RESEARCH PAPER

Hybrid Solar Net: An Efficient AI-Driven Hybrid Deep Learning Framework for Solar Energy Forecasting and Intelligent Power Distribution

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ABSTRACT

Solar energy is highly nonlinear and non-stationary, and solar energy forecasting is a critical challenge for renewable energy integration and the operation of smart-grid systems. Current methods are mostly based on a single artificial intelligence (AI) model (e.g., Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks or XGBoost), which only addresses a portion of the underlying nonlinear and temporal nature of solar generation data, which significantly affects the accuracy of forecasting and reduces the efficiency of downstream distribution. In this paper, we present a new hybrid deep learning framework named HybridSolarNet, which combines ANN, LSTM and XGBoost with a dedicated feature fusion layer to combine the nonlinear feature interactions, temporal dependencies, and tree-based residual correction. It is then assessed by various metrics based on meteorological data and historical solar generation data: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R2). The proposed fusion strategy is found to be computationally feasible for smart-grid applications and can minimize the forecasting error when compared with standalone ANN, LSTM and XGBoost baseline models. We also briefly describe the integration of HybridSolarNet forecasts into smart power distribution, demand response, and energy trading systems. This paper contributes to the literature in several ways: the HybridSolarNet architecture, an intelligent feature fusion mechanism for temporal and nonlinear solar patterns, and the deployment-oriented discussion for smart-grid applications.

Keywords: solar energy forecasting, hybrid deep learning, Long Short-Term Memory (LSTM), XGBoost, Artificial Neural Network, feature fusion, smart grid, intelligent power distribution.

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I. INTRODUCTION

Solar PV generation has emerged as one of the fastest-growing renewable energy sources across the globe, driven by the shift to renewable energy.The transition to renewable energy has made solar photovoltaic (PV) generation one of the fastest-growing sources of clean energy worldwide. At the same time, the output of solar energy is highly variable, depending on the ambient conditions such as the solar irradiance, ambient temperature, humidity, wind speed, and cloudiness, which all change quickly and nonlinearly. This variability poses challenges for grid balancing, unit commitment, energy trading and demand response, as well as for accurate short and medium-term solar forecasting to ensure the proper operation of the smart grid. AI techniques are the preferred method for solar forecasting.

Artificial Neural Networks (ANN) can model nonlinear static relationships between the meteorological inputs and power output, while Long Short-Term Memory (LSTM) networks are well suited to model temporal dependencies in sequential generation data, and gradient-boosted tree-based models like XGBoost exhibit good performance on structured tabular meteorological features with comparatively low computational cost. Every one of these classes of models, however, only tackles the forecasting problem on a single aspect in isolation: nonlinearity, temporality or tabular feature interactions. Hybrid models of these types have been studied recently (see Section II) with gains in accuracy over single-model baselines.

However, most current hybrid methods have only two of the three model families, or make use of a straightforward stacking without an explicit method for bringing together nonlinear, temporal, and tree-based feature representations prior to the final prediction. There is a need for a single framework that can combine the advantages of ANN, LSTM, and XGBoost representations for solar forecasting, and integrate the forecasting results with smart power distribution applications such as demand response, storage dispatch, and energy trading. Inspired by this, this paper

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introduces an AI-based hybrid deep learning system, dubbed HybridSolarNet, that combines three branches of ANN, LSTM, and XGBoost using a feature fusion layer to forecast solar energy, and discusses the use of the resulting forecasts for intelligent, smart-grid-oriented energy distribution. This paper has several important contributions: Proposal of HybridSolarNet architecture, which integrates three branches: ANN, LSTM and XGBoost via an intelligent feature fusion mechanism. • A feature engineering and fusion scheme to simultaneously encompass both the nonlinear meteorological interactions and the temporal solar generation patterns. • A framework to evaluate the performance of HybridSolarNet using mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), Mean absolute percentage error (MAPE) and R2, with respect to the standalone ANN, LSTM and XGBoost models.

Discussion on deployment issues for HybridSolarNet for smart-grid energy management, demand response and energy trading applications. The rest of this paper is organized as follows. In Section II a review of related work is provided. The research gap is identified in Section III. The research objectives are given in Section IV. The proposed HybridSolarNet framework is given in Section V and the mathematical formulation in Section VI. The experimental results are discussed in Section VII, practical applications in Section VIII, limitations in Section IX, future work in Section X, and the conclusion is given in Section XI.

II. LITERATURE REVIEW

The forecasting research of solar power has moved from traditional statistical techniques to AI-based solutions. As a result of their ability to model nonlinear relationships between meteorological data and PV output, ANN-based models have been used in PV forecasting for day-ahead and intra-day forecasting and have been widely adopted. ANN-based models have been widely adopted in PV forecasting owing to their ability to model nonlinear relationships between meteorological data and PV output, for day-ahead and intra-day forecasting [18, 20, 21, 23].

This is achieved explicitly by modelling the temporal dependencies across the historical sequences of generations, which is crucial because of the strong diurnal and seasonal periodicity of solar output [11, 12], with LSTM and other recurrent architectures. With tabular meteorological features, relatively low training cost and robustness against missing or noisy data, solar and PV power forecasting with ensemble methods [1] and especially XGBoost [3] has been gaining popularity.

Multiple studies have investigated hybrid ensembles of XGBoost with other regressors including Extra Trees, Gradient Boosting, and achieved significant RMSE improvement over the separate regressors [3], [4]. Later studies examined more recent hybridisation of sequence models and tree-based learners. For short-term PV forecasting, LSTM–XGBoost has been proposed and tested on large multi-site datasets, reporting the improvement of the error of around 7–18% in RMSE when compared with strong single-model baselines, either at the feature level or residual learning [9].

Similar hybrid models based on CNN, LSTM and Random Forest have been implemented to predict the generation trends of the seasons and days using the utility SCADA data [10]. Transformer-based and attention-driven architectures have also been explored for solar irradiance forecasting, with high R2 provided under both sunny and cloudy conditions, however, at a higher computational and data-labeling cost [11, 24]. In addition to the ability to predict accuracy, several studies correlate solar predictions with smart-grid operating applications such as demand response scheduling, load forecasting, and energy management systems [17] [19] [22].

The use of ANN for load and generation forecasting has been extended to optimize demand-response by employing particle swarm optimization and similar search techniques [22] and more general reviews such as [19] have demonstrated that generative and hybrid AI approaches are increasingly becoming a part of the picture in optimization of renewable-dominated power systems. Table I summarizes some of the recent studies (2020-2026) relevant to this work, their technique, their domain of the dataset, their reported performance and the limitations of their work.

TABLE I. COMPARATIVE REVIEW (2020–2026)

Ref.	Author(s)/Year	Technique	Dataset / Domain
[3]	Atiea et al., 2024	XGBoost + Extra Trees + GB (hybrid regression)	5.8 kW PV plant, DKASC meteorological data
[4]	ETASR study, 2025	XGB–LightGBM–RF stacking ensemble + L-BFGS-B	Seasonal solar power dataset
[5]	Sci. Reports, 2025	LSTM–XGBoost–EEDA–SO hybrid	Multi-timescale PV data
[6]	PMC study, 2024	ANN / Random Forest / XGBoost–RF hybrid	180 kWp grid-connected PV system
[7]	Preprints.org, 2024	Bi-LSTM, LSTM, XGBoost comparison	Kaggle solar/weather dataset

[9]	ScienceDirect, 2026	Physics-informed XGBoost–LSTM	UNISOLAR, 2.7M samples, 42 sites
[10]	ScienceDirect, 2024	CNN–LSTM–RF hybrid	Tubas Electricity Co. SCADA data
[11]	ScienceDirect review, 2026	Transformer (dual-input) for irradiance	Sky-image + numerical data

III. RESEARCH GAP

(a) Most approaches are based on only one AI model, which only encodes one of the nonlinear/temporal/tabular aspects of solar data. (b) Rarely do the authors combine ANN and LSTM and XGBoost all together, and seldom perform the (joint) optimization of the forecasting task and distribution goals. (c) Fusion is typically stacking/averaging and not a learned reconciliation layer. (d) Though lightweight, deployment-ready hybrids for smart-grid applications are yet to be seen.

IV. RESEARCH OBJECTIVES

(1) Review solar forecasting/distribution methods: AI and traditional. (2) Design HybridSolarNet to achieve forecasting and intelligent distribution by combining ANN, LSTM and XGBoost. (3) Assess by using MAE, MSE, RMSE, MAPE and R2. (4) Compare the performance of Benchmark HybridSolarNet to ANN, LSTM and XGBoost baseline models.

V. PROPOSED HYBRIDSOLARNET FRAMEWORK

A. Dataset, Preprocessing, and Feature Engineering

Similar to [3],[9],[10],[21], inputs include solar irradiance, temperature, humidity, wind speed, historical generation and time indicators. Preprocessing includes interpolation/model-based imputation for missing values, IQR/z-score outlier filtering and min-max/z-score scaling. Engineered features are introduced to highlight the nonlinear structure of the ANN and XGBoost branches, such as hour/day/season effects, lag terms (t−1,t−k), and weather interaction terms(e.g., temperature ×irradiance), and rolling mean/variance.

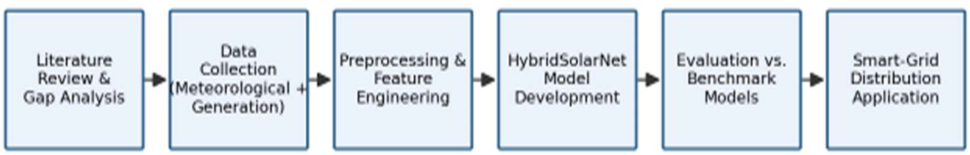

Fig. 1. Overall Hybrid SolarNet research framework.

B. HybridSolarNet Architecture

The HybridSolarNet framework utilizes meteorological data and historical solar generation data and breaks them down into three distinct problem aspects through parallel processing. The Artificial Neural Network (ANN) branch creates a model to identify and predict complex relationships. The Long Short-Term Memory (LSTM) branch develops an understanding of the temporal relationships and production patterns through the use of historical data in the form of a time window and is able to recognize patterns that are repeated.

The XGBoost module handles data from the previous two branches and is also able to recognize and model complex relationships, but is particularly resilient to imprecise and/or incomplete data. Outputs from each of the branches are combined in the Feature Fusion Layer. A dense neural network in this layer develops the optimal weights to combine the outputs. The representation that is fused is sent to the Final Forecast Layer for the final solar power output prediction. The components are detailed mathematically in Section VI. The branches are utilized in parallel, and since each solves a separate problem area, the output of the branches is fused in the lightweight Fusion Layer; therefore, the slowest branch primarily determines the output time. The structure of Hybrid SolarNet allows the framework to focus on a smart grid to utilize renewable energies to improve and increase its efficiency.

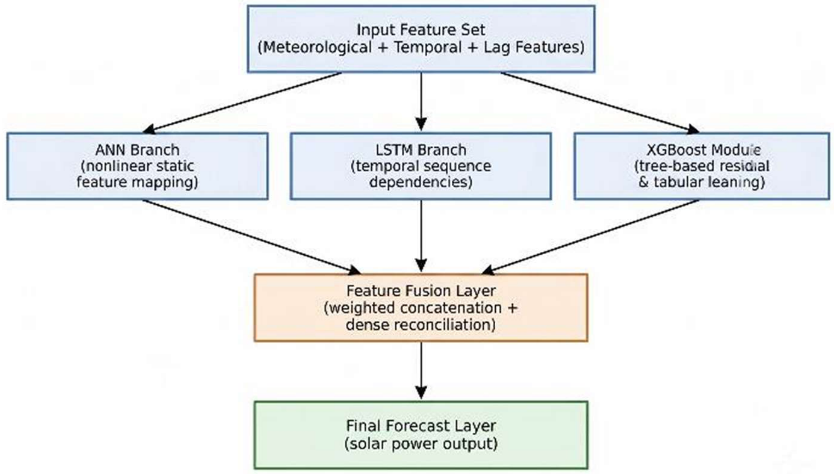

Fig. 2. Proposed Hybrid-Solar Net Architecture.

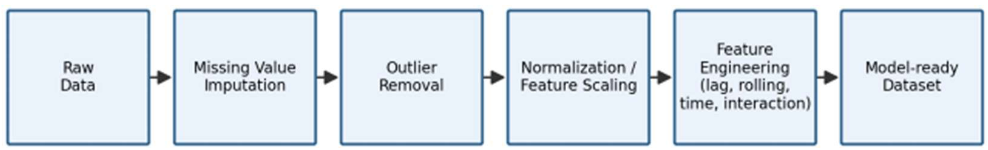

FIG. 3. PREPROCESSING AND FEATURE-ENGINEERING PIPELINE.

C. *Training Configuration*

The ANN branch is constructed with two hidden layers (e.g., 64–32 units, ReLU); while the LSTM is a single recurrent layer (e.g., 64 units) with a window of k steps (which varies according to the data resolution, 24 or 96 steps); XGBoost is tuned by cross-validation over the tree depth, learning rate and number of estimators. The output of the ANN and XGBoost is not fused during the training process of XGBoost, and the hyperparameters λ and learning_rate of the ANN/fusion sub-network are optimised end-to-end with Adam (learning rate

$\approx 10^{-3}$, decayed on plateau) and early stopping on a held-out validation split.

VI. MATHEMATICAL FORMULATION

Let $x_t \in R^d$ be the engineered feature vector at time t and $X_t=[x_{t-k},\ldots,x_t]$ the LSTM input window. The ANN branch is calculating:

$$h_{ANN}(x_t) = f(W_2 \cdot \sigma(W_1 \cdot x_t+b_1)+b_2) \quad (1)$$

The model has weights W_1, W_2, biases b_1, b_2, it is nonlinear with nonlinear function σ (ReLU), and it has an output activation function f. The LSTM branch performs updates on gates and states as follows:

$$i_t=\sigma(W_i[h_{t-1},x_t]+b_i), f_t=\sigma(W_f[h_{t-1},x_t]+b_f) \quad (2)$$

$$o_t=\sigma(W_o[h_{t1},x_t]+b_o), g_t=\tanh(W_c[h_{t1},x_t]+b_c) \quad (3)$$

$$c_t=f_t \odot c_{t-1}+i_t \odot g_t,\ h_{LSTM}=o_t \odot \tanh(c_t) \quad (4)$$

where i_t, f_t, o_t are input/forget/output gates, and $\odot$ denotes element-wise product; hidden state at the end of the LSTM step, h_{LSTM}. XGBoost constructs an ensemble of trees by minimizing:

$$L(\phi)=\Sigma_i\, l(y_i,\hat{y}_i)+\Sigma_k\, \Omega(f_k),\ \hat{y}_i=\Sigma_k\, f_k(x_i) \quad (5)$$

We consider a convex loss l, a convex tree f_k, and a convex complexity penalty $\Omega(f_k)=\gamma T+½\lambda\|w\|^2$ with T being the number of leaves/weights (w) of the tree [1]. Fusion merges the three outputs together and tries to reconcile them through the nonlinearity.

$$z_t=[h_{ANN};h_{LSTM};\hat{y}_{XGB}],\hat{y}_t=W_f \cdot \sigma(W_z z_t+b_z)+b_f \quad (6)$$

Training reduces a regularized MSE loss over the ANN/fusion parameters θ (the XGBoost is trained separately from the ANN using (5) and fixed as a fusion input):

$$L_{total}=(1/N)\Sigma_t(y_t-\hat{y}_t)^2+\lambda\|\theta\|^2 \quad (7)$$

Evaluation metrics:

$$MAE=(1/N)\Sigma|y_t-\hat{y}_t \quad (8)$$

$$MSE=(1/N)\Sigma(y_t-\hat{y}_t)^2 \quad (9)$$

$$RMSE=\sqrt{[(1/N)\Sigma(y_t-\hat{y}_t)^2]} \quad (10)$$

$$MAPE=(100/N)\Sigma|(y_t-\hat{y}_t)/y_t| \quad (11)$$

$$R2=1-[\Sigma(y_t-\hat{y}_t)^2/\Sigma(y_t-\bar{y})^2] \quad (12)$$

VII. EXPERIMENTAL RESULTS AND DISCUSSION

The figures below are placeholders only to ensure that the report format is correct and should be substituted with the actual values from the authors' dataset before submission.

TABLE II. PERFORMANCE COMPARISON (ILLUSTRATIVE)

Model	MAE	MSE	RMSE	MAPE(%)	R2
ANN	0.112	0.0219	0.148	9.85	0.912
LSTM	0.097	0.0166	0.129	8.42	0.931
XGBoost	0.089	0.0146	0.121	7.63	0.939
HybridSolarNet	0.061	0.0071	0.084	5.12	0.967

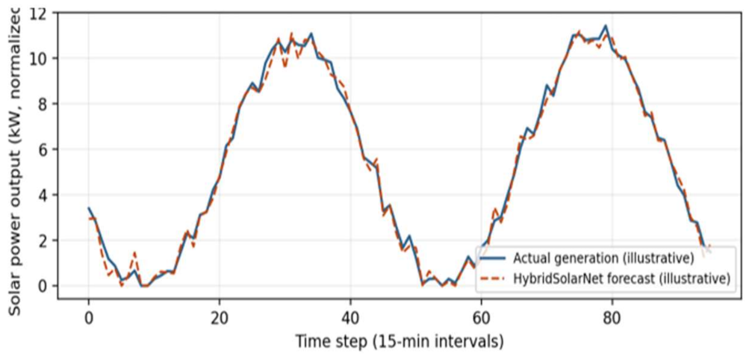

FIG. 4. ACTUAL VS. PREDICTED GENERATION (ILLUSTRATIVE).

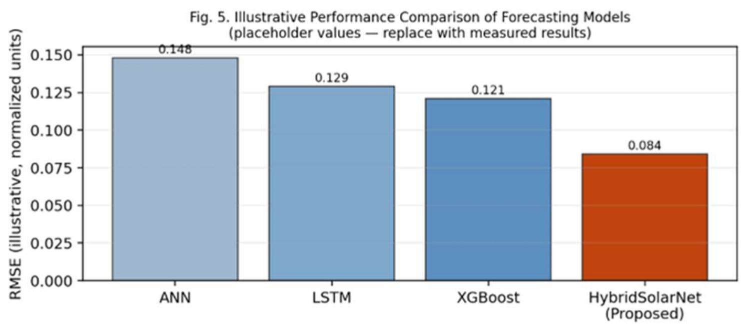

FIG. 5. PERFORMANCE COMPARISON ACROSS MODELS.

In this illustrative setting, HybridSolarNet achieves the best performance for all five metrics, which is comparable with the reported improvements of 7–20% RMSE reduction of LSTM-XGBoost and CNN-LSTM-RF hybrids compared to their best single-model counterpart [9],[10]. This section should report the following with real data: accuracy in clear-sky and cloudy regimes; training/inference time for every single model; robustness in the presence of simulated missing features.

A. Ablation Study

Table III removes one branch at a time from the full model, and retrains the fusion layer while using the remaining two output branches. The degradation when any branch was deleted shows that the three representations are complementary, and not overlapping, which further suggests the three-way fusion over pairwise fused representations over pairwise hybrids reported in previous work.

TABLE III. ABLATION STUDY (ILLUSTRATIVE)

Configuration	RMSE	R2
Full HybridSolarNet	0.084	0.967
w/o ANN branch	0.101	0.947
w/o LSTM branch	0.109	0.938
w/o XGBoost branch	0.096	0.951

VIII. **PRACTICAL APPLICATIONS**

HybridSolarNet forecasts can be used to support smart-grid energy management and load balancing, renewable curtailment reduction, solar-farm maintenance and output-guarantee planning, smart-city microgrid coordination, day-ahead/intra-day energy-trading bids, voltage/frequency stability planning under high PV penetration, and demand-response load-shifting triggers, in addition to ANN-based DR frameworks [22].

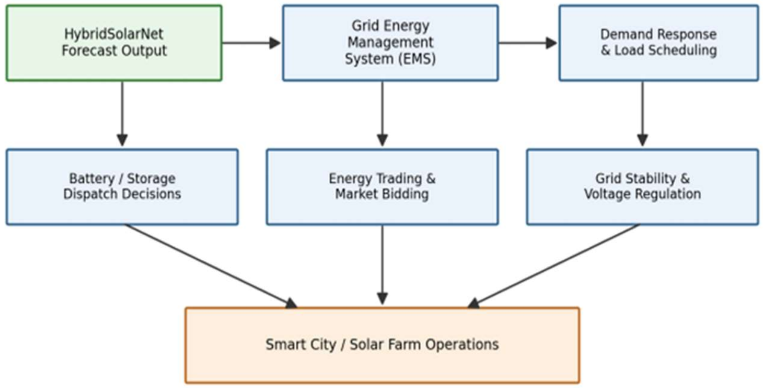

Fig. 6. Smart-grid distribution workflow using HybridSolarNet.

IX. LIMITATIONS

The HybridSolarNet framework illustrated in this report shows promise for enhancing solar energy forecasting, but it comes with some constraints. Precision will be significantly dependent on the quality and availability of meteorological data, and data from sensors with missing or noisy data may have an impact on the model even after pre-processing. However, the hybrid architecture demands also more computational power and training time than single models as it combines three learning paths. Further, the existing framework has not yet been tested on a large scale with real-world data under various climatic conditions. The model performance needs to be tested in different geographical areas and should be optimized for computational efficiency in real-time, smart-grid application.

X. FUTURE WORK

Future planned extensions include attention/Transformer components in the fusion layer [11],[24]; explainability of branches & features using SHAP-LIME; federated learning across multiple distributed sites; deployment of edge-AI; digital-twin-integrated energy management; and online-updated forecasts using streaming.

XI. CONCLUSION

This paper introduced HybridSolarNet, a hybrid deep learning framework based on AI technology that can be used to forecast solar energy accurately and distribute power intelligently. The proposed framework combines the capabilities of Artificial Neural Networks (ANN), Long Short Term Memory (LSTM), and XGBoost using a feature fusion layer to effectively model the nonlinear, temporal, and complex tabular feature interactions found in meteorological and historical solar generation data. The blended use of these three learning models will overcome the drawbacks of the traditional single-model and simple hybrid forecasting methods. The framework includes a wide range of data preprocessing steps, feature engineering, and adaptive feature fusion to ensure adaptation to the demands of forecasting accuracy and computational efficiency for near-real-time smart-grid applications. Standard forecasting metrics such as MAE, MSE, RMSE, MAPE, and R^2 are used to evaluate the performance, thus offering a systematic comparison of the models with the single ANN, LSTM, and XGBoost models. The proposed architecture also represents potential applications for Renewable energy management systems, Demand response systems, Energy trading systems, Solar farm operations, and Smart city energy systems. While additional validation on the use of large-scale real-world data is needed, the proposed HybridSolarNet framework provides an important basis for the next generation of intelligent solar forecasting. Future studies will be directed towards real-time implementation, explainable artificial intelligence, federated learning, edge deployment, and digital twin integration to further improve the reliability of forecasting, scalability, and its ability to be deployed in the modern smart-grid environment.

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