Transfer Learning for Joint Solar and Wind Forecasting in India Using a Hybrid CNN–LSTM Framework

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Abstract

Accurate short-term forecasting of solar irradiance and wind speed is pivotal for renewable energy scheduling and grid stability in India, where climatic diversity complicates resource prediction. This paper presents a hybrid deep learning framework that combines convolutional neural networks (CNNs) and long short-term memory (LSTM) layers within a transfer learning (TL) formulation to improve forecast accuracy in data-scarce regions. Hourly meteorological variables from the NASA POWER database are used, with Jaipur (2019–2024) serving as the source site and Chennai (2023–2024) as the target site. The model is first pre-trained on the Jaipur dataset and then fine-tuned on Chennai data by freezing lower-level layers and updating higher-level layers. Experimental results demonstrate strong cross-regional generalization, achieving a daytime solar mean absolute percentage error (MAPE) of 10.34% and a wind MAPE of 5.53% on the Chennai test set. Compared with a day-ahead persistence baseline, the proposed method reduces daytime solar MAPE by 59% and wind MAPE by 83%, indicating that transfer learning can substantially reduce forecasting uncertainty when local training data are limited.

Keywords- Solar irradiance forecasting, wind speed forecasting, transfer learning, CNN–LSTM, NASA POWER, India.

I. Introduction

India has seen rapid deployment of utility-scale solar photovoltaic (PV) and wind energy installations over the past decade, placing it among the fastest-growing renewable energy producers worldwide [1], [2]. High penetration of variable renewable resources introduces operational uncertainty in economic dispatch, reserve scheduling and real-time grid balancing [3], [4]. Solar irradiance and wind speed are highly sensitive to atmospheric dynamics, terrain, humidity, aerosols and seasonal cycles [5], making short-term prediction technically challenging, especially in regions with strong climatic heterogeneity such as the Indian subcontinent.

Conventional forecasting techniques based on numerical weather prediction (NWP), autoregressive models or simple persistence often struggle to capture nonlinear weather behavior and rapidly changing conditions [3], [6]. Deep learning architectures have demonstrated improved performance by learning nonlinear relationships and multi-scale temporal dependencies directly from meteorological variables [7], [8]. However, their accuracy strongly depends on the availability of long-duration, high-resolution datasets [9]. Many renewable-rich locations in India lack extensive local measurements, restricting the generalizability of site-specific deep learning models.

Transfer learning (TL) has emerged as a powerful paradigm to address data scarcity by utilizing prior knowledge learned from a source domain and transferring it to a target domain with limited training data [10], [11]. Prior studies on renewable forecasting using TL have primarily focused on solar or wind individually and are often concentrated on non-Indian locations [11–13]. From a power-system operation perspective, however, simultaneous forecasting of solar and wind is attractive because the two resources tend to complement each other in daily and seasonal production cycles [14].

To address these gaps, this study proposes a multi-task hybrid CNN–LSTM model with transfer learning for joint forecasting of solar irradiance and wind speed**.** The model is pretrained using long-term hourly data from Jaipur (2019–2024) and fine-tuned using a shorter dataset from Chennai (2023–2024), representing contrasting continental and coastal climatic regimes. During fine-tuning, low-level convolutional and recurrent layers are frozen so that generalized spatio-temporal patterns are preserved, while higher-level layers adapt to the target region.

The major contributions of this work can be summarized as follows. First, the study introduces a unified CNN–LSTM framework capable of jointly forecasting solar irradiance and wind speed, allowing both resources to be modeled within a single architecture and benefited by shared atmospheric representations. Second, a two-stage transfer learning strategy is proposed, in which the model is pretrained on a data-rich source site and then fine-tuned on a data-scarce target site, enabling effective cross-regional generalization without the need for long historical measurements at the deployment location. Third, the framework is validated on real meteorological conditions across India using NASA POWER datasets for Jaipur and Chennai, demonstrating practical relevance for renewable forecasting in contrasting climatic zones. Finally, the evaluation emphasizes daytime-filtered metrics for solar irradiance, ensuring that performance assessment reflects operationally meaningful conditions rather than artificially inflated errors caused by night time zero-irradiance periods. These contributions collectively highlight the potential of transfer learning to improve renewable energy forecasting accuracy while reducing data and computational requirements for emerging power-system regions.

The remainder of this paper is organized as follows. Section II reviews related work on deep learning-based renewable forecasting and transfer learning. Section III describes the datasets and pre-processing. Section IV details the hybrid CNN–LSTM model and transfer learning strategy. Section V presents baseline and proposed model results. Section VI concludes the paper and outlines future research directions.

II. Related Work

Data-driven forecasting of renewable resources has progressed steadily over the last decade. Early studies relied on autoregressive and support vector regression models, as well as NWP-based methods, but the linear nature and limited adaptability of these approaches often led to suboptimal performance under highly variable weather [3], [6]. With the advent of deep learning, researchers began to apply fully connected networks and gated recurrent units to irradiance and wind time series, demonstrating improved accuracy for complex patterns [7], [8].

For solar irradiance forecasting, convolutional neural networks (CNNs) are frequently used to extract local patterns in irradiance, cloudiness and auxiliary meteorological features. LSTM and bidirectional LSTM networks have proven effective in capturing diurnal cycles and sudden changes in solar irradiance [4], [5]. Hybrid CNN–LSTM models combine convolutional feature extraction with recurrent temporal modeling and have been shown to outperform either CNN or LSTM alone for short-term solar forecasting [5], [6]. Recently, transformer-based models have been investigated for solar prediction, although their data requirements and computational cost remain relatively high [7].

The wind forecasting literature exhibits a similar evolution. Basic stochastic models and persistence methods tend to underperform in regions with rapidly changing wind regimes. LSTM networks and temporal convolutional networks (TCNs) have been used to learn non-stationary wind dynamics and have achieved improved forecast skill [8]. Attention-based recurrent networks further enhance the ability to capture wind ramp events and regime changes [9]. However, many of these architectures are trained as single-task models, targeting either solar or wind individually.

Multi-output deep learning for renewable forecasting has emerged only recently. Multi-task frameworks can exploit correlations between solar and wind predictions, and studies have shown that joint learning can yield minor to moderate accuracy gains relative to independent models [10]. Nevertheless, these approaches typically assume abundant training data from the target site and do not explicitly address cross-regional adaptation.

Transfer learning has been explored for renewable forecasting to mitigate data scarcity. Tang *et al.* applied TL to cross-location solar prediction, showing that models pretrained on data-rich regions can be adapted to new sites with fewer samples [11]. Arikan and Ahlstrom reported similar benefits when transferring wind prediction models between wind farms [12]. Kaur and Sharma evaluated deep TL for renewable forecasting across Indian climate zones and emphasized the potential of TL for regional adaptation [13]. However, these studies generally focus on single-resource prediction, use limited adaptation windows or consider relatively homogeneous climates.

Indian-specific studies indicate that models trained in arid north-western regions often degrade when blindly applied to coastal or monsoon-dominant regions [15], and that wind speed models tuned for monsoon patterns do not readily transfer to semi-arid or dry zones [16]. These observations underline the importance of techniques that reuse knowledge from data-rich regions and adapt effectively to sites with limited observations.

In this context, the present work addresses a clear research gap by introducing a transfer learning-enabled, multi-task CNN–LSTM modelcapable of learning shared spatio-temporal weather dynamics from Jaipur and adapting to Chennai. Unlike prior work, the proposed approach: (i) jointly forecasts solar irradiance and wind speed; (ii) explicitly targets cross-climate transfer between continental and coastal Indian regions; and (iii) incorporates a rigorous daytime-filtered evaluation of solar forecasts.

III. Dataset and Preprocessing

A. Data Sources and Study Sites

The study uses hourly meteorological data from the NASA Prediction of Worldwide Energy Resources (POWER) project, which provides satellite-derived and reanalysis-based estimates of surface irradiance and atmospheric variables. Two locations within India were selected to reflect contrasting climatic regimes:

i. Jaipur, Rajasthan (Source site): latitude 26.90° N, longitude 75.79° E; semi-arid continental climate with hot summers and cool winters. Data from January 2019 to December 2024are used for pretraining.
ii. Chennai, Tamil Nadu (Target site): latitude 13.08° N, longitude 80.27° E; coastal tropical climate influenced by the Bay of Bengal and monsoon systems. Data from January 2023 to December 2024 are used for fine-tuning and testing.

This source–target pair was chosen specifically to examine the ability of TL to bridge distinct climatic zones within India.

B. Selected Variables

Four variables were extracted from NASA POWER based on their relevance for solar and wind energy forecasting:

i. Global Horizontal Irradiance (GHI) in W/m²
ii. Wind speed at 10 m in m/s
iii. Air temperature at 2 m in °C
iv. Relative humidity at 2 m in %

GHI and wind speed are treated as forecast targets, while temperature and humidity serve as auxiliary predictors that encode atmospheric conditions, cloud behavior and moisture content [5], [17].

C. Sliding-Window Sequence Generation

Renewable resource dynamics depend on preceding hours. To capture this temporal context, a sliding-window strategy is used. For each time step ttt, the model input is a sequence of the previous 24 hours of all four variables:

$$X_t = [x_{t-23}, x_{t-22}, \dots\dots, x_t]$$

where each $x_k \in R^4$contains GHI_k, WS_k, T_k and RH_k. The model predicts the next-hour outputs:

$$Y_{t+1} = [GHI_{t+1}, WS_{t+1}]$$

Thus, the learning task is a 1-step-ahead, multi-output regression problem conditioned on a 24-hour input sequence.

D. Normalization and Data Splits

To stabilize optimization and reduce scale disparities, all four variables are normalized using min–max scaling with parameters computed from the source (Jaipur) dataset. The same scaling is applied to the target (Chennai) data without recomputing statistics, preventing information leakage.

The data are split as: (i)Jaipur (pretraining): 70% training, 15% validation, 15% testing and (ii) Chennai (fine-tuning): 60% training, 20% validation, 20% testing.These splits balance the need for training data with robust evaluation, while reflecting realistic limitations of the target site.

E. Daytime Filtering for Solar Evaluation

Solar MAPE becomes numerically unstable during night because GHI equals zero, causing division by zero in the percentage error expression. To avoid misleading metrics, solar performance is assessed only for daytime samples, defined by:

$GHI > 20\ W/m^2$

This threshold approximates the onset of usable irradiance for PV generation. All training procedures still use 24-hour sequences to maintain temporal continuity across night and day.

IV. Methodology

A. Hybrid CNN–LSTM Architecture

The proposed forecasting model integrates convolutional and recurrent components to exploit both local patterns and long-range dependencies. The input tensor for each sequence has shape 24×4 (time steps × features). A 1-D convolutional layer is first applied along the temporal dimension to extract local patterns such as sharp irradiance peaks or rapid wind changes. CNNs have proven effective at capturing localized variability in meteorological time series [17].

The resulting feature maps are then fed into a stacked LSTM module that models temporal dependencies across the 24-hour horizon. LSTMs are well suited for non-stationary weather sequences thanks to their gating mechanism and capacity to retain long-term memory [18]. The final LSTM hidden state is passed through a shared dense layer followed by two separate linear heads that output next-hour GHI and wind speed, respectively. This multi-task learning design encourages the network to learn shared representations of atmospheric conditions that benefit both tasks [10], [14].

B. Loss Function and Optimization

The model is trained using a combined mean squared error (MSE) loss:

$$\mathcal{L} = \propto . MSE(\hat{y}_{GHI}, y_{GHI}) + \beta . MSE(\hat{y}_{WS}, y_{WS})$$

where $\hat{y}$and y denote predicted and true values, and α and β are weighting coefficients. In this study α=β=1, giving equal importance to both outputs. The Adam optimizer is used with an initial learning rate of 0.001 during pretraining and 0.0003 during fine-tuning.

Training hyperparameters are summarized below:

i. Batch size: 32
ii. Epochs (Jaipur pretraining): 20
iii. Epochs (Chennai fine-tuning): 10 (converged by epoch 9)
iv. Sequence length: 24 hours
v. Output horizon: 1 hour

Early stopping based on validation loss is applied to avoid over-fitting during both stages.

C. Transfer Learning Strategy

The transfer learning procedure comprises two phases: pretraining on Jaipur and fine tuning on Chennai. On the preliminary phase the CNN and LSTM layers are trained end-to-end using the Jaipur dataset. Given the six-year coverage and pronounced seasonal variation, the model learns generalized spatio-temporal patterns of irradiance and wind dynamics [22].Moreover the later phase of fine tuning on Chennai, all convolutional weights and the first LSTM layer are frozen, thereby retaining low-level meteorological features. Only the upper LSTM layer and fully connected heads are updated using the Chennai training data. This strategy reduces the number of trainable parameters and accelerates convergence while enabling adaptation to coastal tropical behavior[23], [24].

This pretrain–freeze–fine-tune process is central to the proposed TL framework and is designed to mimic a realistic deployment scenario where high-quality data are available at a few reference sites but scarce at newly developed renewable locations.

V. Results and Discussion

A. Evaluation Metrics

Forecast performance is measured using mean absolute percentage error (MAPE), mean absolute error (MAE) and root mean squared error (RMSE). For solar irradiance, metrics are computed only for daytime samples (GHI > 20 W/m²), while wind metrics use the full test set. A day-ahead persistence model is used as the baseline, where the forecast for a given hour is the value observed exactly 24 hours earlier.

B. Baseline vs. Transfer Learning Performance

The baseline and proposed model performances on Chennai test data are summarized in Table I. Solar values correspond to daytime samples; full-period solar metrics are shown only for completeness and are not used for comparison due to night-time distortions.

Table I – Baseline vs. Proposed Model Performance (Chennai)

Metr	**Solar (Daytime) – Baselin**	**Solar (Daytime) – TL Mod**	**Wind – Baselir**	**Wind – TL Mod**
MAP	25.26%	10.34%	32.81%	5.53%
MAE	74.68 W/m²	26.34 W/m²	0.717 m/s	0.121 m/s

RMS	–	39.93 W/m²	–	0.171 m/s

The proposed TL model reduces daytime solar MAPE by approximately 59% relative to the persistence baseline, from 25.26% to 10.34%, and reduces MAE from 74.68 W/m² to 26.34 W/m². For wind speed, the improvement is even more pronounced: MAPE drops from 32.81% to 5.53%, and MAE from 0.717 m/s to 0.121 m/s. Such large reductions indicate that the CNN–LSTM with transfer learning is capturing underlying atmospheric dynamics that simple temporal persistence cannot.

Fig. 1 shows that the model accurately captures the diurnal shape and magnitude of solar irradiance across multiple days, with only minor deviations around rapidly changing conditions. Fig. 2 illustrates that wind forecasts closely follow observed variability, including localized peaks and troughs.

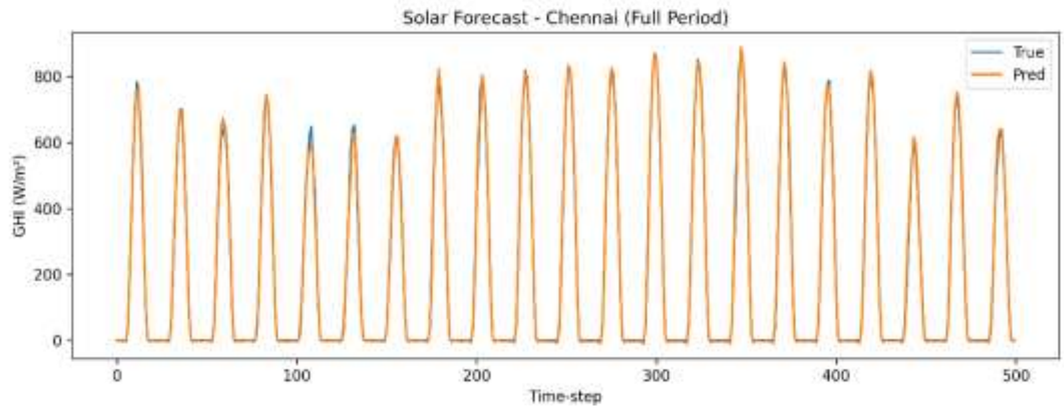

Fig. 1. Solar forecast for Chennai (full period) – true vs. predicted irradiance.

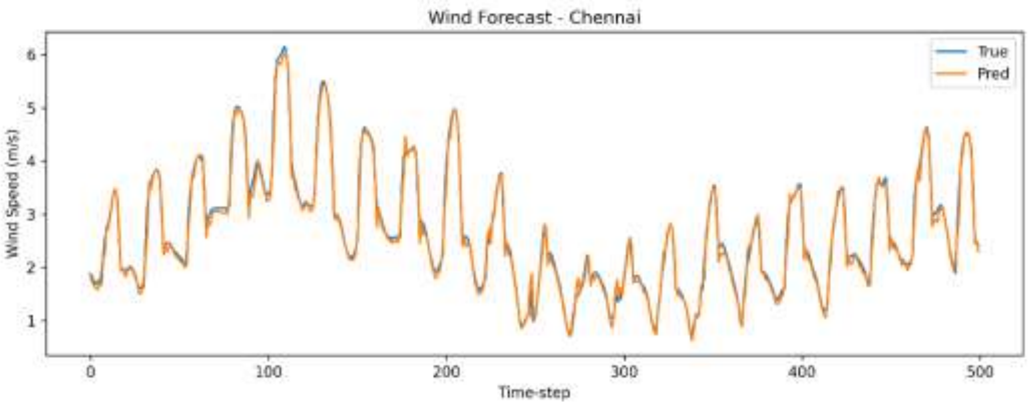

Fig. 2. Wind forecast for Chennai – true vs. predicted wind speed.

C. Training Dynamics and Convergence

During pretraining on Jaipur data, training and validation losses decrease smoothly and stabilize after roughly 10 epochs, indicating that the network has learned a stable representation of semi-arid weather patterns. Fine-tuning on Chennai data converges even faster: validation loss decreases within the first few epochs and stabilizes by epoch 9, demonstrating effective reuse of pretrained features. The absence of divergence between training and validation curves suggests that over-fitting is controlled despite the smaller target dataset.

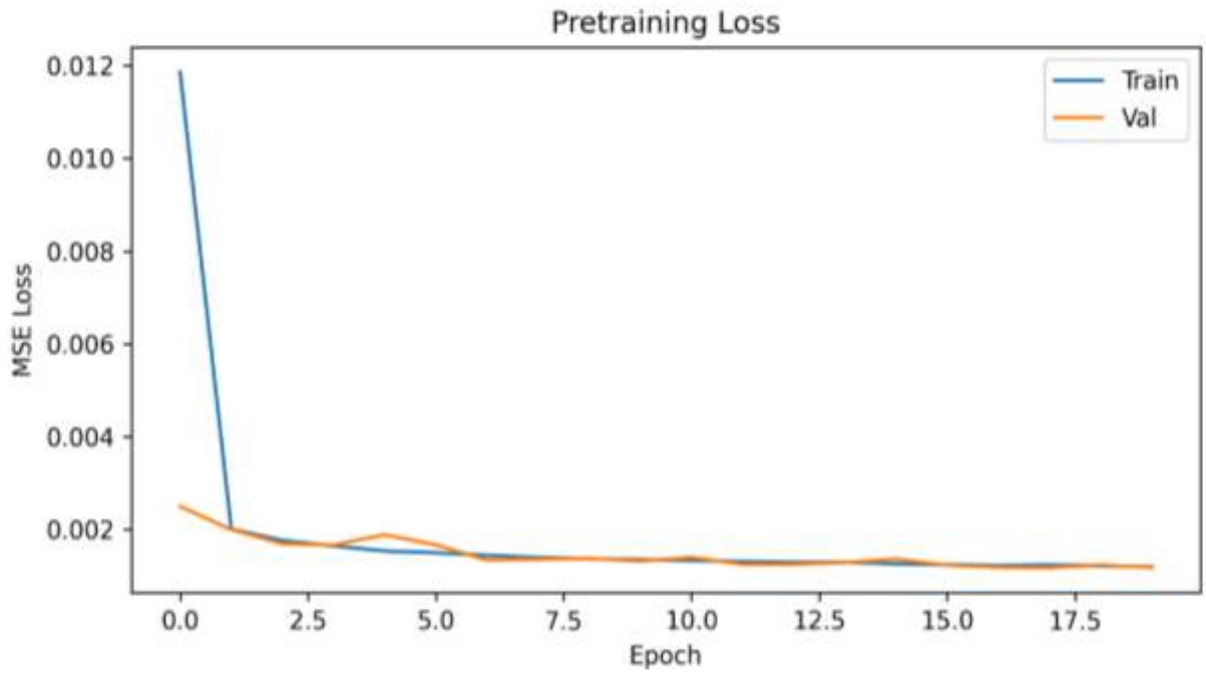

Fig. 3. Pretraining loss curves for Jaipur dataset (training and validation).

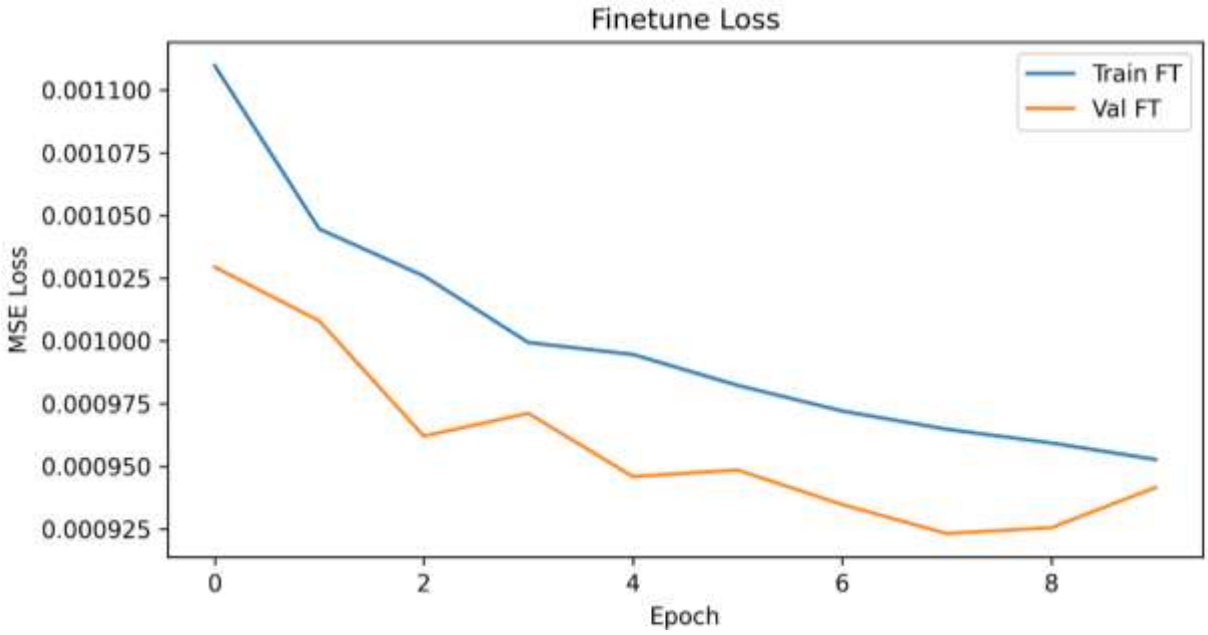

Fig. 4. Fine-tuning loss curves for Chennai dataset (training and validation).

D. Scatter Analysis for Solar Forecasts

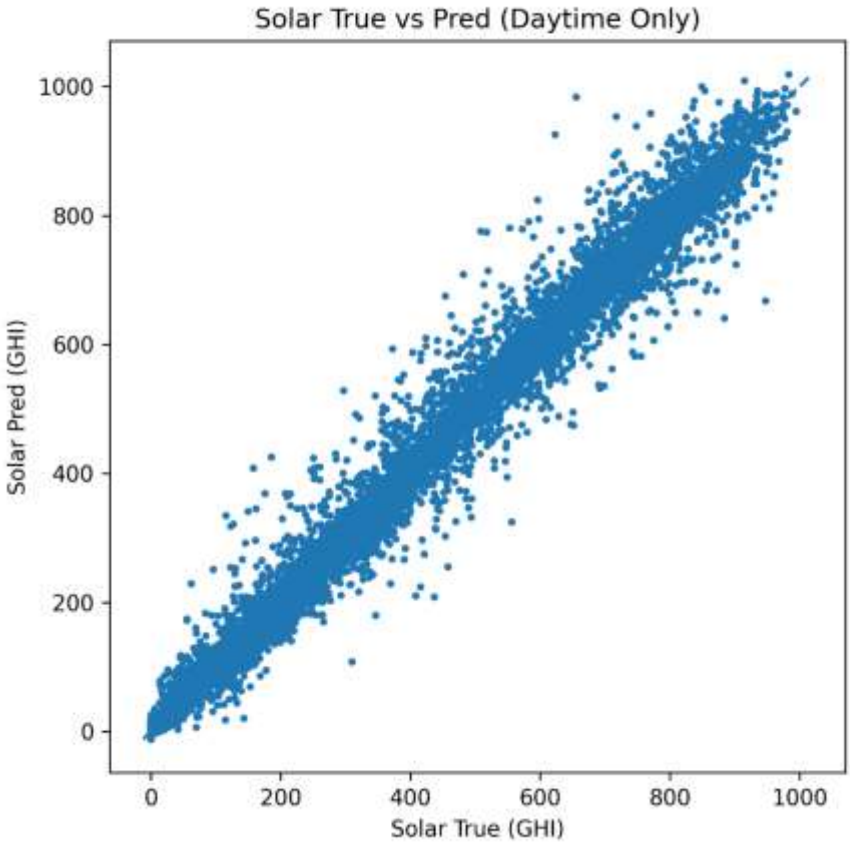

Fig. 5. Scatter plot of daytime solar predictions vs. ground truth for Chennai.

Fig. 5 provides a scatter plot of daytime solar predictions against ground truth. Most points cluster along the 45° reference line, indicating high fidelity across a broad range of irradiance values. Deviations increase at very high GHI levels, likely reflecting enhanced sensitivity to transient cloud edges and aerosol loadings, but errors remain within acceptable limits for operation-level planning.

The results highlight several important observations. First, the significant performance gains over the persistence baseline demonstrate that transfer learning is highly effective for cross-regional forecasting, confirming that meteorological patterns learned from Jaipur can be successfully adapted to Chennai despite their contrasting climatic characteristics. Second, the multi-task design of the proposed model appears to enhance generalization, as joint learning of solar irradiance and wind speed yields strong performance on both tasks. Third, the achieved accuracy — with daytime solar MAPE near 10% and wind MAPE near 5% — is competitive with, or better than, many recently reported deep learning forecasting models in the literature [4], [5], [8], [10], indicating that the model is suitable for practical power-system applications. Another critical insight is the high data efficiency of the framework: fine-tuning with only two years of target-site observations delivers reliable predictions, which is advantageous for new renewable installations where long historical datasets are not yet available.

Nonetheless, the study has limitations, including the use of a single source–target site pair and reliance on satellite-derived NASA POWER data rather than ground-station measurements. Future work may extend the approach to multiple source regions, explore ensemble transfer-learning schemes and adopt probabilistic forecasting to quantify uncertainty for grid-operation use cases.

VI. Conclusion

This paper presented a transfer learning-enabled hybrid CNN–LSTM model for joint forecasting of solar irradiance and wind speed across Indian climatic regimes. A multi-task architecture was pretrained on a six-year dataset from Jaipur and fine-tuned on a shorter Chennai dataset, with lower-level layers frozen during adaptation. The proposed method achieved a daytime solar MAPE of 10.34% and a wind MAPE of 5.53% on the Chennai test set, representing 59% and 83% improvements over a day-ahead persistence baseline, respectively. Training curves showed rapid and stable convergence, confirming that the pretrained features generalized well to the coastal target climate.

The findings suggest that transfer learning is a promising strategy for deploying accurate renewable energy forecasting models in data-scarce regions of India. Future research will extend this framework to multi-site domain adaptation, incorporate satellite imagery and sky-camera data, and investigate uncertainty quantification for grid-aware dispatch and reserve allocation.

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