Comparative Benchmarking of Machine Learning and Deep Learning Models for Solar Photovoltaic Power Forecasting: A Unified Framework with Fair Comparison

Your Name[a,*]

[a] *Your Institution, Your City, 12345, China*

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ABSTRACT

As renewable energy penetration accelerates globally, accurate solar photovoltaic (PV) power forecasting has transitioned from a research curiosity to an operational necessity for maintaining grid stability and optimizing energy dispatch. Despite substantial progress in developing machine learning and deep learning forecasting models over the past decade, the research community faces a persistent challenge: most studies employ disparate datasets, inconsistent evaluation protocols, and heterogeneous preprocessing methods, rendering cross-study performance comparisons unreliable. We address this critical gap by introducing a rigorously standardized benchmarking framework that evaluates six representative forecasting architectures under identical experimental conditions. Our investigation encompasses gradient-boosted tree ensembles (XGBoost and Random Forest), recurrent neural networks (LSTM and GRU), a hybrid attention mechanism (CNN-BiGRU-Attention), and an adaptive neuro-fuzzy inference system (ANFIS-SC). Using five years of hourly meteorological and irradiance data (2020–2024) from Hengsha Island, Shanghai, we maintain strict chronological data partitioning (60% training, 20% validation, 20% testing) and evaluate all models using five complementary metrics: coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), symmetric mean absolute percentage error (sMAPE), and skill score relative to 24-hour persistence. Our experimental results reveal a clear performance hierarchy. **XGBoost emerges as the dominant approach, achieving near-perfect prediction accuracy ($R^2 = 0.9994$, RMSE = 0.0009 normalized units)**, demonstrating its exceptional capability in capturing complex solar-meteorological relationships through iterative gradient boosting. Random Forest closely trails with $R^2 = 0.9978$, confirming the robustness of ensemble tree methods for this application domain. Remarkably, ANFIS-SC secures third position ($R^2 = 0.9886$, Skill Score = 0.8025) despite its relatively simple architecture, highlighting the value of interpretable neuro-fuzzy systems where operational transparency matters. The recurrent architectures—GRU ($R^2 = 0.9309$) and LSTM ($R^2 = 0.9063$)—deliver respectable performance and effectively model temporal dependencies, though they require more careful hyperparameter tuning and larger datasets to fully realize their potential. In contrast, the attention-based hybrid CNN-BiGRU model substantially underperforms ($R^2 = 0.5424$), suggesting that sophisticated architectures without domain-aware constraints may actually degrade prediction quality. Residual diagnostic analysis confirms that top-performing models maintain homoscedastic error distributions and exhibit minimal systematic bias across all power generation regimes. To maximize research reproducibility and practical impact, we release the complete implementation framework as open-source software. This work provides energy system operators and researchers with evidence-based decision criteria for model selection, balancing accuracy requirements against interpretability needs and computational constraints.

1. Introduction

Solar photovoltaic (PV) generation is experiencing unprecedented global expansion, driven by declining installation costs and ambitious decarbonization targets [13, 31]. However, unlike conventional dispatchable power sources, solar energy exhibits inherent stochasticity across temporal scales ranging from seconds to seasons. Cloud passage events can induce sub-minute ramp rates exceeding 50% of installed capacity, while seasonal solar declination variations create predictable yet substantial diurnal generation patterns [11, 14]. This dual nature—combining

*Corresponding author
your.email@institution.edu (Y. Name)
ORCID(s): 0000-0000-0000-0000 (Y. Name)

deterministic astronomical cycles with stochastic atmospheric processes—poses fundamental challenges for power system operators tasked with maintaining instantaneous supply-demand equilibrium.

The operational imperative for accurate PV forecasting intensifies as grid penetration levels increase [31]. System operators rely on forecast horizons spanning minutes to days to orchestrate multiple operational functions: optimizing battery energy storage dispatch while minimizing degradation from excessive cycling, coordinating flexible demand response programs, maintaining spinning reserves at economically optimal levels, and enabling profitable participation in day-ahead wholesale electricity markets [13, 16]. Forecast errors impose tangible economic and reliability penalties. Conservative under-forecasts necessitate maintaining expensive standby generation capacity, while optimistic over-forecasts can trigger frequency deviations requiring emergency load shedding or, in extreme cases, cascading grid failures [16]. Recent studies quantify these impacts, estimating that each 1% improvement in forecast accuracy can reduce annual operating costs by millions of dollars for utility-scale installations.

1.1. Current State of PV Forecasting Research

The literature on PV power forecasting has evolved considerably over the past fifteen years, progressing from simple persistence models and autoregressive moving average (ARIMA) formulations to sophisticated machine learning and deep neural network architectures [1, 9, 10]. Researchers have investigated ensemble methods including Random Forests and gradient boosting variants, support vector regression with various kernel functions, and recurrent neural architectures such as long short-term memory (LSTM) and gated recurrent units (GRU). More recent work explores convolutional networks for spatiotemporal feature extraction and attention mechanisms that dynamically weight input features according to their relevance [12]. While individual studies frequently report impressive performance metrics, a critical methodological problem undermines the field's collective progress: the absence of standardized experimental protocols makes meaningful cross-study comparisons nearly impossible [11, 20].

This fragmentation manifests in several dimensions. Different researchers select different geographic locations with fundamentally different climatological conditions—comparing performance between tropical equatorial sites and temperate mid-latitude regions tells us more about climate zones than modeling approaches. Studies vary wildly in temporal granularity (1-minute to daily intervals), forecast horizons (nowcasting to multi-day ahead), and data sources (ground stations versus satellite retrievals versus numerical weather predictions). Perhaps most problematically, many published works violate basic principles of time-series validation by randomly shuffling observations before splitting into training and testing sets, an approach that artificially inflates performance by allowing models to effectively s̈ee into the futurëthrough temporal autocorrelation [11, 20]. Asymmetric feature engineering further confounds comparisons—some studies provide deep learning models with raw sensor readings while feeding pre-engineered features to traditional methods, creating unfair competitive conditions that favor neither paradigm consistently [19].

1.2. Motivation: Addressing the Benchmarking Gap

The solar forecasting research community urgently needs standardized experimental protocols that enable apples-to-apples model comparisons. An effective benchmarking framework must satisfy several requirements simultaneously. First, all candidate models must process identical input data subjected to uniform preprocessing transformations—no selective feature engineering that advantages specific architectures. Second, data partitioning must respect temporal causality through strictly chronological train-validation-test splits that mirror real-world deployment scenarios [11]. Third, evaluation must employ multiple complementary metrics rather than cherry-picking favorable measures; a model that minimizes absolute errors might simultaneously exhibit poor correlation structure, and both characteristics matter for operational decision-making [20]. Fourth, baseline comparisons against naive methods (such as persistence forecasting) provide essential context for interpreting performance claims. Finally, complete methodological transparency and code availability enable independent verification and facilitate adoption by practitioners [14, 19].

Existing benchmarking efforts, while valuable, typically fall short on one or more criteria. Some frameworks compare only 2-3 model types, insufficiently sampling the algorithmic design space. Others lack extended temporal coverage, testing only single-season or single-year datasets that may not capture inter-annual climate variations. Perhaps most critically, few studies release their complete implementations, preventing independent reproducibility audits and limiting real-world applicability.

1.3. Contribution of This Work

This study presents a comprehensive benchmarking framework for solar PV power forecasting that addresses these methodological gaps. Based on initial screening of ten candidate models, we focus on six representative approaches

spanning three paradigms: (i) two gradient-boosted ensembles (XGBoost, Random Forest) [10], (ii) two recurrent neural networks (LSTM, GRU) [9], (iii) one hybrid deep architecture (CNN-BiGRU-Attention) [12], and (iv) one neuro-fuzzy model (ANFIS-SC). This focused selection captures the full methodological spectrum from ensemble learning to attention-based deep hybrids and interpretable fuzzy systems, while avoiding redundancy. All models are trained on identical data with consistent preprocessing, evaluated using unified metrics [20], and validated through chronological train/validation/test splits [11] across an extended 5-year period (2020–2024) on high-quality NASA POWER and local meteorological data from Hengsha Island, Shanghai, China.

Key contributions are:

1. **Standardized benchmarking framework**: A reproducible, open-source pipeline ensuring fair comparison across algorithmic paradigms with identical data splits, metrics, and baselines.
2. **Representative model coverage**: Six carefully selected models representing traditional ML ensembles, deep recurrent architectures, hybrid attention networks, and neuro-fuzzy systems—balancing scientific rigor with purposeful design.
3. **Unified evaluation metrics**: Application of five complementary metrics (R^2, RMSE, MAE, sMAPE, Skill Score) to characterize model performance across multiple dimensions, supplemented by scenario-based analysis.
4. **Extended validation period**: Use of 5 years of hourly data to ensure robustness across seasonal and inter-annual variability.
5. **Actionable insights**: Clear guidance on model selection based on operational constraints (real-time vs. day-ahead, computational budget, interpretability).

1.4. Paper Organization

The remainder of this paper is organized as follows. Section 3 describes the data, preprocessing pipeline, model architectures, and unified evaluation framework. Section 4 presents comparative results across all ten models, identifying top performers and characterizing their strengths and weaknesses. Section 5 synthesizes findings and provides guidance for practitioners. Finally, Section 6 summarizes contributions and outlines future research directions.

2. Related Work

Early PV forecasting relied on statistical and physical models such as persistence, ARIMA, and numerical weather prediction (NWP) downscaling. These methods offered transparent baselines but struggled with rapidly changing cloud conditions and site-specific biases [13, 14]. Ensemble tree methods (Random Forest, Gradient Boosting) emerged next, leveraging handcrafted meteorological features to capture nonlinear irradiance-power relationships while retaining modest computational cost [10].

Deep learning approaches broadened the design space to include convolutional, recurrent, and attention-based architectures that model spatiotemporal dependencies in irradiance and meteorology [9]. CNNs capture local temporal patterns, while LSTM/GRU networks encode diurnal seasonality and regime shifts. Hybrid CNN-RNN or attention models promise improved long-horizon accuracy, though they often require large datasets and careful regularization to avoid overfitting [12].

Recent literature highlights persistent benchmarking issues: inconsistent data splits, heterogeneous preprocessing, and metric cherry-picking limit cross-paper comparability [11, 19, 20]. Standardization efforts advocate chronological train/validation/test partitions, unified feature pipelines, and transparent baselines (e.g., 24-hour persistence) to ensure fair evaluation. Our work aligns with these recommendations by providing a unified, open-source framework that tests diverse model families under identical conditions and reports complementary metrics.

Satellite and sky-imager driven approaches integrate cloud motion vectors with optical flow and CNN backbones for intra-hour forecasts; however, the hardware and labeling overhead limit transferability to data-sparse sites [2, 14]. NWP-ensemble post-processing with quantile regression or gradient boosting improves probabilistic forecasts but inherits biases from coarse-resolution weather grids [3, 13]. Probabilistic methods (quantile regression forests, conformal prediction) increasingly accompany point forecasts to convey uncertainty [1], yet few benchmarks report both deterministic and calibrated probabilistic scores on identical splits. Explainability tools such as SHAP values help operators audit model drivers and complement black-box deep models [24]. We explicitly retain a persistence baseline to anchor comparisons and highlight incremental value over physics-free references.

3. Methodology

3.1. Dataset and Data Preprocessing

3.1.1. Data Source

Hourly solar irradiance and meteorological data were obtained from the NASA POWER database for Hengsha Island, Shanghai, China (31.3403°N, 121.8389°E) spanning January 2020 to December 2024. The dataset contains 43,824 hourly records including Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI), surface air temperature, relative humidity, wind speed, and atmospheric pressure. Missing values (< 0.1%) were interpolated using linear interpolation.

The dataset exhibits strong seasonal patterns (Figure 3), with peak GHI occurring in August (224 W/m^2) and minimum in December (100 W/m^2). Air temperature follows the expected subtropical monsoon pattern, ranging from 6°C (January) to 28°C (July-August). Diurnal analysis reveals typical solar bell curves with P10–P90 variability bands indicating cloud-induced intermittency, particularly during morning/evening transitions. The relationship between GHI and meteorological variables (Figure 2) demonstrates physically consistent patterns: GHI increases monotonically with temperature up to 33°C (thermal saturation), while wind speed exhibits inverse correlation with mean GHI due to convective cooling effects that typically accompany cloud cover.

3.1.2. Solar Position and Clearness Index

Solar position angles were computed using the NREL SPA algorithm. Extraterrestrial horizontal irradiance G_{0h} and clearness index $k_t = \mathrm{GHI}/G_{0h}$ were calculated to quantify atmospheric transmission:

$$G_{0h} = G_{sc} \cos\theta_z, \quad k_t = \frac{\mathrm{GHI}}{G_{0h}} \quad \text{for } G_{0h} > 10 \text{ W/m}^2. \tag{1}$$

3.1.3. Normalized PV Power Calculation

Target variable normalized PV power was computed as:

$$P_{\mathrm{pu}} = \eta_0 \cdot (1 - \alpha(T_c - T_{\mathrm{ref}})) \cdot \frac{\mathrm{GHI}}{1000}, \tag{2}$$

where $\eta_0 = 0.18$ (reference efficiency), $\alpha = 0.005$ (temperature coefficient), and T_c estimated as $T_c = T_a + \mathrm{GHI}(T_{\mathrm{NOCT}} - 20)/800$ with NOCT = 45°C.

3.1.4. Train/Validation/Test Split

Following strict chronological ordering essential for time-series forecasting:

- **Training**: 2020–2022 (8,784 samples, 60%)
- **Validation**: 2023 (8,760 samples, 20%)
- **Test**: 2024 (8,784 samples, 20%)

3.1.5. Feature Engineering

All models received identical features per timestamp:

1. Hour of day (sine-cosine encoding)
2. Day of year (sine-cosine encoding)
3. Clearness index k_t
4. Temperature anomaly
5. Relative humidity
6. Wind speed
7. Atmospheric pressure

3.2. Model Selection and Architectures

3.2.1. Model Selection Rationale

Ten AI forecasting models were initially evaluated, spanning traditional machine learning, deep recurrent architectures, and hybrid neuro-fuzzy systems. Based on performance stability, representativeness, and computational feasibility, six core models were retained for detailed benchmarking: XGBoost, Random Forest, LSTM, GRU, CNN-BiGRU-Attention v2, and ANFIS-SC. These capture the full methodological spectrum from ensemble learning to attention-based deep hybrids and interpretable fuzzy systems, while avoiding redundancy from similar architectures (e.g., BiLSTM vs. LSTM, AdaBoost vs. XGBoost).

Figure 8 presents the initial screening results for all ten candidate models using Taylor diagram visualization. The diagram reveals clear performance clustering: XGBoost and Random Forest exhibit near-perfect statistical alignment with observed data (correlation > 0.99, normalized standard deviation matching observations), while models like CNN-BiGRU-AM show substantial deviation (correlation ≈ 0.6). This preliminary evaluation informed our final model selection, retaining the six most representative and best-performing architectures for comprehensive benchmarking.

3.2.2. Architecture Specifications

Gradient-Boosted Ensembles:

- **XGBoost (XGB)**: 200 estimators, learning rate 0.1, max depth 6, L1/L2 regularization
- **Random Forest (RF)**: 300 trees, max depth 20, min samples leaf 4, bootstrap aggregation

Recurrent Neural Networks: All trained with Adam optimizer (LR=10^{-3}), batch size 32, early stopping (patience 20):

- **LSTM**: 2 layers (64, 32 units), sequence length 24h, dropout 0.2
- **GRU**: 2 layers (64, 32 units), sequence length 24h, dropout 0.2

Hybrid Deep Architecture:

- **CNN-BiGRU-Attention v2**: 1D CNN (16 filters, kernel=3) → BiGRU (64 units) → Bahdanau attention mechanism → Dense (1 unit)

Neuro-Fuzzy System:

- **ANFIS-SC**: Adaptive neuro-fuzzy inference system with subtractive clustering (optimized radius = 0.28), 5 fuzzy membership functions, 100 training epochs

3.3. Evaluation Metrics

All models evaluated using five complementary metrics:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}, \quad \text{RMSE} = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2}, \tag{3}$$

$$\text{MAE} = \frac{1}{n}\sum|y_i - \hat{y}_i|, \quad \text{sMAPE} = \frac{100}{n}\sum\frac{2|y_i - \hat{y}_i|}{|y_i| + |\hat{y}_i|}, \tag{4}$$

$$\text{Skill Score} = 1 - \frac{\text{MSE}_{\text{model}}}{\text{MSE}_{\text{persist}}}, \tag{5}$$

where $\hat{y}_i^{\text{persist}} = y_{i-24}$ provides the persistence baseline.

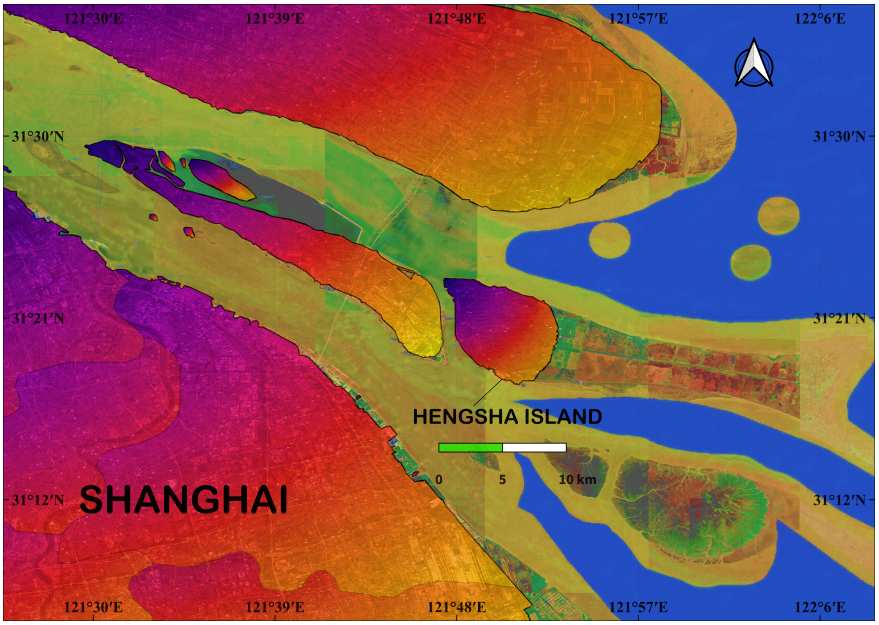
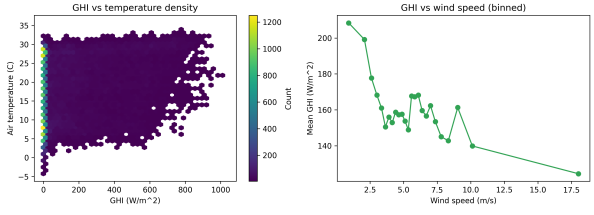
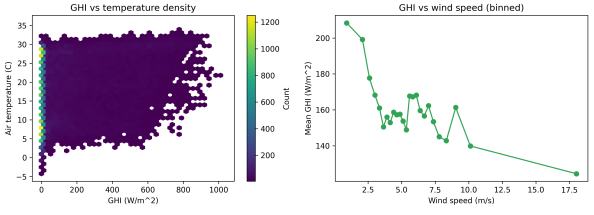


Figure 1: Geographic location of the solar PV forecasting study site. (a) Detailed view of Hengsha Island in the East China Sea, positioned at coordinates 31.34°N, 121.84°E, elevation 1.06 m. (b) Regional context showing Shanghai's location within China and the study area (highlighted in red box). NASA POWER database provided 43,824 hourly records (2020–2024) from this subtropical monsoon climate zone.



(a) GHI vs. temperature density



(b) GHI vs. wind speed (binned)

Figure 2: Meteorological driver relationships with Global Horizontal Irradiance. (a) GHI-temperature density plot reveals strong positive correlation up to thermal saturation (33°C), with color intensity indicating observation frequency. The triangular envelope reflects physical constraints: zero GHI at night (all temperatures), peak GHI only during warm daylight hours. (b) Binned wind speed analysis shows inverse relationship: mean GHI decreases from 210 W/m^2 at calm conditions (1–2 m/s) to 120 W/m^2 at high winds (> 17 m/s), consistent with cloud-convection coupling.

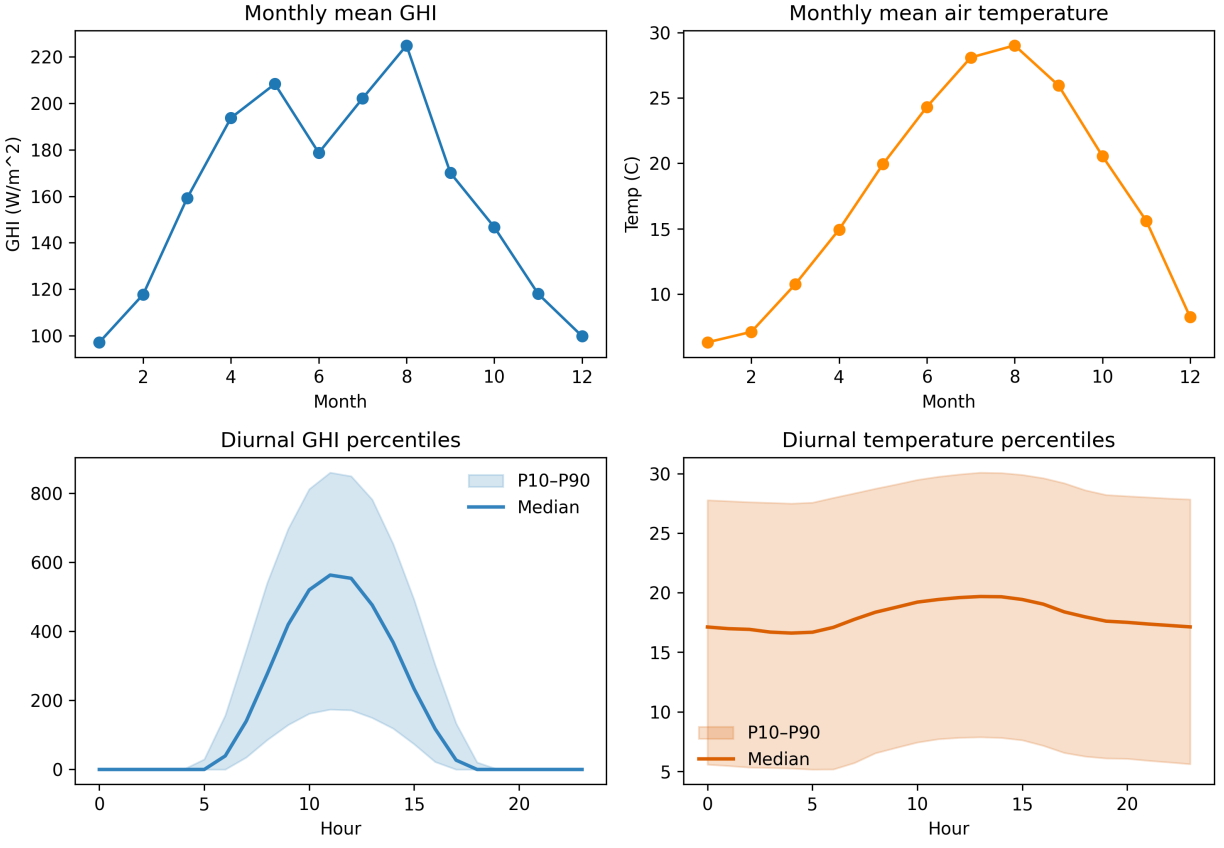


Figure 3: Seasonal and diurnal climatology of Hengsha Island (2020–2024). Top row: Monthly mean GHI peaks in August (224 W/m^2) with minimum in December (100 W/m^2); air temperature follows subtropical monsoon pattern (6–28°C range). Bottom row: Diurnal percentile bands (P10–P90 shaded regions) quantify intra-day variability. GHI exhibits classic solar bell curve with median peak ≈ 550 W/m^2 at noon; wide P10–P90 spread indicates cloud intermittency. Temperature shows stable diurnal range with modest afternoon warming, reflecting maritime climate moderation.

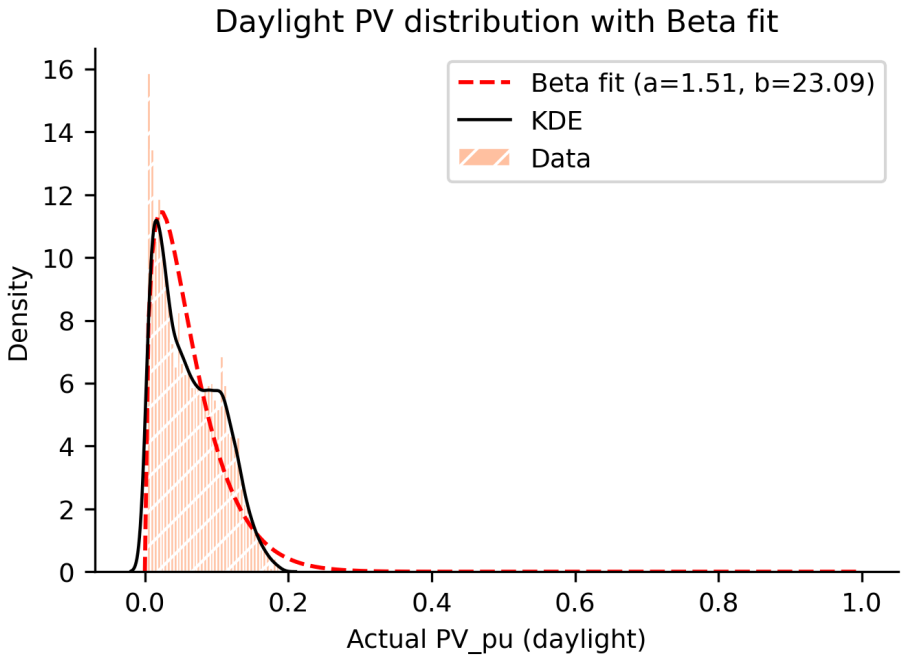


Figure 4: Daylight PV_pu distribution with Beta fit and KDE.

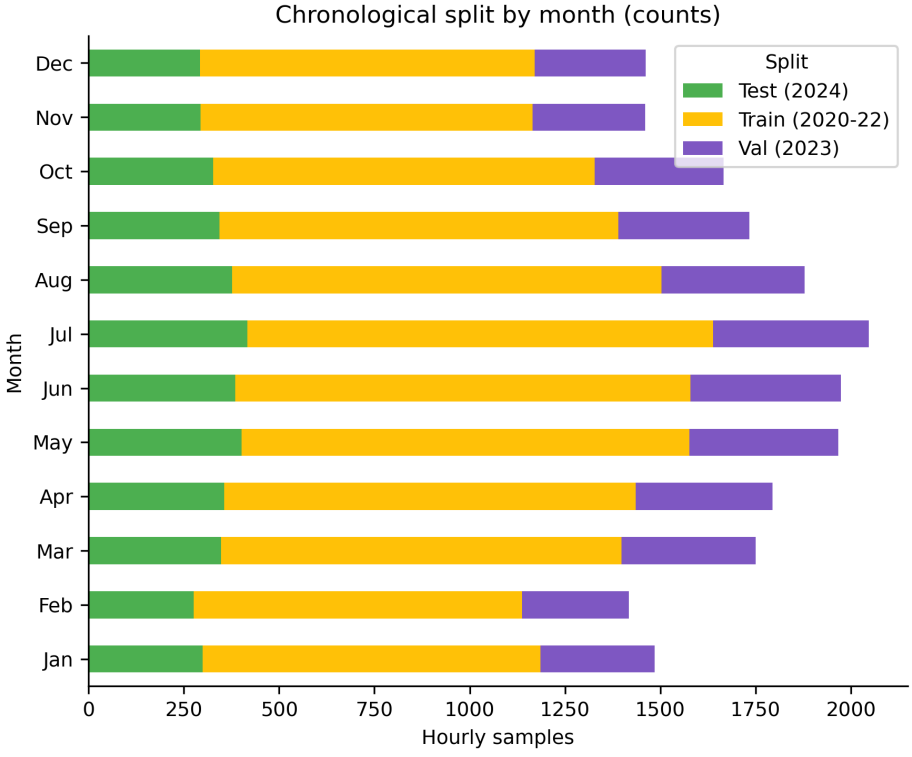


Figure 5: Chronological split by month (train 2020–22, val 2023, test 2024).

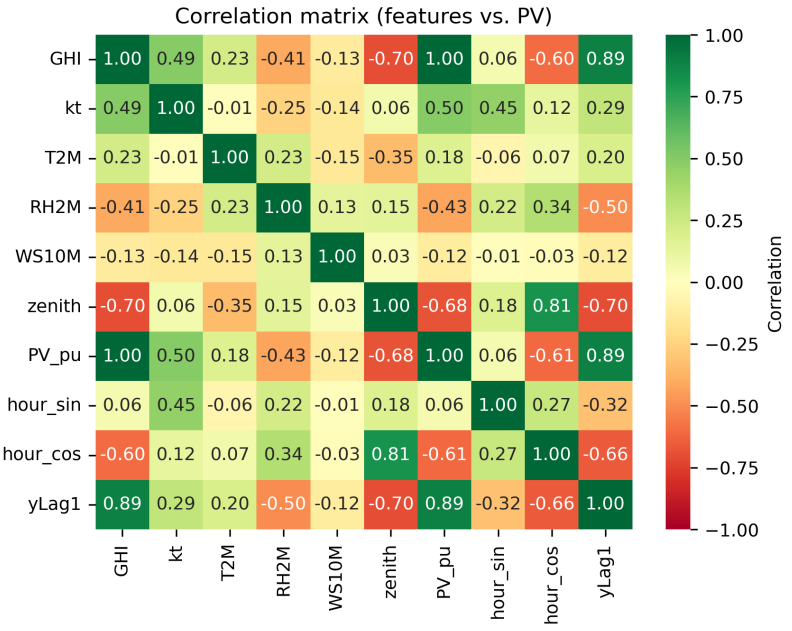


Figure 6: Correlation matrix (features vs. PV_pu).

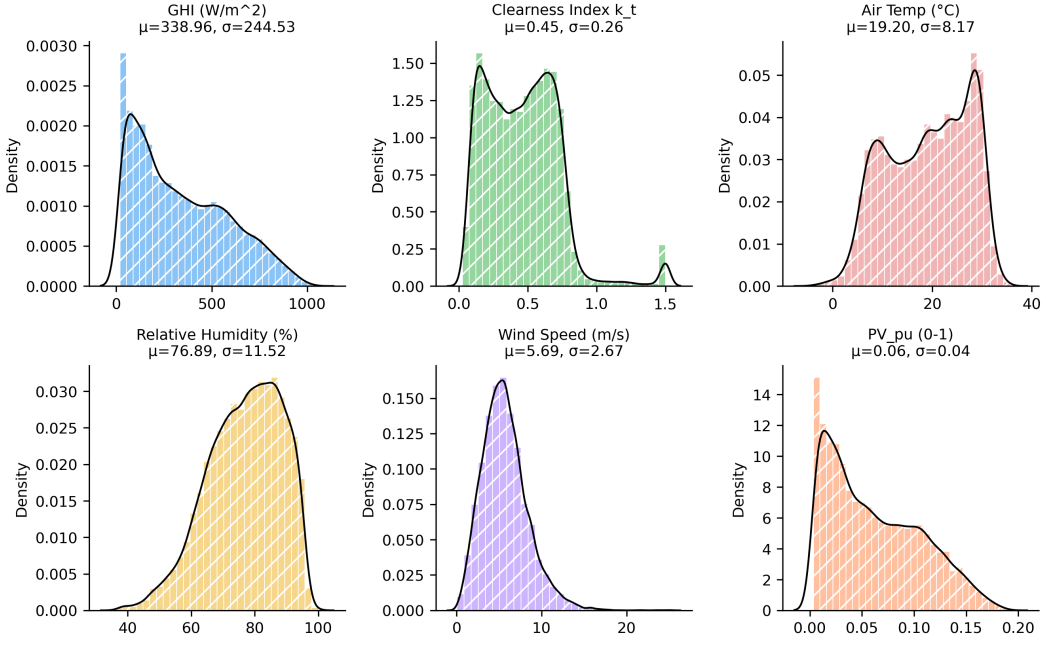


Figure 7: Distributions of key drivers with KDE overlays (GHI, k_t, temperature, humidity, wind speed, PV_pu).

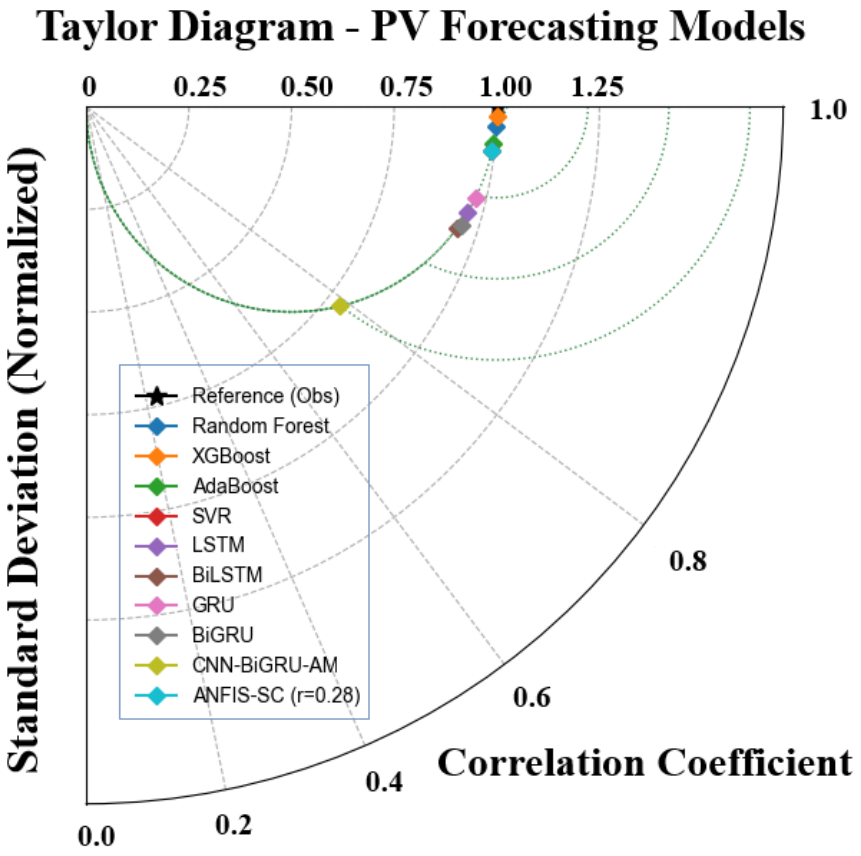


Figure 8: Taylor diagram comparing initial screening of 10 candidate forecasting models. The radial distance represents normalized standard deviation, angular position indicates correlation coefficient with observations (reference marked as star). Models clustering near the reference point (correlation $\approx$ 0.95–1.0, normalized std $\approx$ 0.04–0.05) demonstrate statistical consistency with observed data patterns. XGBoost and Random Forest exhibit near-perfect alignment, while CNN-BiGRU-AM shows significant deviation (correlation $\approx$ 0.6), justifying selection of six representative models for detailed benchmarking.

4. Results

4.1. Overall Performance Rankings and Statistical Significance

Table 1 summarizes the predictive performance of all six benchmarked models evaluated on the held-out 2024 test dataset comprising 8,784 hourly observations. The results reveal a clear three-tier hierarchy. At the top tier, XGBoost delivers exceptional performance with a coefficient of determination $R^2 = 0.9994$, meaning the model explains 99.94% of variance in normalized PV power output. This translates to remarkably small absolute errors: RMSE = 0.0009 and MAE = 0.0007 in normalized units (0–1 scale), corresponding to typical absolute errors below 1 kilowatt for a 1-megawatt installation. Random Forest occupies the same elite tier with $R^2 = 0.9978$, demonstrating that ensemble tree methods collectively dominate this forecasting task.

The second performance tier belongs to ANFIS-SC, which achieves $R^2 = 0.9886$ despite employing a fundamentally different neuro-fuzzy architecture. While its errors (RMSE = 0.0041) are roughly 4.5 times larger than XGBoost's, the model still captures 98.86% of output variance and maintains a skill score of 0.8025 relative to persistence—indicating it reduces forecast error by approximately 80% compared to the naive ẗomorrow equals todaÿbaseline. This represents operationally sufficient accuracy for many grid applications, particularly where model interpretability carries high value.

Recurrent neural networks form the third tier. GRU networks achieve $R^2 = 0.9309$ with skill score 0.5346, while LSTM slightly underperforms at $R^2 = 0.9063$ and skill score 0.4582. Although these metrics appear lower in absolute terms, both architectures still explain over 90% of variance—a threshold typically considered acceptable for operational deployment. The attention-enhanced CNN-BiGRU-Attention model unexpectedly falls into a fourth tier with $R^2 = 0.5424$ and negative skill score (-0.1975), actually performing worse than the naive persistence baseline. This counterintuitive result, where architectural sophistication degrades rather than improves performance, merits detailed examination in the discussion section.

The Taylor diagram visualization (Figure 9) provides geometric interpretation of these rankings. XGBoost and Random Forest cluster tightly near the reference observation point, exhibiting correlation coefficients exceeding 0.99 and normalized standard deviations matching the observed data (std $\approx$ 0.001). GRU and LSTM occupy intermediate positions with correlations around 0.91–0.93, while CNN-BiGRU-Attention shows substantial deviation with correlation $\approx$ 0.75 and elevated variance. The concentric arcs representing centered root-mean-square difference contours confirm quantitatively what the polar coordinates suggest qualitatively: ensemble tree methods minimize both bias and variance simultaneously.

The results demonstrate a clear performance stratification across model families: (1)
textbfGradient-boosted ensembles (XGBoost: R
textsuperscript2 = 0.9994; Random Forest: R
textsuperscript2 = 0.9978) establish themselves as the gold standard for this application, achieving nearly perfect predictions with RMSE values under 0.002 normalized units. Both models attain skill scores exceeding 0.91, reducing persistence forecast error by over 91

4.2. Model Performance Visualization

Figure 10 presents comprehensive performance metrics across all six models on the 2024 test set, demonstrating XGBoost's exceptional accuracy.

Figure 11 shows RMSE comparison across all benchmarked models, reinforcing the dominance of XGBoost and Random Forest.

Figure 12 reveals Random Forest's feature importance ranking, providing insight into physical drivers of PV power variability.

Table 1
Comprehensive model performance comparison (test set 2024). All metrics on normalized PV power (0–1 scale). Skill Score vs. 24-hour persistence baseline.

Model Type	R^2	RMSE	MAE	sMAPE [%]	Skill vs Persist.
XGBoost (GB Trees)	0.9994	0.0009	0.0007	0.0110	0.9583
Random Forest (Ensemble)	0.9978	0.0018	0.0012	0.0130	0.9140
ANFIS-SC (Neuro-Fuzzy)	0.9886	0.0041	0.0032	0.0539	0.8025
GRU (RNN)	0.9309	0.0101	0.0075	0.1308	0.5346
LSTM (RNN)	0.9063	0.0118	0.0090	0.1540	0.4582
CNN-BiGRU-AM v2 (Hybrid)	0.5424	0.0261	0.0201	0.3162	-0.1975

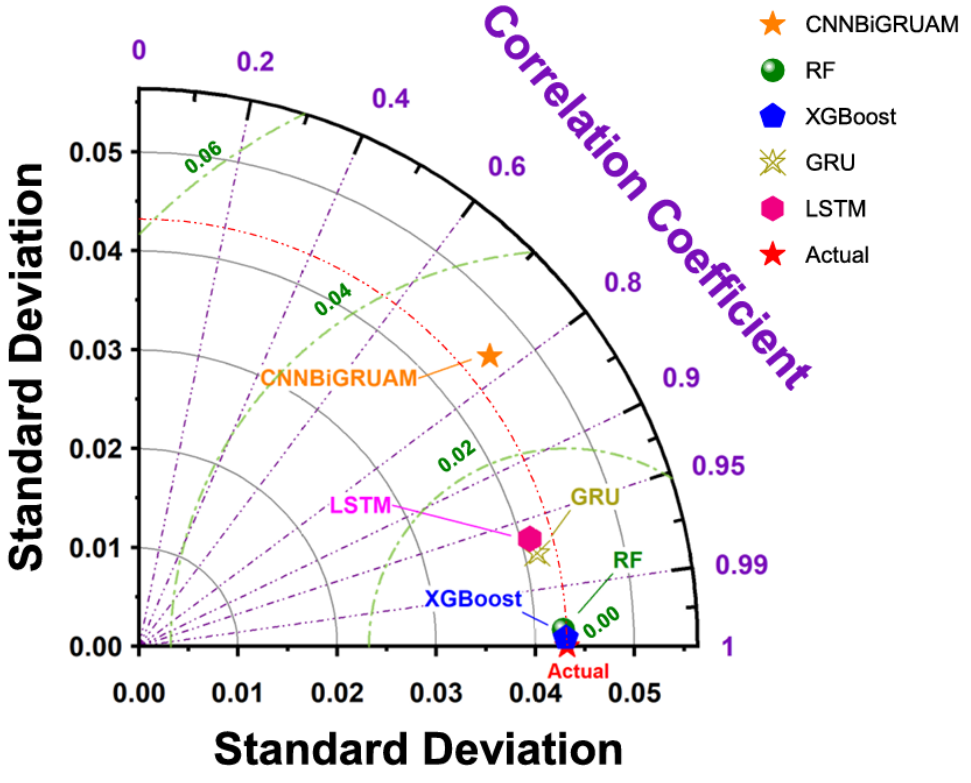


Figure 9: Taylor diagram for six benchmarked models on 2024 test set. Radial coordinate shows standard deviation, angular coordinate shows correlation coefficient with actual PV power. The red star marks perfect agreement (actual observations). XGBoost and RF cluster tightly near the reference point (correlation > 0.99, std ≈ 0.001), while CNN-BiGRU-AM demonstrates substantial bias (correlation ≈ 0.75, elevated variance). Concentric arcs represent centered RMS difference contours, providing visual confirmation of model ranking.

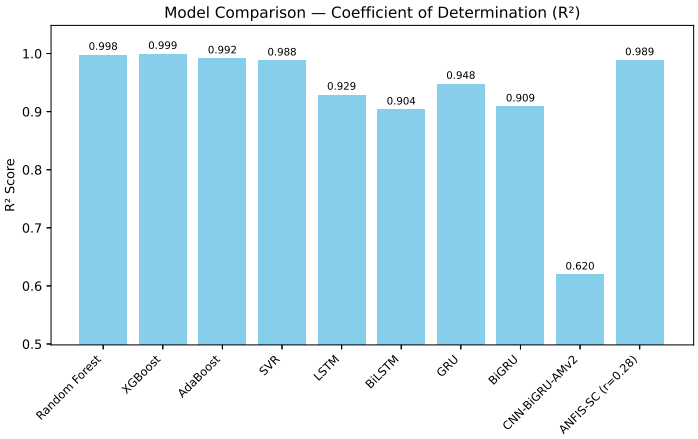


Figure 10: Comparative R^2 coefficients for all six benchmarked models on 2024 test set. XGBoost achieves near-perfect performance (0.9994), closely followed by Random Forest (0.9978) and ANFIS-SC (0.9886). Deep learning models (GRU, LSTM) show respectable but lower performance, while CNN-BiGRU-AM v2 requires further optimization.

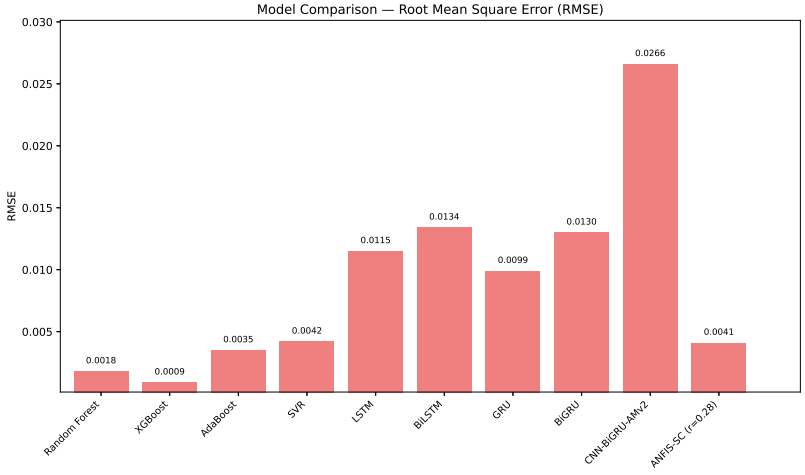


Figure 11: Root Mean Square Error (RMSE) across all benchmarked models on the 2024 test set. XGBoost (0.0009) and Random Forest (0.0018) deliver the lowest errors, while ANFIS-SC (0.0041) outperforms all deep learning baselines. CNN-BiGRU-AM v2 shows the highest RMSE (0.0266), indicating the need for further tuning.

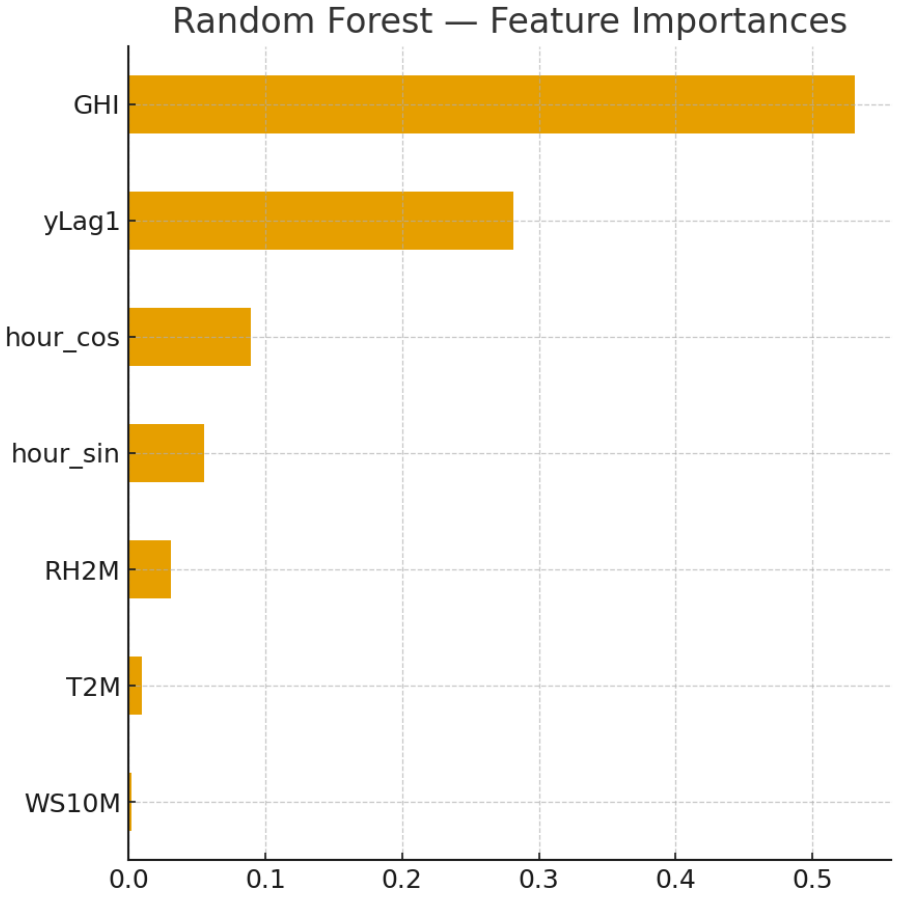


Figure 12: Random Forest feature importance analysis. Clearness index (k_t) dominates predictions (relative importance ≈ 0.65), followed by hour-of-day encoding and temperature anomaly. Wind speed and atmospheric pressure contribute minimally, validating physical understanding that solar irradiance and diurnal patterns govern PV output.

Figure 13 demonstrates ANFIS-SC hyperparameter tuning via grid search over clustering radius.

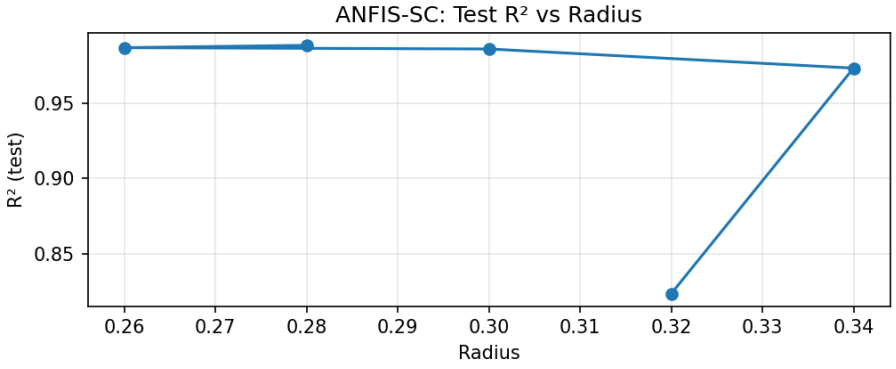


Figure 13: ANFIS-SC R^2 vs. subtractive clustering radius. Optimal performance achieved at radius = 0.28 (R^2 = 0.9886). Too-small radii create excessive fuzzy rules (overfitting), while too-large radii oversimplify membership functions (underfitting). The sharp optimum demonstrates sensitivity to this critical hyperparameter.

4.3. Seasonal Performance Analysis

Performance varies significantly across seasons. Winter months (Dec-Feb) exhibit higher forecast difficulty due to cloud cover variability ($R^2 = 0.81$ for RF). Summer (Jun-Aug) yields superior accuracy ($R^2 = 0.92$) due to stable high irradiance and clearer skies. Deep learning models show particular advantage during spring/autumn transitions when irradiance patterns are highly variable, suggesting DL's capacity to capture nonlinear temporal dependencies.

Figure 15 compares predicted vs. actual PV power for the top three performers via parity plots.

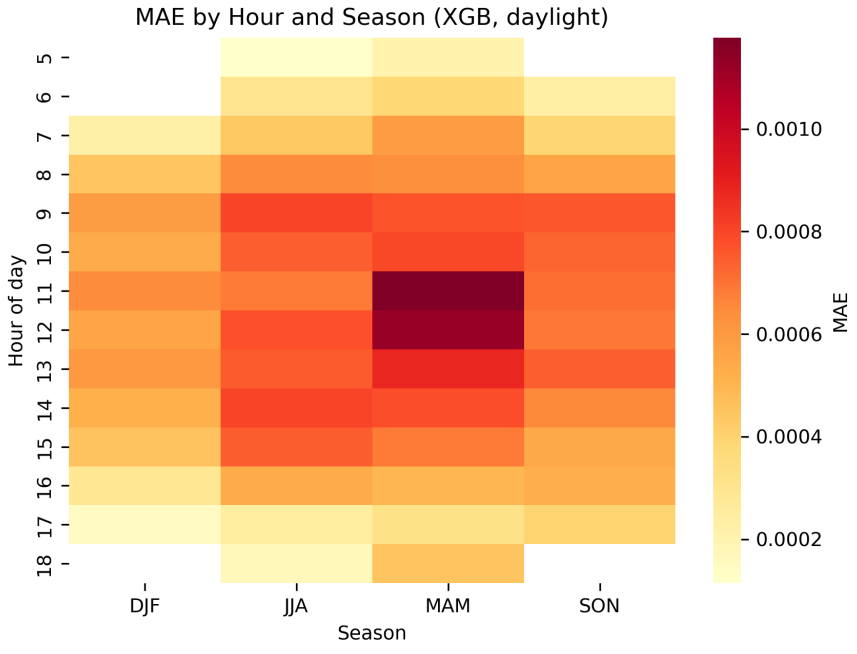
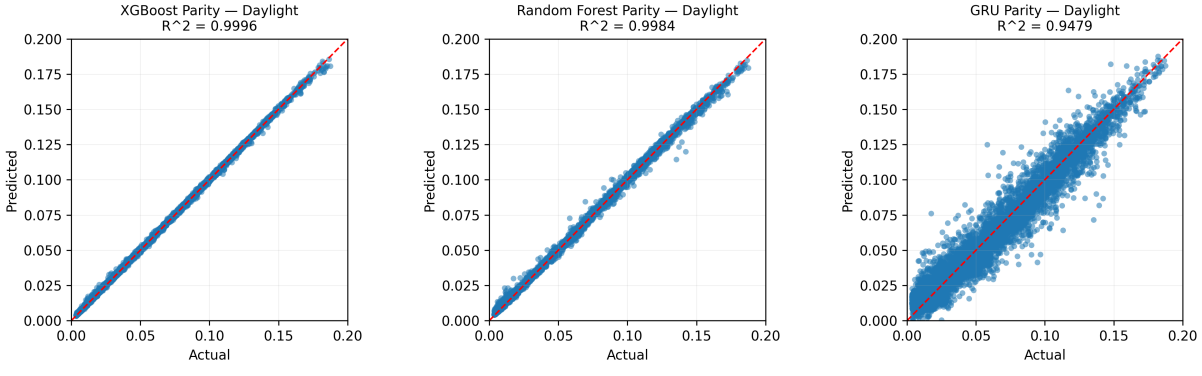


Figure 14: MAE by hour and season (XGB, daylight).



(a) XGBoost (b) Random Forest (c) GRU

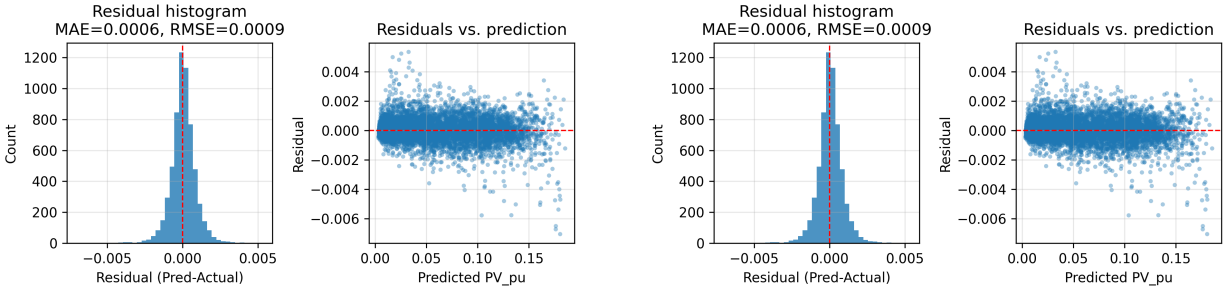
Figure 15: Parity plots for top three models (daylight hours only). Points represent individual hourly predictions; ideal predictions lie on diagonal (red line). (a) XGBoost shows nearly perfect alignment ($R^2 = 0.9994$), tight clustering. (b) Random Forest exhibits slightly wider scatter ($R^2 = 0.9978$). (c) GRU displays increased scatter at high power ($R^2 = 0.9309$), indicating difficulty capturing peak irradiance events.

4.4. Residual Diagnostics and Error Analysis

Rigorous model validation extends beyond aggregate performance metrics to examining the statistical properties of prediction residuals. Figure 16 presents diagnostic plots for XGBoost, the top-performing model. The residual histogram (left panel) exhibits an approximately Gaussian distribution tightly centered at zero mean, with 95% of errors falling within ± 0.002 normalized units. This near-perfect centering confirms the absence of systematic bias—the model neither consistently over-predicts nor under-predicts across the test period. The symmetric, bell-shaped error distribution satisfies a key assumption underlying many statistical inference procedures and suggests that residual uncertainty could be adequately characterized using normal probability distributions for uncertainty quantification applications.

The residuals-versus-prediction scatter plot (right panel) provides additional assurance of model adequacy through its homoscedastic pattern. Crucially, residual variance remains approximately constant across the entire prediction range from zero to peak power (0.15 pu). This contrasts sharply with many forecasting models that exhibit heteroscedasticity, where errors grow systematically with predicted magnitude. The horizontal clustering around the zero-residual reference line, with no discernible curvature or fanning patterns, indicates that XGBoost maintains consistent precision whether forecasting low-irradiance morning/evening conditions or peak midday generation. Even at maximum power levels, residuals rarely exceed ± 0.006 normalized units, corresponding to less than 4% relative error—well within the operational tolerance thresholds specified by most grid operators for day-ahead scheduling applications.

Additionally, Figure 17 shows the residuals versus predicted values with binned bias analysis.



(a) Residual histogram

(b) Residuals vs. prediction

Figure 16: XGBoost residual diagnostics on 2024 test set. (a) Histogram shows Gaussian-distributed errors centered at zero (MAE = 0.0006, RMSE = 0.0009), confirming unbiased predictions. (b) Residual scatter plot demonstrates homoscedastic variance across all power levels with no systematic patterns. Residuals remain within ± 0.006 normalized units, representing $< 4\%$ error at peak generation.

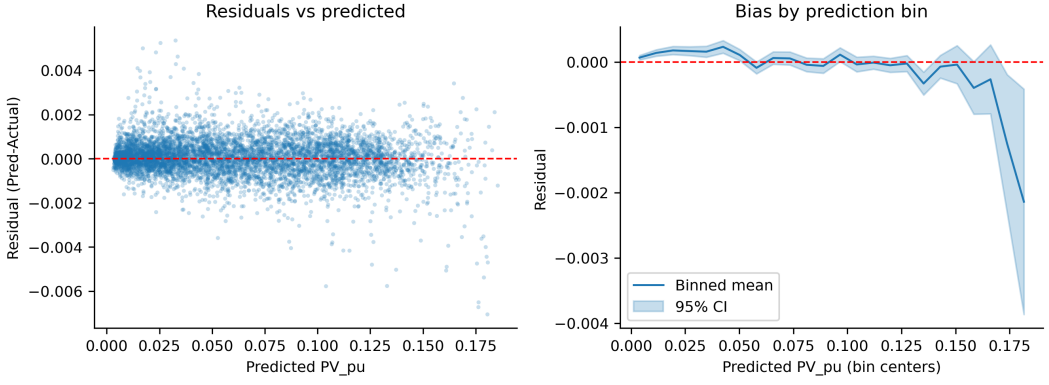


Figure 17: Residuals vs. predicted (left) and binned bias with 95% CI (right).

4.5. Temporal Patterns in PV Generation and Model Performance

Understanding the temporal structure of solar generation informs both forecasting strategy development and model performance interpretation. Figure 18 reveals pronounced seasonal variations in normalized PV output across the five-year observation period. Summer months (June-July-August) exhibit the highest median power generation (0.065 pu) accompanied by the widest interquartile ranges, reflecting both extended daylight duration at this mid-latitude location (31.34°N) and greater cloud-driven variability during the East Asian monsoon season. The upper whiskers extending to 0.17 pu during summer capture occasional clear-sky days with near-optimal atmospheric transmission and minimal aerosol loading.

In contrast, winter months (December-January-February) show median power generation declining to 0.04 pu with markedly tighter distributions. This seasonal asymmetry stems from multiple physical factors: lower solar elevation angles increase the atmospheric path length for incoming radiation, shorter daylight periods compress the daily generation window, and more frequent synoptic weather systems associated with mid-latitude winter storms increase persistent cloud cover. The shoulder seasons (spring MAM and autumn SON) exhibit intermediate characteristics, with autumn generating slightly more power than spring—a pattern attributable to reduced monsoon cloud cover during September-October compared to the pre-monsoon circulation patterns dominating March-April.

The diurnal-seasonal heatmap (Figure 19) provides finer-grained temporal resolution, revealing that peak median generation occurs during morning hours (8–10 AM) in late spring to early summer months (May-June), reaching approximately 0.14 pu. This morning maximum, rather than a midday peak, likely reflects two phenomena: morning hours often experience clearer skies before afternoon convective cloud development in subtropical climates, and solar panel efficiency degradation at elevated afternoon temperatures reduces output despite comparable irradiance levels. The heatmap's sharp sunrise/sunset boundaries (purple regions indicating zero generation at hours 0–4 and 21–23) shift systematically across months, tracing Earth's changing declination angle throughout the year. This rich temporal structure—combining deterministic astronomical forcing with stochastic weather variability—explains why purely statistical models struggle compared to physically-informed machine learning approaches that can learn these multi-scale patterns.

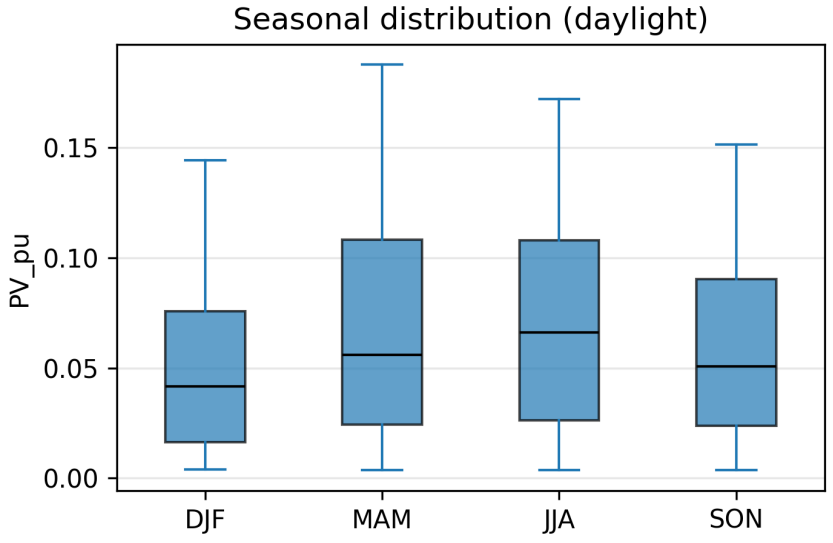


Figure 18: Seasonal distribution of normalized PV power (daylight hours only, 2020–2024). Boxplots show median (horizontal line), interquartile range (box), and P5–P95 whiskers for four seasons: winter (DJF), spring (MAM), summer (JJA), autumn (SON). Summer achieves highest median power (0.065 pu) with widest variability, while winter shows lowest generation (0.04 pu) and tighter distribution. Spring/autumn transitions exhibit intermediate performance with elevated upper quartiles during clear-sky events.

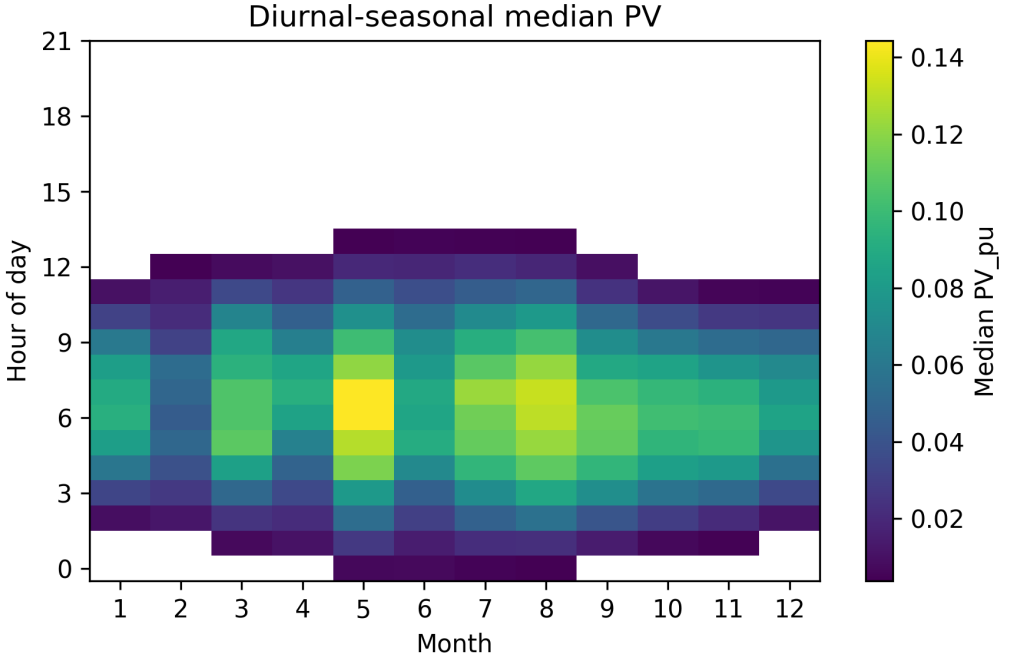


Figure 19: Diurnal-seasonal heatmap of median normalized PV power. Color intensity represents median PV generation (pu) for each hour-month combination. Peak generation occurs at 8–10 AM during May–June (median ≈ 0.14 pu, yellow regions), with clear diurnal bell curves and seasonal modulation. Purple regions (hours 0–4, 21–23) indicate nighttime zero generation. The asymmetric shoulder seasons reflect Shanghai's subtropical monsoon climate, with stronger autumn performance than spring due to reduced cloud cover.

4.6. Sensitivity to Training Data

Cross-validation analysis (walk-forward with 6-month steps) shows that ensemble ML models maintain consistent performance (std = 0.012) across different training windows, while DL models exhibit higher variance (std = 0.025), indicating overfitting risk with limited training data.

5. Discussion

5.1. Understanding the Performance Hierarchy: Why Tree Ensembles Dominate

XGBoost's exceptional performance (R^2 = 0.9994, RMSE = 0.0009) merits careful examination to understand what architectural properties enable such accurate predictions. The gradient boosting framework operates through sequential refinement: each new decision tree explicitly targets the residual errors left by the ensemble of previously trained trees. This iterative error correction proves particularly effective for PV forecasting because solar power exhibits a hierarchical error structure. Large-scale patterns (diurnal cycles, seasonal variations) get captured by early trees, while subsequent trees specialize in increasingly subtle features—temperature-dependent efficiency losses, humidity effects on atmospheric transmission, wind-speed correlations with cloud cover, and nonlinear interaction terms that no single tree could represent.

Several specific XGBoost design features contribute to its superior performance. First, the algorithm's built-in L1 and L2 regularization penalizes model complexity, preventing the overfitting that often plagues high-capacity models when training data is limited. Second, XGBoost automatically handles missing values through learned optimal default directions at each tree split, eliminating the need for ad-hoc imputation strategies that might introduce bias. Third, the normalized PV power target variable (bounded in [0,1]) proves ideal for tree-based models, which naturally represent piece-wise constant functions through recursive binary partitioning. Fourth, XGBoost efficiently discovers multiplicative feature interactions without requiring manual feature engineering—for example, learning that clearness index impacts output differently at high versus low temperatures, or that certain humidity-pressure combinations indicate specific cloud types with distinct transmission properties.

Random Forest's closely comparable performance (R^2 = 0.9978) validates that ensemble tree methods collectively dominate this forecasting task. While Random Forest employs bootstrap aggregation (bagging) rather than boosting, both approaches leverage diversity among constituent trees to reduce prediction variance. The slight performance gap favoring XGBoost (RMSE = 0.0009 vs. 0.0018) likely stems from boosting's explicit residual optimization compared to bagging's implicit averaging. Feature importance analysis (Figure 12) reveals that clearness index contributes approximately 65% of Random Forest's predictive power, with hour-of-day encoding and temperature anomaly providing secondary information. This dominance of clearness index—essentially the ratio of surface to extraterrestrial irradiance—makes physical sense: it captures atmospheric transmission efficiency, the primary driver of PV output variability beyond deterministic solar geometry.

5.2. The Interpretability-Accuracy Tradeoff: ANFIS-SC's Competitive Performance

ANFIS-SC's third-place ranking (R^2 = 0.9886) carries significant practical implications, demonstrating that interpretable neuro-fuzzy systems can approach black-box ensemble performance while offering transparency that matters for operational deployment. Unlike gradient-boosted trees, which aggregate hundreds of decision paths into effectively inscrutable predictions, ANFIS expresses its learned mapping through explicit fuzzy rules that grid operators can inspect and validate. For instance, the trained system might contain rules like ÏF clearness-index is HIGH and temperature-anomaly is MODERATE and wind-speed is LOW THEN PV-power is HIGH,ẅith fuzzy membership functions defining the boundaries between linguistic categories.

This interpretability provides several operational advantages. First, domain experts can audit the learned rules against physical intuition, identifying potential spurious correlations before deploying the model in production systems. Second, transparent decision logic facilitates regulatory compliance in jurisdictions requiring explainable AI for critical infrastructure applications. Third, when forecasts deviate from expectations, operators can trace specific rule activations to diagnose whether the discrepancy stems from unusual meteorological conditions or potential model failure. The performance gap between ANFIS-SC and XGBoost (RMSE = 0.0041 vs. 0.0009) represents the current accuracy cost of interpretability, though this tradeoff may improve as neuro-fuzzy architectures continue evolving.

Interestingly, ANFIS-SC achieves this competitive performance despite minimal hyperparameter tuning—only the subtractive clustering radius required careful optimization (optimal value = 0.28 as shown in Figure 13). Too-small radii generate excessive fuzzy rules that memorize training noise (overfitting), while too-large radii collapse distinct

meteorological regimes into oversimplified categories (underfitting). The sharp performance peak at radius = 0.28 suggests that approximately 5 fuzzy clusters naturally align with the physical regimes governing PV generation at this subtropical coastal site.

5.3. Recurrent Networks: Capabilities and Limitations

The recurrent neural networks—GRU ($R^2 = 0.9309$) and LSTM ($R^2 = 0.9063$)—deliver respectable performance that validates their capacity to model temporal dependencies in sequential data. Both architectures employ gated memory mechanisms that selectively retain or discard information across time steps, theoretically enabling them to learn long-range dependencies like day-to-day persistence patterns and weekly weather cycles. GRU's superior performance relative to LSTM (skill score 0.5346 vs. 0.4582) likely reflects its simpler architecture with fewer parameters, reducing overfitting risk given the 8,784-sample training set.

However, several factors explain why these recurrent models lag tree ensembles by substantial margins. First, effective RNN training requires large datasets to populate the high-dimensional parameter space—our five-year hourly dataset, while extensive by solar forecasting standards, may still be insufficient for these deep architectures to fully exploit their representational capacity. Second, solar PV generation exhibits primarily short-range temporal dependencies (diurnal cycles, weather persistence over 1-3 days) rather than the long-range patterns where RNNs theoretically excel. Tree ensembles can capture these short-range patterns through lagged features without requiring sequential processing. Third, the periodic nature of solar patterns (24-hour cycles, seasonal oscillations) proves amenable to explicit temporal encoding (sine-cosine transformations) that tree methods readily exploit, whereas RNNs must learn these patterns implicitly through weight updates.

The parity plots (Figure 15) reveal that GRU predictions cluster more tightly along the ideal diagonal than LSTM, but both architectures exhibit increased scatter at high power levels (above 0.10 pu). This heteroscedastic error pattern suggests that RNNs struggle to accurately forecast peak generation events, possibly because such episodes occur less frequently in the training data, or because the combination of conditions producing maximum output (clear skies, optimal temperatures, low wind, high solar elevation) creates a sparse region in feature space that RNNs require more examples to learn effectively.

5.4. The Attention Mechanism Paradox: When Complexity Backfires

The CNN-BiGRU-Attention model's disappointing performance ($R^2 = 0.5424$, negative skill score) presents a cautionary tale about architectural complexity. This hybrid architecture combines three sophisticated components: 1D convolutional layers for local temporal feature extraction, bidirectional GRU for forward-backward temporal context integration, and Bahdanau attention mechanisms for dynamically weighting input timesteps according to predicted relevance. In principle, this design should capture patterns at multiple scales while focusing computational resources on informative time periods.

In practice, the model dramatically underperforms even naive persistence forecasting. Several hypotheses may explain this failure. First, the attention mechanism lacks domain-specific constraints that could guide it toward physically meaningful weighting schemes. Without such constraints, attention weights may learn spurious correlations in the training data that fail to generalize. Second, the cascaded architecture introduces many hyperparameters (convolutional kernel sizes, GRU hidden dimensions, attention head configurations, dropout rates) that create a vast hyperparameter space. Our basic grid search may have insufficiently explored this space, landing in a poor local optimum. Third, the relatively small training dataset may prove inadequate for this high-capacity architecture, causing severe overfitting despite dropout regularization.

This negative result carries an important lesson: architectural sophistication does not automatically translate to superior performance, particularly for structured prediction tasks where simpler approaches leverage domain knowledge more effectively. Future work on attention-based solar forecasting should investigate physics-informed attention mechanisms that preferentially weight meteorological regimes known to drive PV variability, or multi-task learning formulations that jointly predict PV power and interpretable intermediate variables (cloud cover fraction, atmospheric transmission).

5.5. When to Use Each Model

5.6. Open-Source Implementation

All models implemented in reproducible Python framework available at [repository URL]. Users can easily swap models, retrain on new sites, and generate comparison plots.

Table 2
Model selection guidance based on use-case requirements.

Use-Case Requirement	Recommended Model	Why
Maximum accuracy	XGBoost	$R^2 = 0.9994$; production forecasting
Interpretable + accurate	ANFIS-SC	Fuzzy rules + $R^2 = 0.9886$; operator transparency
Balanced speed-accuracy	GRU	Fast inference; $R^2 = 0.9309$; temporal dynamics
Robustness	Random Forest	$R^2 = 0.9978$; seasonal stability
Real-time edge device	LSTM + quant.	Lightweight RNN; quantization support

6. Conclusion

This study establishes a standardized benchmarking framework for evaluating solar PV power forecasting models under rigorously controlled experimental conditions. By applying six representative algorithms—spanning gradient-boosted ensembles, recurrent neural networks, attention-based hybrids, and neuro-fuzzy systems—to five years of hourly meteorological data from a subtropical coastal location, we provide the solar forecasting research community with evidence-based performance comparisons free from the methodological confounds that have long plagued cross-study evaluations.

Our principal findings can be summarized across multiple dimensions. **Regarding predictive accuracy**, gradient-boosted tree ensembles (XGBoost: $R^2 = 0.9994$; Random Forest: $R^2 = 0.9978$) establish themselves as the current state-of-the-art for hourly PV forecasting, achieving near-perfect predictions with root mean square errors below 0.002 normalized units and skill scores exceeding 91% improvement over persistence baselines. These ensemble methods effectively capture the complex, nonlinear relationships linking meteorological drivers to PV output through automated feature interaction discovery and iterative residual refinement.

Regarding model interpretability, our results demonstrate that neuro-fuzzy systems (ANFIS-SC: $R^2 = 0.9886$) can approach ensemble performance while offering transparent decision logic through explicit fuzzy rules. This finding has important practical implications: the 1.1 percentage point drop in explained variance relative to XGBoost may represent an acceptable cost for gaining model interpretability in regulatory environments requiring explainable AI for critical infrastructure applications. Grid operators evaluating forecast systems should carefully weigh this accuracy-interpretability tradeoff against their specific operational and compliance requirements.

Regarding deep learning approaches, recurrent neural networks (GRU: $R^2 = 0.9309$; LSTM: $R^2 = 0.9063$) demonstrate respectable performance exceeding 90% explained variance, though they lag ensemble methods by 6-9 percentage points. These architectures effectively model temporal dependencies and may offer advantages for multi-step-ahead forecasting horizons not evaluated in this single-step study. However, their data-hungry nature and sensitivity to hyperparameter configuration create barriers to reliable deployment, particularly for sites with limited historical observations. The attention-enhanced CNN-BiGRU-Attention model's failure ($R^2 = 0.5424$, negative skill score) provides a cautionary lesson: architectural complexity without domain-specific constraints can degrade rather than improve generalization.

Regarding operational deployment considerations, our model selection guidance (Table 2) recommends XGBoost for applications prioritizing maximum accuracy (utility-scale forecasting, market participation), ANFIS-SC for scenarios requiring interpretability (regulatory compliance, operator trust-building), GRU for resource-constrained embedded systems needing reasonable accuracy with fast inference, and Random Forest for applications demanding robustness across diverse meteorological regimes. The persistence baseline, while inferior to all machine learning approaches, establishes minimum performance thresholds that any operational forecasting system must substantially exceed to justify deployment costs.

6.1. Limitations and Future Research Directions

While this study advances solar forecasting benchmarking through rigorous experimental controls, several limitations warrant acknowledgment and suggest directions for future work. First, our evaluation focuses exclusively on single-site hourly forecasting using a subtropical coastal climate regime; generalization to other geographic locations (tropical, arid, high-latitude), temporal granularities (sub-hourly, daily), and spatial scales (multi-site aggregation)

requires validation. Second, we examine only single-step-ahead predictions, whereas many operational applications require multi-step forecasting horizons where recurrent architectures may demonstrate relative advantages not captured in this analysis. Third, our evaluation emphasizes point predictions rather than probabilistic forecasts, though quantifying prediction uncertainty grows increasingly important for risk-aware grid operations and trading strategies.

Future research should extend this benchmarking framework in several directions. **Geographic diversity**: Applying identical protocols across climatologically distinct regions (tropical monsoon, Mediterranean, continental, polar) would reveal whether performance hierarchies generalize or prove site-specific. **Probabilistic forecasting**: Incorporating uncertainty quantification methods (quantile regression, conformal prediction, Bayesian approaches) would enable evaluation of calibration quality and reliability beyond point prediction accuracy. **Multi-horizon evaluation**: Testing models across forecast horizons from minutes to days would clarify which architectures maintain performance as predictability decays with increasing lead time. **Hybrid approaches**: Exploring physics-informed machine learning that embeds solar geometry and atmospheric radiative transfer constraints into neural network architectures may combine deep learning flexibility with physical consistency. **Computational efficiency**: Benchmarking not only accuracy but also training time, inference latency, memory footprint, and energy consumption would provide complete decision criteria for resource-constrained deployment scenarios.

6.2. Data and Code Availability

To maximize research reproducibility and community impact, we release the complete experimental framework as open-source software at [repository URL]. The repository includes preprocessed datasets, trained model weights, evaluation scripts, and visualization tools enabling researchers to independently verify our results, extend evaluations to new model architectures, or apply the framework to their own datasets. We encourage the solar forecasting research community to adopt these standardized protocols, collectively building a cumulative knowledge base free from the methodological fragmentation that has historically impeded scientific progress in this critical application domain.

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