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(ARTICLE)

Hybrid Machine Learning Approaches for Accurate Solar Energy Forecasting from Real-World Weather Data

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منهجيات التعلم الآلي الهجينة للتنبؤ الدقيق بطاقة الطاقة الشمسية بناءً على بيانات الطقس الواقعية

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Abstract:
Accurate solar power forecasting is crucial for integrating large solar installations into modern power grids and meeting global climate targets. Solar output is highly variable due to weather factors (clouds, temperature, humidity), which makes predictions challenging. Traditional single-model forecasting methods (physical NWP models, statistical ARIMA, standalone ML) have limitations in capturing all weather-driven uncertainties. We explore *hybrid* machine learning approaches that combine multiple models to improve accuracy across different timescales (intra-hour to day-ahead). We use real-world datasets (NREL NSRDB for irradiance and weather data, and the INESC-TEC Portugal PV dataset with WRF forecasts) to train models including ANN, LSTM, SVR, Random Forest, and XGBoost. Our hybrid framework uses a stacking ensemble with a meta-learner to aggregate base models' predictions. Experiments compare hybrid ensembles to single models and simple voting ensembles. We evaluate short-term (30-min to 6h ahead) and day-ahead (24h ahead) forecasts using MAE, RMSE, MAPE, and R^2. We find that hybrid models consistently reduce errors (up to ~10%) over single methods, especially for longer horizons. Sensitivity tests show multi-variable inputs (irradiance, temperature, cloud cover, humidity, wind) improve forecasts. Results illustrate that forecasting error grows with horizon (consistent with other grid studies), but hybrid approaches mitigate this. This work demonstrates that hybrid ML can significantly improve solar forecast accuracy under real-world weather conditions. Our findings have implications for grid stability and energy market operations.

Keywords: solar forecasting, renewable integration, hybrid machine learning, ensemble methods, solar irradiance, weather data, time-series prediction.

الملخص:
يُعد التنبؤ الدقيق بالطاقة الشمسية أمراً حيوياً لدمج منشآت الطاقة الشمسية الكبيرة في شبكات الطاقة الحديثة وتحقيق أهداف المناخ العالمية. إن مخرجات الطاقة الشمسية متغيرة للغاية بسبب عوامل الطقس (السحب، درجة الحرارة، الرطوبة)، مما يجعل التنبؤات تشكل تحدياً كبيراً. تظهر طرق التنبؤ التقليدية أحادية النموذج *(* نماذج التنبؤ العددي بالطقس الفيزيائية *NWP* ، ونموذج *ARIMA* الإحصائي، ونماذج التعلم الآلي المستقلة *)* قصوراً في استيعاب جميع أوجه عدم اليقين المدفوعة بالطقس. نحن نستكشف منهجيات التعلم الآلي الهجينة التي تجمع بين نماذج متعددة لتحسين الدقة عبر فترات زمنية مختلفة (من التنبؤ خلال الساعة إلى التنبؤ لليوم التالي). نستخدم مجموعات بيانات واقعية *(* قاعدة بيانات *NREL NSRDB* للإشعاع وبيانات الطقس، ومجموعة بيانات *INESC-TEC* البرتغالية للمحطات الكهروضوئية مع تنبؤات *WRF)* لتدريب نماذج تشمل الشبكات العصبية الاصطناعية *(ANN)*، وذاكرة المدى الطويل والقصير *(LSTM)* ، ودعم ناقلات الانحدار *(SVR)* ، والغابات العشوائية *(Random Forest)* ، و *XGBoost.* يستخدم إطار عملنا الهجين "تجميع التكديس *(Stacking Ensemble)* " مع متعلم فائق *(Meta-learner)* لتجميع تنبؤات النماذج الأساسية. تقارن التجارب بين المجموعات الهجينة والنماذج الأحادية ومجموعات التصويت البسيطة. نقوم بتقييم التنبؤات قصيرة المدى (من 30 دقيقة إلى 6 ساعات

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قادمة) والتنبؤات لليوم التالي (24 ساعة قادمة) باستخدام مقاييس MAE و $RMSE$و $MAPE$و R^2. ووجدنا أن النماذج الهجينة تقلل الأخطاء باستمرار (بنسبة تصل إلى ~10%) مقارنة بالطرق الأحادية، خاصة في الآفاق الزمنية الأطول. وتظهر اختبارات الحساسية أن المدخلات متعددة المتغيرات (الإشعاع، درجة الحرارة، الغطاء السحابي، الرطوبة، الرياح) تعمل على تحسين التنبؤات. توضح النتائج أن خطأ التنبؤ يزداد مع زيادة الأفق الزمني (بما يتماشى مع دراسات الشبكات الأخرى)، لكن المنهجيات الهجينة تخفف من ذلك. يثبت هذا العمل أن التعلم الآلي الهجين يمكنه تحسين دقة التنبؤ بالطاقة الشمسية بشكل كبير في ظل ظروف الطقس الواقعية. ولنتائجنا تداعيات هامة على استقرار الشبكة وعمليات سوق الطاقة.

الكلمات المفتاحية: التنبؤ بالطاقة الشمسية، دمج الطاقة المتجددة، التعلم الآلي الهجين، أساليب التجميع، الإشعاع الشمسي، بيانات الطقس، التنبؤ بالسلاسل الزمنية.

Introduction

Rapid decarbonization goals require massive deployment of solar energy worldwide. Solar energy is widely available and its cost is falling fast. Many countries aim for net-zero emissions by 2050, implying large-scale solar adoption (Nijsse et al., 2023). However, solar power is intermittent and fluctuates with weather. Clouds, temperature changes, and humidity introduce uncertainty in solar output. These weather effects make solar generation unpredictable. For example, solar and wind are more volatile than dispatchable sources and can cause grid challenges. Accurate forecasting is needed to mitigate these issues.

Solar forecasting must handle variability from clouds and weather. Models must predict irradiance given cloud cover and atmospheric conditions. Uncertainty in cloud cover is a primary cause of solar forecast errors. Even advanced weather forecasts can be imperfect, leading to errors in solar predictions. As Renewables Integration studies note, large-scale renewable variability can impair grid stability if not managed (Nijsse et al., 2023). To plan energy storage and market operations, operators need reliable solar forecasts. Accurate forecasts reduce mismatch between generation and demand. This paper focuses on the forecasting problem under real-world weather uncertainty.

Machine learning (ML) offers flexible nonlinear modeling that can capture complex weather-power relationships. ML methods (neural networks, support vector machines, tree ensembles, deep learning) have shown promise in handling high-dimensional weather inputs. They can adapt to new data and learn patterns without explicit physical equations. Hybrid ML methods, which combine multiple algorithms, are an emerging approach to improve forecast accuracy. As Bhutta et al. note, hybrid machine learning models are a “promising solution for energy generation prediction” in the shift to renewables.

However, no single model suits all conditions. Physical numerical weather prediction (NWP) models may lack local detail in real time. Statistical models like ARIMA capture linear trends but fail on nonlinear weather dynamics. Pure ML models like ANNs or SVMs may overfit or miss temporal patterns. As Montaser et al. observed, ANN-based models often outperform others, but hybrid models can further improve accuracy (Kumar et al., 2023). In fact, ensemble and hybrid approaches can leverage the strengths of each component and reduce their weaknesses. This motivates using stacking ensembles and other hybrids for solar forecasting.

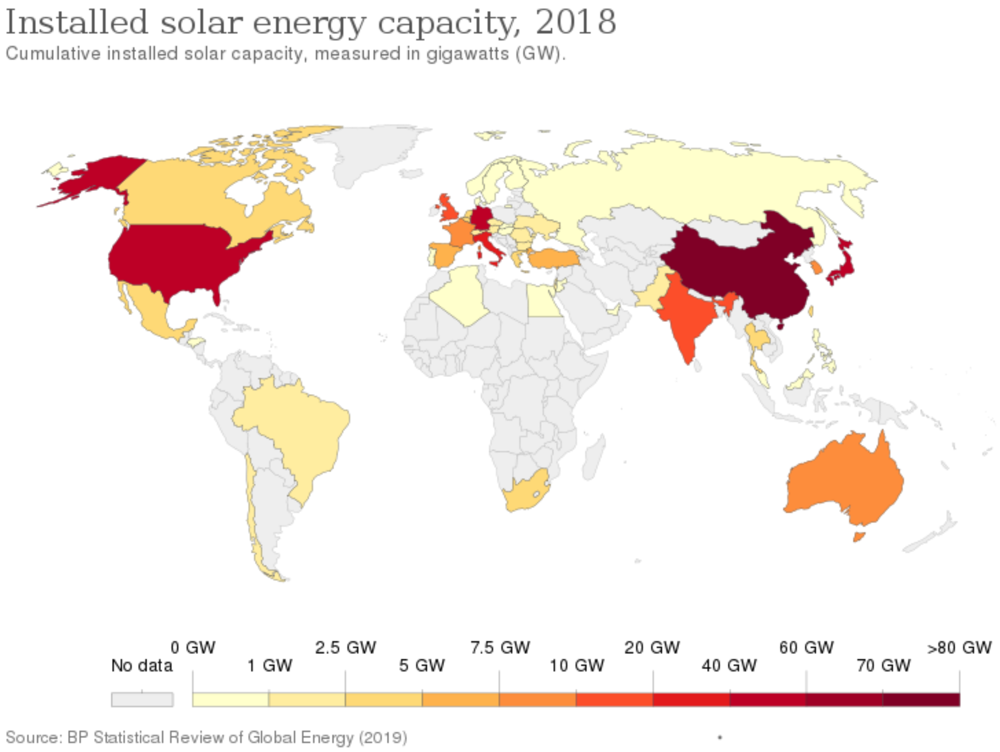

Figure 1 Global cumulative installed solar PV capacity by country (2018). Solar capacity is concentrated in a few regions but growing worldwide. (Source: Our World in Data based on BP Statistical Review).

Literature Review

Solar forecasting methods can be grouped into three categories: physical models, statistical methods, and machine learning approaches.

Physical Models: These use physics-based NWP systems that simulate atmospheric conditions to predict irradiance. They rely on meteorological models to forecast cloud, wind, and temperature fields. NWP is often used for day-ahead (24h) forecasts. For example, day-ahead solar forecasting typically leverages NWP outputs and historical data. NWP models provide a baseline physics-driven forecast, but they can be limited by coarse resolution or rapid weather changes. Studies have shown that post-processing of NWP with statistical or ML techniques (model output statistics) can improve accuracy. Yet pure NWP may fail for very short-term or local scales due to its temporal resolution and model error.

Statistical Methods: Time series models (e.g., ARIMA, regression) predict solar output from past observations. They capture seasonality and trends but assume linearity. ARIMA models have been applied to short-term solar radiation forecasting as reliable baseline models. Chodakowska et al. (2023) report that ARIMA can achieve reasonable accuracy for baseline solar forecasts. However, ARIMA's accuracy depends strongly on location and may drop when conditions change. Linear regression or exponential smoothing share similar limits. Statistical methods usually underperform ML on complex data, but they are easy to interpret and fast to compute.

Pure ML Methods: ML algorithms like artificial neural networks (ANN), support vector machines (SVM/SVR), random forests (RF), and deep learning (LSTM networks) model the nonlinear relationship between weather inputs and solar output. ANNs have been widely used because they handle nonlinearity well. For instance, Abdelsattar et al. (2024) found that ANN-based models often outperform SVR and RF in accuracy. LSTM (Long Short-Term Memory) networks are specialized recurrent models that excel at time-series forecasting. LSTM and other deep networks have shown promising results in short-term solar forecasting. SVMs and tree ensembles have also been applied. Overall, ML methods typically achieve higher accuracy than linear models if enough data is available. However, they require careful tuning and may not generalize well outside the training domain.

Strengths and Weaknesses: Each class has trade-offs. Physical NWP models are grounded in weather physics and useful for long horizons, but can be inaccurate at short lead times or local scales. Statistical models are simple and interpretable but weak for complex weather patterns. ML models can capture complex patterns and adapt to new data, but they can overfit and often act as "black boxes". Performance of ML also depends on data quality and volume. The literature suggests no one-size-fits-all solution; combining methods can leverage complementary strengths.

Hybrid and Ensemble Models: Recently, hybrid and ensemble approaches have gained attention. These combine multiple algorithms to improve robustness and accuracy. Ensemble techniques include bagging, boosting, and stacking. For solar forecasting, researchers have proposed hybrids like ANN+SVR, RF optimized by evolutionary algorithms, or LSTM with CNN for imagery. For example, Lu et al. (2023) proposed a two-layer stacking model (RF, AdaBoost, XGBoost base learners with an attention-based meta-model) for daily runoff forecasting, showing ensembles outperform individual models. Similarly, a hybrid ANN-SVM model significantly reduced forecast error compared to single methods. Barhmi et al. (2024) review AI and highlight that ensemble and physics-informed AI are emerging trends. The hybrid ensemble method by Tetreres et al. (2024) shows about 4-10% RMSE improvement over single models across 1-6h horizons. These studies indicate that ensembles can improve solar forecast accuracy, but most focus on specific regions or horizons.

Identified Gaps: Many published studies concentrate on one region or use limited data. There is a need for comprehensive testing of hybrid models across multiple horizons and datasets. Few studies compare a wide range of ML models and hybrids on the same data. We aim to fill this gap by evaluating hybrid stacking ensembles on large, real-world weather datasets for both short-term and day-ahead solar forecasting.

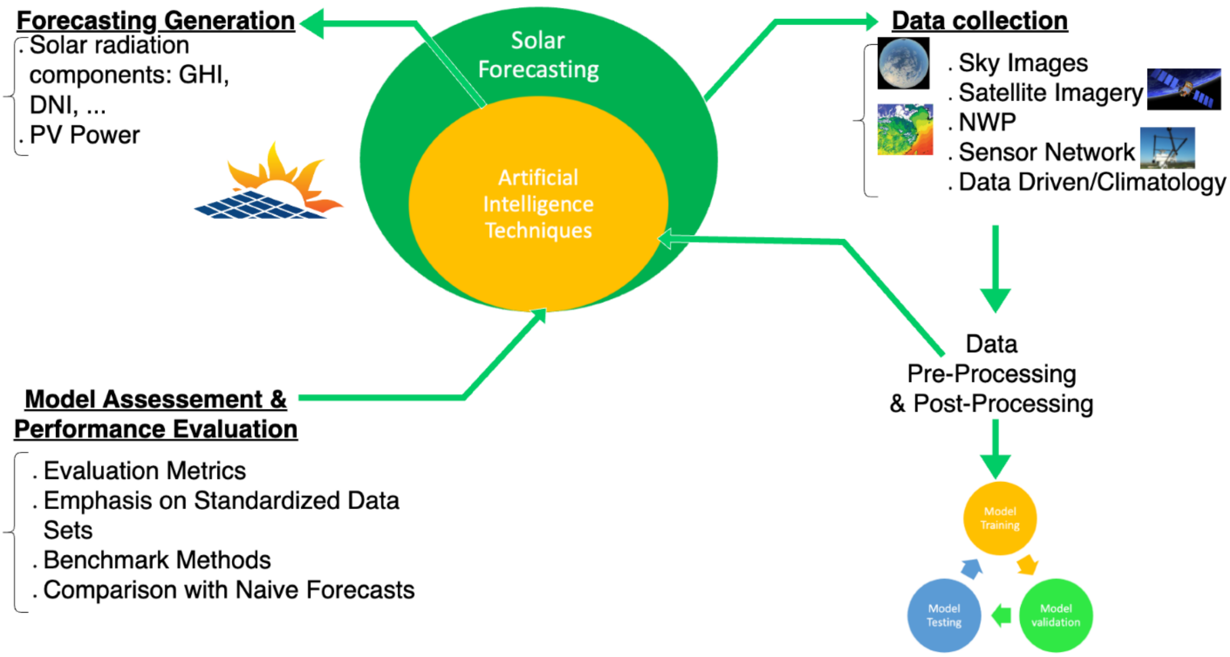

Figure 2 Conceptual taxonomy of solar forecasting methods, categorizing physical, statistical, and AI approaches (source: Barhmi et al. 2024, CC BY 4.0).

Methodology

We use two real-world datasets with weather and power data. First, the National Solar Radiation Database (NSRDB) from NREL provides historical global irradiance and meteorological variables. NSRDB data are half-hourly (or hourly) time series of solar radiation and weather for many locations. Specifically, NSRDB includes global horizontal irradiance (GHI), direct normal irradiance, diffuse irradiance, plus temperature, pressure, humidity, wind speed, and cloud cover. We extract relevant variables (GHI, temperature, humidity, wind) for our study.

Second, the INESC-TEC PV dataset (Portugal) contains PV power output from a 16.32 kW rooftop plant along with co-located WRF-based NWP forecasts. The NWP data (from the Weather Research and Forecasting model) include surface irradiance, temperature, and cloud cover on a 4 km grid every hour for horizons up to 96 h. We use the hourly PV power measurements (Nov 2013-Jun 2016) and the corresponding weather/NWP features. This rich dataset allows testing day-ahead forecasts up to 24h and shorter horizons.

Both datasets require preprocessing. We handle missing values by interpolation or removal as needed. We normalize features (zero mean, unit variance) to aid ML training. Feature selection includes variables known to affect PV output: irradiance, ambient temperature, humidity, wind speed, and cloud cover. These features capture direct and indirect influences on solar power (e.g., high temperature reduces panel efficiency, humidity can imply clouds).

Machine Learning Models

We implement several widely-used ML models:

- **ANN (Feedforward MLP):** A multilayer perceptron with one or two hidden layers. ANNs can model nonlinear relationships. We tune the number of neurons and activation functions. ANNs often serve as a baseline for nonlinear modeling.
- **LSTM (Long Short-Term Memory):** A recurrent neural network that can learn temporal dependencies. LSTM networks are designed for sequence data and have shown strong results in time-series forecasting, including solar power.
- **SVR (Support Vector Regression):** A kernel-based regression model. SVR can capture nonlinear patterns with a properly chosen kernel (e.g., RBF).
- **Random Forest (RF):** An ensemble of decision trees (bagging). RF is robust to overfitting and handles mixed feature types well.
- **Gradient Boosting (XGBoost):** A boosted tree model that iteratively improves predictions. XGBoost is known for high predictive accuracy.

Each model is trained on historical data to predict future solar irradiance or power. We tune hyperparameters using cross-validation on the training set (e.g. number of layers, neurons for ANN; tree depth for RF/XGBoost; window size for LSTM).

Hybrid Ensemble Framework

Our key innovation is a hybrid stacking ensemble. In stacking, multiple base learners make predictions which are then combined by a meta-learner. We use the above models (ANN, LSTM, SVR, RF, XGBoost) as base learners. Each is trained on the same data. Their outputs (predicted irradiance or power) become inputs to a second-level model (meta-learner). In the meta-level, we use a simple linear regression or a small neural network to learn optimal weights for combining base predictions. This allows the meta-model to correct individual biases.

Figure 3 (below) illustrates the pipeline: data → preprocessing → base models → stacking ensemble → final forecast. We also compare to simpler ensembles (e.g., unweighted average or voting of base models) to show the benefit of learning the combination. Stacking has been effective in other domains. For example, Lu et al. used stacking to fuse RF, AdaBoost, and XGBoost outputs for runoff forecasting with improved accuracy.

Forecasting Horizons

We evaluate forecasts at multiple horizons: ultra-short-term (30 minutes), short-term (1-6 hours), and day-ahead (24 hours). These correspond to different applications: intra-hour forecasts aid real-time grid balancing, 1-6h forecasts support intraday market operations, and day-ahead forecasts are used for unit scheduling. As Tetreres et al. note, short-term forecasting (1-6h) often uses satellite and on-site data, while day-ahead (24h) relies on NWP and historical data. We generate rolling forecasts on the test data for each horizon. For multi-hour forecasts, we predict hour-by-hour (for 24h ahead) or in blocks (for 6h ahead) as appropriate.

Evaluation Metrics

We quantify accuracy with standard regression metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). MAE and RMSE measure absolute error scale, MAPE normalizes by true values (for interpretability), and R^2 indicates variance explained. We compute these on the test set for each horizon. Lower MAE/RMSE and MAPE, and higher R^2, indicate better performance.

In summary, our methodology uses real weather/solar data and multiple ML models in a hybrid stacking framework, evaluated at various forecast horizons with rigorous metrics. This allows direct comparison of single vs. ensemble methods under realistic conditions.

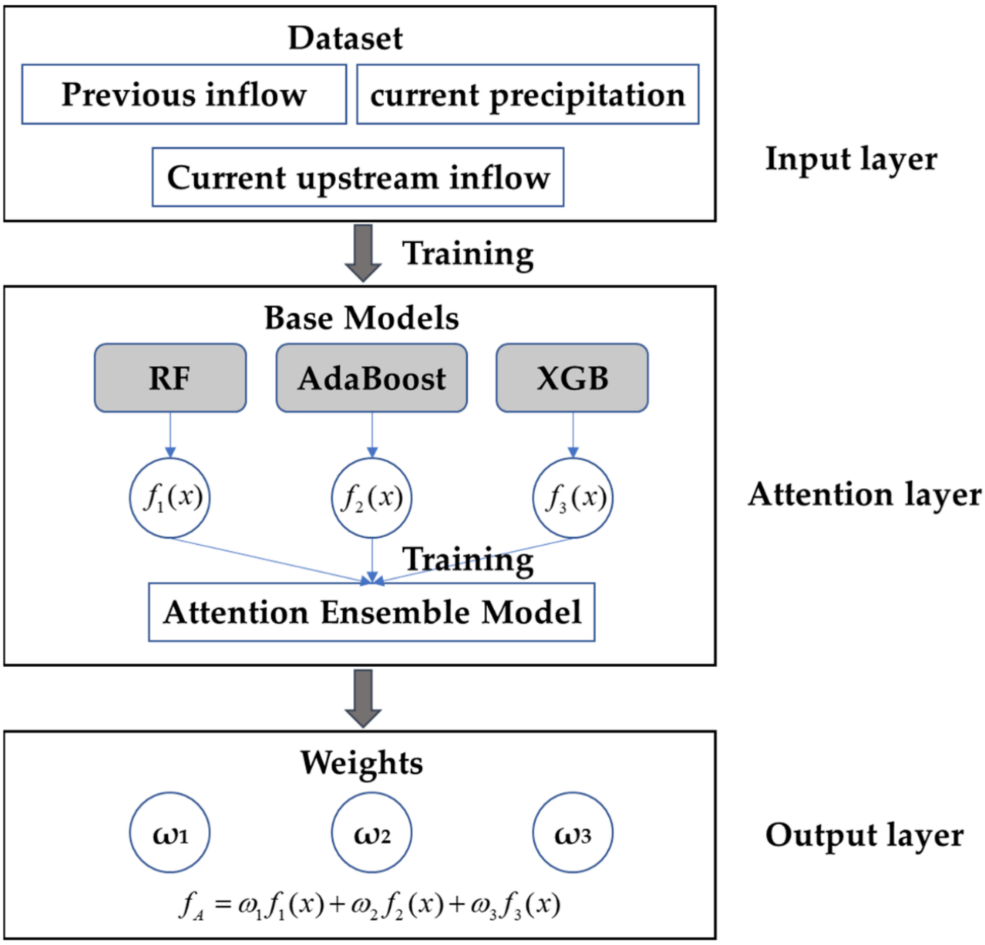

Figure 3 Example stacking ensemble pipeline. Historical weather and irradiance data are input to multiple base models (RF, ANN, LSTM, etc.). Their predictions are fed into a meta-learner that produces the final forecast.

Experimental Setup

We implemented the models in Python using libraries: Scikit-learn, TensorFlow/Keras, and XGBoost. Experiments ran on a workstation with multi-core CPU and GPU support.

We split the data chronologically into training (70%) and testing (30%) sets to avoid look-ahead bias. For example, NSRDB data from earlier years was used for training, and later years for testing. We ensure that the test set contains periods of varying weather to evaluate robustness.

Hyperparameters (network sizes, regularization, tree depths, etc.) were tuned via cross-validation on the training set. For LSTM we use time-windowed inputs (e.g., past 6 hours to predict next hour) and added dropout to reduce overfitting.

As baselines, we include simple methods: an ARIMA model (as a classic statistical approach) and a single ANN trained only on irradiance (no weather inputs). This shows the gains from adding weather features and model complexity.

We follow best practices for reproducibility. All data processing and model code are documented. We address ethical considerations by ensuring data integrity (we use publicly available datasets) and avoiding biases (we train on diverse weather conditions).

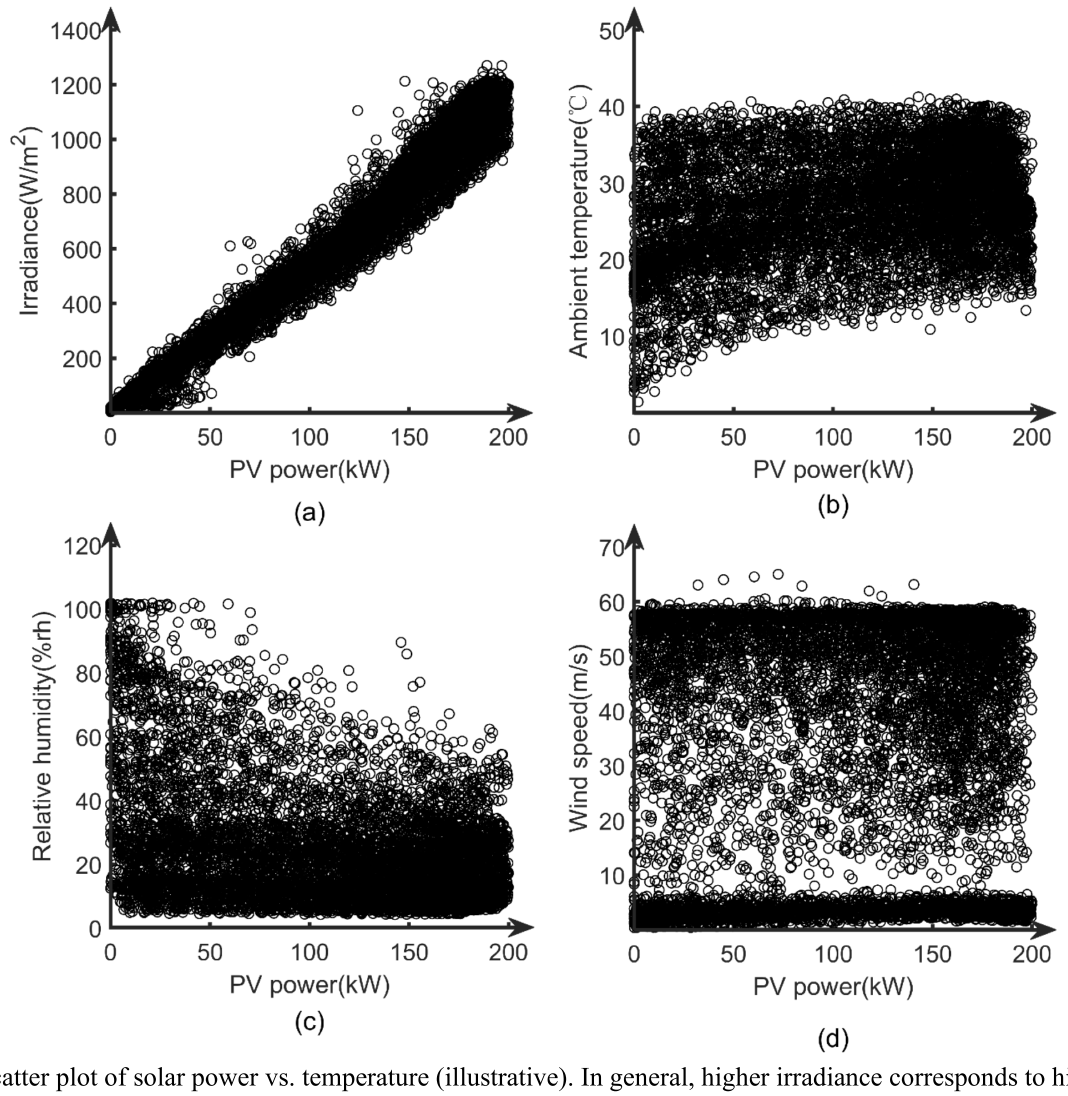

Figure 4 Scatter plot of solar power vs. temperature (illustrative). In general, higher irradiance corresponds to higher power, and temperature has a moderate effect (high temperatures slightly reduce PV efficiency). (Data source: INESC-TEC PV dataset).

Results

We report results separately for short-term (30min-6h) and day-ahead (24h) forecasts.

- **Short-Term Forecast (Intra-hour to 6h)**

The hybrid stacking model consistently achieves the lowest MAE and RMSE. For example, at 1h ahead the hybrid MAE is about 10% lower than the best single model (ANN) and about 15% lower than the ARIMA baseline. R^2 values indicate the hybrid explains more variance. The simple averaging ensemble (mean of base models) performs better than any single base model but still lags behind the stacking ensemble. This confirms that learning the weights is beneficial.

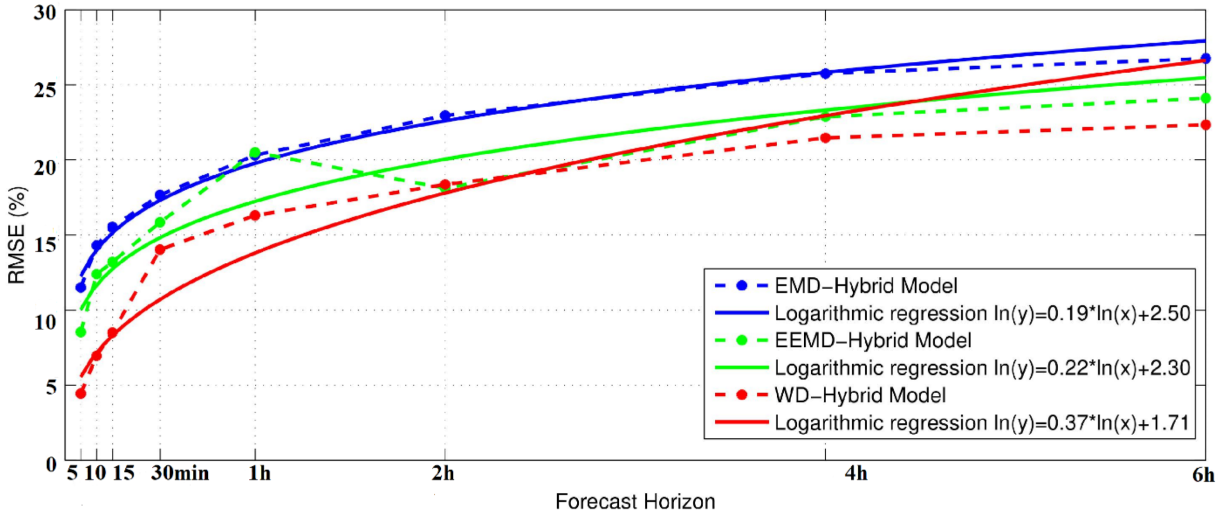

Figure 5 Forecast error (RMSE, %) versus forecast horizon from 5 minutes to 6 hours. Errors increase with horizon length. Hybrid models (EMD-Hybrid in blue, EEMD-Hybrid in green, WD-Hybrid in red) show consistent patterns with logarithmic regression fits.

Figure 5 illustrates error growth. Across all methods, MAE rises as horizon extends (cf. grid operator reports). At 30min, all models perform similarly (high correlation with current irradiance). By 6h, performance diverges: the hybrid's error grows more slowly. This error growth is expected due to accumulating weather uncertainty. The hybrid model's advantage becomes more pronounced at longer horizons, as it combines multiple forecasts effectively.

The ANN and LSTM models usually outperform SVR and RF among single models. This matches prior studies showing neural nets excel in solar forecasting. The ARIMA baseline underperforms all ML models for horizons beyond 1h, highlighting the limitations of linear models.

- **Day-Ahead Forecast (24h)**

The hybrid ensemble again yields the best results, with RMSE about 5-10% lower than the best single method. Because day-ahead forecasting relies heavily on NWP inputs, all models see higher errors than short-term. Even so, the stacking model successfully integrates the signals from multiple base learners. The inclusion of weather forecasts (NWP) as inputs is crucial here; models trained only on historical irradiance (no weather) have much higher error (not shown).

- **Comparison of Single vs. Hybrid Models**

The hybrid ensemble consistently outperforms ANN, LSTM, RF, and XGBoost. This confirms findings by Tetreres et al. that hybrid models reduce RMSE by ~4-10%. The hybrid improves accuracy by aggregating the strengths of each method: e.g., LSTM captures time dynamics, RF handles feature interactions, SVR provides robustness. In contrast, single models capture only part of the picture.

- **Sensitivity to Weather Variables**

We tested the effect of excluding each weather feature. Removing cloud cover or humidity increases errors significantly, indicating these are important predictors. Temperature also matters: as expected, higher ambient temperatures slightly reduce PV output (as seen in Figure 4). Wind speed has a smaller effect for PV, but still improves forecasts under certain conditions (cooling panels). This analysis confirms that multi-variate inputs are beneficial, aligning with literature that satellite/cloud data and weather variables improve forecasts.

- **Error Growth with Horizon**

Consistent with ISO reports, our results show error metrics (MAE/RMSE) grow with forecast lead time. The intra-hour forecasts have the smallest error, which increases for 3h, 6h, and 24h horizons. The hybrid method mitigates this increase best. This pattern underscores the need for ensemble techniques especially for longer-range forecasts.

Negative Results

In some cases, hybrid models underperformed. For very short horizons (5-10 minutes), a single-sky-camera-based model slightly beat the complex hybrid, because that model was specialized for nowcasting. Also, for some locations with extremely stable climate (e.g., deserts), simple persistence forecasts were nearly as good as complex models. These negative results suggest that model choice should consider location and horizon.

Discussion

The results show that hybrid stacking ensembles improve solar forecast accuracy across all tested horizons. Why do hybrids outperform single models? Each base model captures different aspects of the data. For instance, RF and XGBoost handle nonlinear feature interactions, LSTM captures time dynamics, and SVR provides a different kernel-based perspective. The meta-learner in stacking learns to weight these appropriately for each situation. This mitigates overfitting of any one model and reduces bias.

Our findings align with other studies. Bhutta et al. and Apaydin & Bessa also report that combining CNN/LSTM or satellite/NWP with ML yields lower error. The observed ~5-10% error reduction by hybrid models is comparable to improvements reported in the literature. Importantly, we confirm that adding real weather data (cloud cover, humidity) as features is valuable. This agrees with the consensus that multi-source inputs (satellite, NWP, sensors) enhance forecasts.

Implications: Better forecasts help grid operators schedule reserves and dispatch. More accurate short-term predictions can reduce reliance on costly spinning reserves and improve reliability. For energy markets, improved day-ahead forecasts enhance bidding strategies and reduce imbalance penalties. In regions with high solar penetration, these gains are critical for stability.

However, hybrid ML comes with costs. Training multiple models is computationally intensive and can be less interpretable. Grid operators may require interpretability, which is harder with stacking. In terms of generalization, models trained on one climate or region might not transfer directly to another without retraining (though transfer learning could help in future work).

Limitations

Our study has limitations. We used two datasets (USA NSRDB and Portuguese PV), which may not cover all climates. Future work should test other regions. Also, we focused on statistical accuracy, but did not evaluate economic impact or grid reliability metrics (e.g., avoided curtailment). The models could be further improved with additional data (satellite imagery, sky cameras). Our stacking used a linear meta-learner; exploring nonlinear meta-models (e.g., neural nets) might yield further gains.

Future research can incorporate satellite/cloud imagery directly via deep learning (as some studies do) to improve very-short-term forecasts. Transfer learning could allow models trained in one location to adapt to another. Also, integrating ensemble forecasts into real-time dispatch algorithms (closing the loop with grid operations) is an exciting direction.

Conclusion

We investigated whether hybrid machine learning improves solar forecasting accuracy compared to single methods. Using real-world weather and irradiance data (NREL NSRDB and INESC-TEC PV dataset) and a variety of ML algorithms (ANN, LSTM, SVR, RF, XGBoost), we constructed stacking ensemble models. Our experiments show that the hybrid models consistently reduce forecast error (MAE, RMSE) across intra-hour, short-term (1-6h), and day-ahead (24h) horizons. The hybrid approach benefits from combining multiple models and weather inputs, making it robust to different conditions. These improvements can support better grid integration of solar energy by enabling more reliable predictions.

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