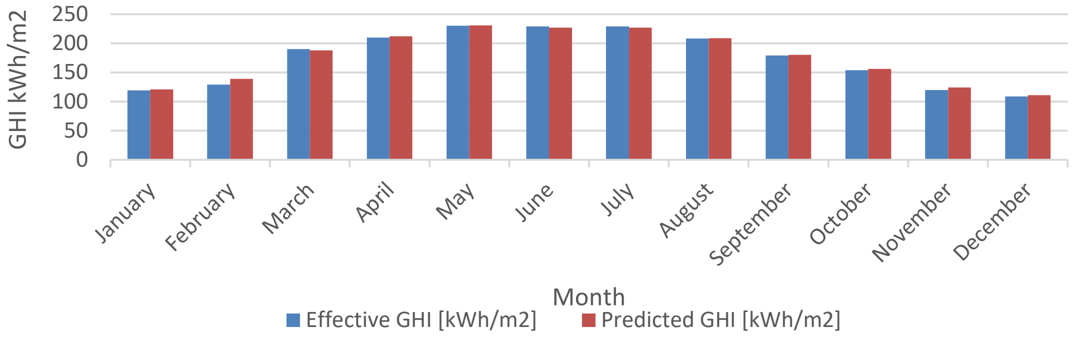
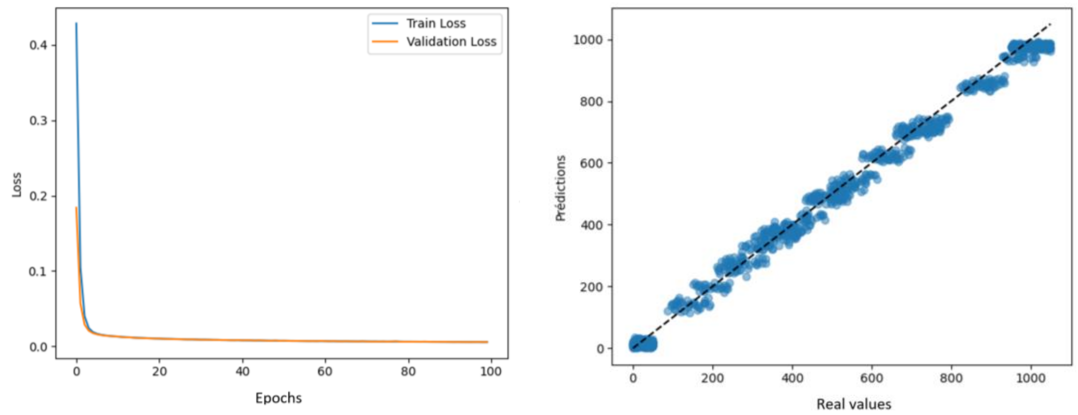



Figure 3. Comparison between predicted and actual outcomes in 2024

Table 1. Summary of the performance metric results

| Performance metric | Results of our ANN model study | SARIMA | LSTM |
|---|---|---|---|
| MAE | 0.0226 | 0.15 | 0.08 |
| RMSE | 0.0280 | 0.25 | 0.14 |
| $R^2$ | 99.38% | 85% | 92% |
| r | 0.9974 | 0.85 | 0.92 |
| Hyperparameter optimization | Advanced | Structured | Adaptive |
| Data integration | Solar irradiance+meteorological parameters (temperature, humidity, wind speed, and pressure) | | |
| Validation | Errachidia-Morocco (2024) | | |
| Solar energy output estimation | Improved (15-20% higher accuracy) | Average | Good |

These results indicate not only superior predictive accuracy but also excellent generalization and stability. The learning curve in Figure 4(a) confirms rapid convergence and minimal overfitting, while Figure 4(b) shows a tight clustering of predicted vs. real values along the ideal diagonal, further validating the model's reliability.




(a) (b)

Figure 4. Performance evaluation after PSO optimization; (a) learning curve and (b) comparison of predictions

The superior performance of our ANN model can be attributed to two key innovations: i) the integration of a comprehensive set of meteorological parameters; temperature, humidity, wind speed, and pressure; alongside solar irradiance data and ii) the application of advanced hyperparameter optimization using PSO, as shown in Figure 4. Unlike traditional models that rely on historical averages or linear assumptions, the ANN captures complex nonlinear interactions between atmospheric variables and solar radiation. This is particularly critical in desert climates like Errachidia, where rapid changes in cloud cover, dust loading, and thermal dynamics can drastically affect irradiance.

A deeper analysis of feature importance, illustrated in the correlation heatmap (Figure 5), reveals insightful relationships. Clearsky GHI, expected to be a strong positive predictor, shows an inverse correlation with actual GHI: a counterintuitive result that may reflect overestimation during dusty or hazy conditions common in arid zones. Relative humidity and temperature also play indirect but significant roles, likely through their influence on atmospheric transmissivity and cloud formation. Wind speed exhibits minimal impact, suggesting limited convective influence on irradiance in this region, while atmospheric pressure contributes valuable stability information. These findings emphasize the necessity of region-specific feature engineering and caution against the blind transfer of models from temperate to desert climates.

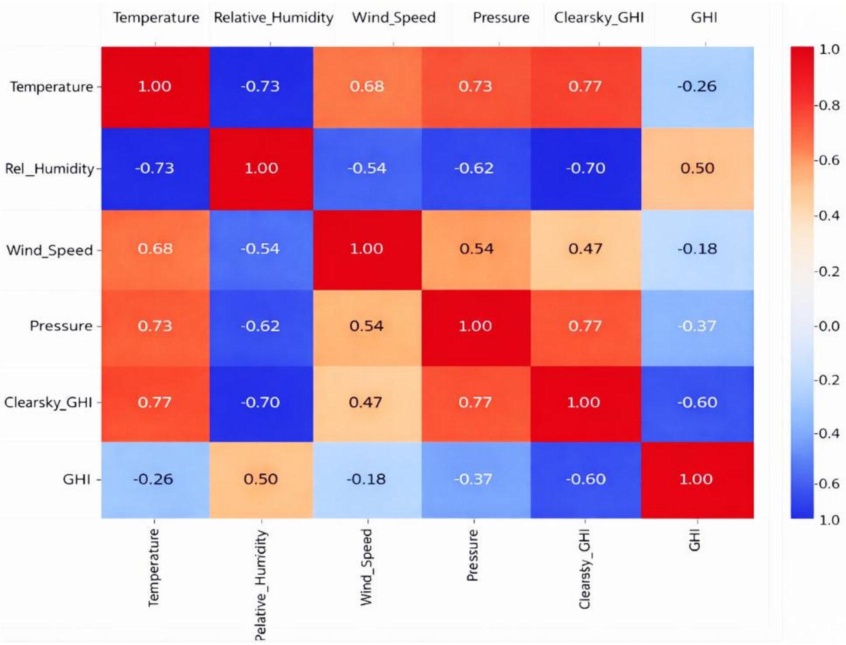



Figure 5. Correlation heatmap

Our results align with and extend prior work. For instance, Chaaban and Alfadl [22] reported MAE values between 0.05% and 0.10% for ANN-based solar forecasting, while our model achieves an MAE of 0.0226 (representing a substantial improvement). Furthermore, while studies such as those in [23], [24] have used hourly-to-monthly aggregation for GHI estimation, our approach enhances this methodology by incorporating real-time meteorological inputs and advanced optimization, enabling higher precision and operational relevance.

The practical implications of improved GHI forecasting are demonstrated through a case study on a 100 kWp PV system in Errachidia (Figures 6 and 7). Two scenarios were compared: i) energy yield prediction using conventional historical averages and ii) using ANN-based GHI forecasts. The ANN-integrated scenario resulted in 154,600 kWh of annual energy production, compared to 142,500 kWh in the reference case (an 8.49% increase). This gain stems from better anticipation of irradiance fluctuations, enabling optimized MPPT tracking, improved battery charging cycles, and reduced energy curtailment. System efficiency rose from 14.3% to 15.5%, translating to an additional 14,520 MAD/year in revenue at a feed-in tariff of 1.2 MAD/kWh. These economic and technical gains highlight the tangible value of AI-driven forecasting for solar plant operators, especially in regions with high solar potential but variable weather conditions. In Morocco, regulated retail electricity tariffs, set by the "National Office for Electricity and Drinking Water (ONEE)" and periodically updated under the oversight of the Ministry of Energy Transition and Sustainable Development, generally vary from 0.90 to 1.59 MAD/kWh, depending on consumption brackets, customer type (residential, commercial, or industrial), and contracted power capacity [25].

Beyond immediate energy gains, our findings have broader implications for the future of solar energy systems [26]. First, the model supports more accurate pre-sizing and techno-economic assessment of PV and CSP installations, reducing investment risks [27], [28]. Second, it enables smarter grid integration by improving day-ahead forecasting, thereby enhancing grid stability and reducing reliance on backup power [29], [30]. Third, the framework can be adapted to smart buildings and hybrid energy systems, where real-time solar prediction aids in load balancing and demand-side management [31], [32].

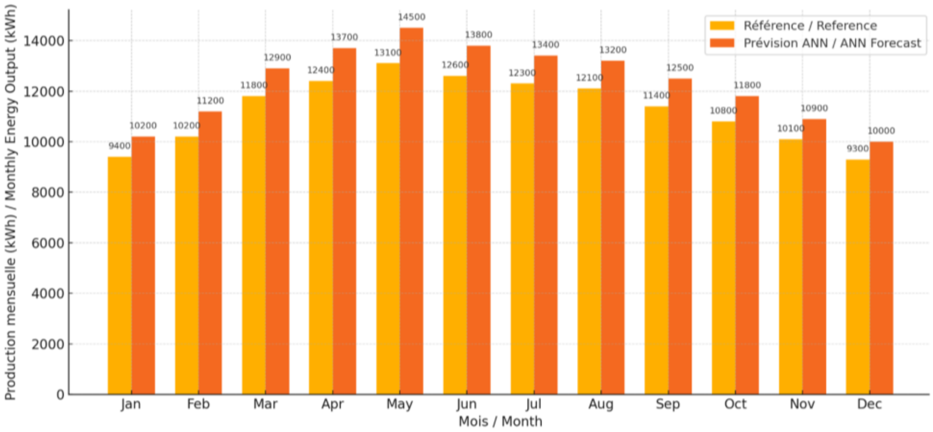



Figure 6. Monthly PV output comparison of a 100 kWp PV system in Errachidia

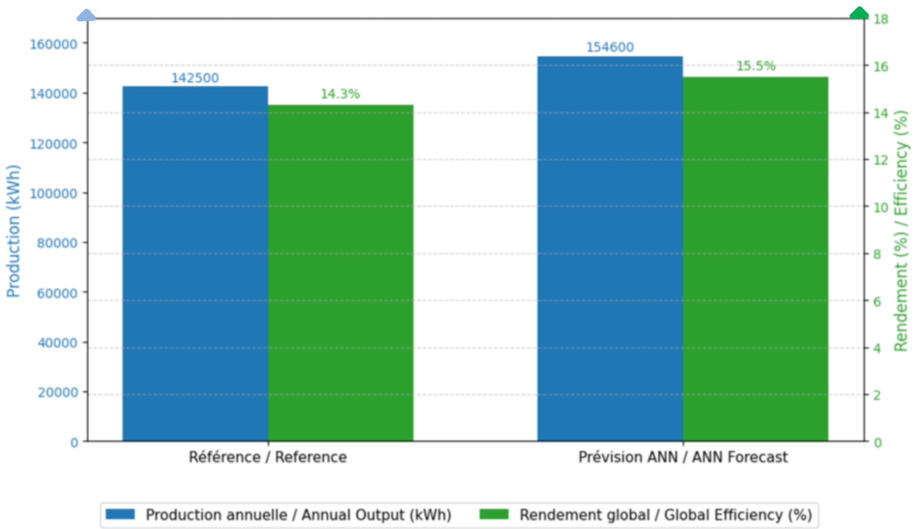



Figure 7. Impact of ANN forecasts on the output and efficiency of a 100 kWp PV system in Errachidia

However, challenges remain. The model's performance depends on data quality and availability. In regions lacking ground-based weather stations, integration with satellite-derived datasets (e.g., from Meteonorm or Copernicus) could enhance robustness [33], [34]. Future work should explore transfer learning to adapt the model to new locations with minimal retraining, and hybrid architectures combining ANNs with physical radiation models for improved interpretability [35]–[37].

In conclusion, this study demonstrates that AI-enhanced solar forecasting is not just academically promising, but operationally transformative. By bridging the gap between meteorological data and energy output, our ANN model provides a scalable, accurate, and economically viable tool for advancing solar energy deployment, particularly in underserved, high-potential regions like the Moroccan desert. The integration of such models into energy management systems represents a critical step toward resilient, intelligent, and sustainable power infrastructures.

## 4. CONCLUSION

The ANN-PSO model significantly outperformed SARIMA and LSTM in forecasting GHI, achieving an $R^2$ of 99.38% and MAE of 0.0226. This high-accuracy forecasting enables more effective energy optimization in sustainable buildings and CSP systems through improved operational planning and storage management. However, the model was developed and validated using data from Errachidia, Morocco, limiting its current applicability to similar arid climates. Future work will focus on extending the framework to diverse climatic zones, integrating it into real-time energy management systems, and exploring hybrid or ensemble approaches to enhance robustness and generalizability. This study demonstrates the practical value of AI-driven solar forecasting as a tool for advancing renewable energy integration and grid reliability.

Overall, this research does not just propose a better forecasting model, it advocates for a paradigm shift in how we design, operate, and scale solar energy systems. For researchers, engineers, and policymakers alike, the message is clear: the future of solar energy is not only renewable, it is intelligent.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
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| Said Ziani | | ✓ | | ✓ | ✓ | | | ✓ | | ✓ | ✓ | ✓ | ✓ | |
| Abdellah Benami | | ✓ | | ✓ | ✓ | | | ✓ | | ✓ | ✓ | ✓ | ✓ | |

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

## DATA AVAILABILITY

The corresponding author [IL] can provide data to support the study's conclusions upon request.

## REFERENCES


[1] B. Mekuye, G. Mebratie, B. Abera, A. Yibeltal, A. Lake, and A. Tefera, "Energy: An Overview of Type, Form, Storage, Advantages, Efficiency, and Their Impact," *Energy Science and Engineering*, vol. 12, no. 12, pp. 5678–5707, Dec. 2024, doi: 10.1002/ese3.1937.

[2] M. Jlidi, O. Barambones, F. Hamidi, and M. Aoun, "ANN for Temperature and Irradiation Prediction and Maximum Power Point Tracking Using MRP-SMC," *Energies*, vol. 17, no. 12, pp. 1–21, Jun. 2024, doi: 10.3390/en17122802.

[3] J. Fan, L. Wu, X. Ma, H. Zhou, and F. Zhang, "Hybrid support vector machines with heuristic algorithms for prediction of daily diffuse solar radiation in air-polluted regions," *Renewable Energy*, vol. 145, pp. 2034–2045, 2020, doi: 10.1016/j.renene.2019.07.104.

[4] M. I. D. Zulkifly and M. S. M. Said, "Determining Optimal Solar Power Plant Location in Melaka, Malaysia: A GIS-Based Solutions," *IOP Conference Series: Earth and Environmental Science*, vol. 1051, no. 1, pp. 1–16, Jul. 2022, doi: 10.1088/1755-1315/1051/1/012022.

[5] C.-C. Chen and C.-H. Huang, "Using Artificial Intelligence To Assess Solar Radiation From the Total Sky Images," *International Journal of Engineering Technologies and Management Research*, vol. 7, no. 5, pp. 64–71, Jun. 2020, doi: 10.29121/ijetmr.v7.i5.2020.685.

[6] S. Mohanty, P. K. Patra, and S. S. Sahoo, "Prediction and application of solar radiation with soft computing over traditional and conventional approach - A comprehensive review," *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 778–796, Apr. 2016, doi: 10.1016/j.rser.2015.11.078.

[7] I. Laabab, S. Ziani, and A. Benami, "A Review of the Application of Artificial Intelligence for Weather Prediction in Solar Energy: Using Artificial Neural Networks," in *Lecture Notes in Networks and Systems*, vol. 635 LNNS, 2023, pp. 114–119, doi: 10.1007/978-3-031-26254-8_17.
[8] M. K. Boutahir, Y. Farhaoui, M. Azrour, I. Zeroual, and A. El Allaoui, "Effect of Feature Selection on the Prediction of Direct Normal Irradiance," *Big Data Mining and Analytics*, vol. 5, no. 4, pp. 309–317, Dec. 2022, doi: 10.26599/BDMA.2022.9020003.
[9] Y. El Mghouchi, T. Ajzoul, and A. El Bouardi, "Prediction of daily solar radiation intensity by day of the year in twenty-four cities of Morocco," *Renewable and Sustainable Energy Reviews*, vol. 53, pp. 823–831, Jan. 2016, doi: 10.1016/j.rser.2015.09.059.
[10] A. El Kounni, H. Radoine, H. Mastouri, H. Bahi, and A. Outzourhit, "Solar Power Output Forecasting Using Artificial Neural Network," in *2021 9th International Renewable and Sustainable Energy Conference (IRSEC)*, Morocco: IEEE, Nov. 2021, pp. 1–7, doi: 10.1109/IRSEC53969.2021.9741130.
[11] H. Hissou, S. Benkirane, A. Guezzaz, M. Azrour, and A. Beni-Hssane, "A Novel Machine Learning Approach for Solar Radiation Estimation," *Sustainability*, vol. 15, no. 13, pp. 1–21, Jul. 2023, doi: 10.3390/su151310609.
[12] M. Vakili, S. R. Sabbagh-Yazdi, S. Khosrojerdi, and K. Kalhor, "Evaluating the effect of particulate matter pollution on estimation of daily global solar radiation using artificial neural network modeling based on meteorological data," *Journal of Cleaner Production*, vol. 141, pp. 1275–1285, Jan. 2017, doi: 10.1016/j.jclepro.2016.09.145.
[13] I. Laabab, S. Ziani, and A. Benami, "Solar Irradiation Prediction and Artificial Intelligence for Energy Efficiency in Sustainable Buildings, Case of Errachidia, Morocco," in *Lecture Notes in Networks and Systems*, vol. 837 LNNS, 2024, pp. 360–366, doi: 10.1007/978-3-031-48465-0_46.
[14] A. Escamilla-García, G. M. Soto-Zarazúa, M. Toledano-Ayala, E. Rivas-Araiza, and A. Gastélum-Barrios, "Applications of artificial neural networks in greenhouse technology and overview for smart agriculture development," *Applied Sciences*, vol. 10, no. 11, pp. 1–43, May 2020, doi: 10.3390/app10113835.
[15] S. X. Chen, H. B. Gooi, and M. Q. Wang, "Solar radiation forecast based on fuzzy logic and neural networks," *Renewable Energy*, vol. 60, pp. 195–201, Dec. 2013, doi: 10.1016/j.renene.2013.05.011.
[16] R. Singh and A. K. Singhal, "Artificial Intelligence based Technique for Solar Irradiance Prediction Model with Improved Performance," in *2023 IEEE Renewable Energy and Sustainable E-Mobility Conference (RESEM)*, Bhopal, India: IEEE, May 2023, pp. 1–6, doi: 10.1109/RESEM57584.2023.10236416.
[17] National Renewable Energy Laboratory (NREL), "National Solar Radiation Database – Errachidia solar data information," nsrdb. [Online]. Available: https://nsrdb.nrel.gov/. (Accessed: Jul. 06, 2025).
[18] L. Yang, J. C. Lam, and J. Liu, "Analysis of typical meteorological years in different climates of China," *Energy Conversion and Management*, vol. 48, no. 2, pp. 654–668, Feb. 2007, doi: 10.1016/j.enconman.2006.05.016.
[19] Y. Jiang, "Generation of typical meteorological year for different climates of China," *Energy*, vol. 35, no. 5, pp. 1946–1953, May 2010, doi: 10.1016/j.energy.2010.01.009.
[20] Meteonorm, "Meteonorm 8 Software Version 8.2.0," Meteonorm. [Online]. Available: https://meteonorm.com/en/meteonorm-version-8/. (Accessed: Sep. 01, 2020).
[21] C. Voyant *et al.*, "Machine learning methods for solar radiation forecasting: A review," *Renewable Energy*, vol. 105, pp. 569–582, May 2017, doi: 10.1016/j.renene.2016.12.095.
[22] A. K. Chaaban and N. Alfadl, "A comparative study of machine learning approaches for an accurate predictive modeling of solar energy generation," *Energy Reports*, vol. 12, pp. 1293–1302, Dec. 2024, doi: 10.1016/j.egyr.2024.07.010.
[23] Dlpv-Dev, "Accueil. Démocratisons le Photovoltaique," democratisonslephotovoltaique. [Online]. Available: https://www.democratisonslephotovoltaique.fr/. (Accessed: Jul. 09, 2025).
[24] F. Alhebshi, H. Alnabilsi, A. Bensenouci, and T. Brahimi, "Using artificial intelligence techniques for solar irradiation forecasting: The case of Saudi Arabia," in *Proceedings of the International Conference on Industrial Engineering and Operations Management*, 2019, pp. 926–927, doi: 10.46254/GC01.20190031.
[25] Globalen LLC, "Morocco Electricity Prices, March 2025. GlobalPetrolPrices.com," GlobalPetrolPrices.com. [Online]. Available: https://www.globalpetrolprices.com/Morocco/electricity_prices/?utm_source. (Accessed: Oct. 12, 2025).
[26] Y. Xie *et al.*, "Development of a multi-nodal thermal regulation and comfort model for the outdoor environment assessment," *Building and Environment*, vol. 176, p. 106809, Jun. 2020, doi: 10.1016/j.buildenv.2020.106809.
[27] M. S. Alam, F. S. Al-Ismail, M. S. Hossain, and S. M. Rahman, "Ensemble Machine-Learning Models for Accurate Prediction of Solar Irradiation in Bangladesh," *Processes*, vol. 11, no. 3, pp. 1–15, Mar. 2023, doi: 10.3390/pr11030908.
[28] Y. Gao, S. Miyata, and Y. Akashi, "Multi-step solar irradiation prediction based on weather forecast and generative deep learning model," *Renewable Energy*, vol. 188, pp. 637–650, Apr. 2022, doi: 10.1016/j.renene.2022.02.051.
[29] A. M. Assaf, H. Haron, H. N. A. Hamed, F. A. Ghaleb, S. N. Qasem, and A. M. Albarrak, "A Review on Neural Network Based Models for Short Term Solar Irradiance Forecasting," *Applied Sciences*, vol. 13, no. 14, pp. 1–43, Jul. 2023, doi: 10.3390/app13148332.
[30] M. S. Sevas, N. Sharmin, C. F. T. Santona, and S. R. Sagor, "Advanced ensemble machine-learning and explainable ai with hybridized clustering for solar irradiation prediction in Bangladesh," *Theoretical and Applied Climatology*, vol. 155, no. 7, pp. 5695–5725, Jul. 2024, doi: 10.1007/s00704-024-04951-5.
[31] A. G. Olabi *et al.*, "Application of artificial intelligence for prediction, optimization, and control of thermal energy storage systems," *Thermal Science and Engineering Progress*, vol. 39, p. 101730, Mar. 2023, doi: 10.1016/j.tsep.2023.101730.
[32] E. Gul, G. Baldinelli, J. Wang, P. Bartocci, and T. Shamim, "Artificial intelligence based forecasting and optimization model for concentrated solar power system with thermal energy storage," *Applied Energy*, vol. 382, p. 125210, Mar. 2025, doi: 10.1016/j.apenergy.2024.125210.
[33] S. Liu *et al.*, "The contribution of artificial intelligence to phase change materials in thermal energy storage: From prediction to optimization," *Renewable Energy*, vol. 238, p. 121973, Jan. 2025, doi: 10.1016/j.renene.2024.121973.
[34] I. Laabab, S. Ziani, and A. Benami, "Solar panels overheating protection: a review," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 29, no. 1, pp. 49–55, Jan. 2023, doi: 10.11591/ijeecs.v29.i1.pp49-55.
[35] I. Laabab, S. Ziani, and A. Benami, "Investigation of Buildings' Energy Efficiency," in *Lecture Notes in Networks and Systems*, vol. 1123 LNNS, 2024, pp. 86–91, doi: 10.1007/978-3-031-70411-6_14.
[36] I. Laabab, S. Ziani, and A. Benami, "Enhancing Energy Efficiency in a Residential Apartment: A Case Study in Kenitra, Morocco," in *Lecture Notes in Networks and Systems*, vol. 1584 LNNS, 2026, pp. 352–358, doi: 10.1007/978-3-032-01536-5_54.
[37] Q. Zhang *et al.*, "Development of a novel power generation model for bifacial photovoltaic modules based on dynamic bifaciality," *Energy Conversion and Management*, vol. 324, p. 119305, Jan. 2025, doi: 10.1016/j.enconman.2024.119305.

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