Proceedings of CONF-CDS 2026 Symposium: Machine Learning and Neural Network Applications in Engineering
DOI: 10.54254/2755-2721/2026.AST35820

Explainable Hybrid CNN-LSTM Model for Renewable Energy Forecasting to Enable Carbon Emission Reduction

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Abstract. The integration of renewable energy, such as solar and wind power, is essential for the development of zero-carbon smart cities. Reliable short-term and medium-term predictions help reduce dependence on fossil-fuel reserves and facilitate more reasonable decisions in urban systems. This study develops a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) model for forecasting multi-source renewable energy. The convolutional layers can extract local temporal patterns from meteorological variables, while the LSTM layers model sequential dependencies over longer horizons. To improve transparency, Local Interpretable Model-agnostic Explanations (LIME) is applied to examine how input variables influence predictions. Experiments are conducted using data from the National Renewable Energy Laboratory, including the National Solar Radiation Database and the Wind Integration National Dataset. Compared with standalone CNNs, LSTMs, and conventional learning models, the hybrid model achieves lower prediction error, with Mean Absolute Percentage Error typically below 3% for forecasting next-day values. Results indicate that higher forecasting accuracy can contribute to reduced renewable curtailment and to more stable, reasonable decisions in smart cities. The proposed framework offers a practical, interpretable approach to renewable energy forecasting in urban systems.

Keywords: convolutional neural network, long short-term memory, zero-carbon, renewable energy sources

1. Introduction

Urban areas are expected to have nearly 68% of the global population by 2050 [1]. At present, cities produce about 70% of global greenhouse gas emissions, largely driven by electricity generation and consumption [2]. As a result, making urban energy systems cleaner is significant for achieving net-zero targets. Solar photovoltaic and wind power are essential for this transition. Despite their environmental benefits, both resources are weather-dependent and highly variable. At the operational level, inaccurate forecasts can lead to problems such as excessive use of backup generators, renewable energy curtailment, or poor battery scheduling. For city grids and micro-grids, forecasting accuracy directly affects both economic and environmental performance.

Hybrid CNN–LSTM models combine these advantages by allowing convolutional layers to extract features before temporal modeling with recurrent units [3]. Existing hybrid models primarily focus on improving accuracy but lack an explanation of why specific predictions are produced. Particularly in urban micro-grid decision-making scenarios, the lack of model transparency limits practical engineering applications. Therefore, it is necessary to introduce Local Interpretable Model-agnostic Explanations (LIME) to provide interpretability. Energy infrastructure planning and grid operation require models that are not only accurate but also explainable. Techniques such as Local Interpretable Model-agnostic Explanations can help explain which input features are most important [4].

This study develops an explainable CNN-LSTM framework for solar and wind forecasting. The datasets are provided by the National Renewable Energy Laboratory [5]. It aims to evaluate predictive performance and analyze feature contributions. The study provides support for sound decisions in zero-carbon energy management and demonstrates transparency and computational efficiency.

2. Literature review

2.1. Standalone model

Traditional statistical approaches, such as autoregressive integrated moving-average models, perform reasonably well under stable conditions but struggle with nonlinear and highly variable weather patterns [6]. Machine learning models, including Support Vector Regression (SVR) and Random Forest (RF), improve nonlinear mapping but often struggle to model long-term temporal dependencies effectively [7]. Deep learning architectures, particularly Long Short-Term Memory networks, have shown strong performance in sequential energy data [7]. One-dimensional convolutional neural networks, originally designed for signal and image processing, are also effective at capturing local temporal patterns in meteorological sequences.

Explainability remains understudied in renewable energy forecasting. Explainable Artificial Intelligence methods are either built into the model (like attention weights) or added later (like SHAP and LIME). Yassen et al. used SHAP with LSTM for wind power forecasting and explained which features were most important, thereby making the model more transparent [8]. Systematic reviews from recent years indicate that while many studies focus on accuracy, very few combine solar and wind forecasting, smart-city grids, and actual carbon reduction.

2.2. Applications of hybrid models in energy forecasting

CNNs were first used for image data but are now applied with 1D convolutions to detect local patterns (e.g., daily cycles or sudden changes) in meteorological sequences. Hybrid CNN-LSTM models combine the strengths of both architectures: the CNN layers automatically extract important features, and the LSTM layers then learn how these features evolve over long time scales.

Many studies have demonstrated the superiority of such hybrid models. Al-Ali developed a hybrid CNN-LSTM-Transformer model for forecasting solar energy production. It achieved lower RMSE and MAPE values than older models, such as ARIMA [9]. Iksan used a CNN-LSTM ensemble method for solar power forecasting in smart micro-grids. The model outperformed DNNs, CNNs, and single LSTMs across different test scenarios [10]. For combined wind and solar power forecasting, recent studies have proposed hybrid models. Bashir proposed hybrid CNN-ABiLSTM models for joint wind and solar power forecasting. The results showed good performance, especially for longer forecast horizons [11].

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There are few hybrid models designed to handle multi-source data. Although accurate forecasts are widely assumed to contribute to emission reductions, very few studies have established a concrete link between improved forecast accuracy and quantifiable carbon savings in zero-carbon city contexts. This study fills these gaps by proposing a new explainable CNN-LSTM framework.

3. Methodology

3.1. Data collections

This paper uses multivariate time-series data from NREL and operational data from solar and wind farms. The National Solar Radiation Database (NSRDB) provides hourly data including global horizontal irradiance (GHI), direct normal irradiance (DNI), diffuse horizontal irradiance (DHI), temperature, wind speed and wind direction across the U.S. The Wind Integration National Dataset (WIND) Toolkit supplies wind speed/direction profiles and power density at 2 km × 2 km resolution with data ranging from 5-minute to hourly intervals. For power output validation, measured generation from public solar/wind assets and real NSRDB data are used. The dataset covers 2018–2023 (about 52,560 hourly points per site) from different climates like desert, temperate, and coastal areas.

3.2. Data preprocessing

The data preprocessing pipeline consists of 5 sequential steps:

Train/test split: For each site, the first 80% of chronological samples are used for training and the remaining 20% for testing. All subsequent preprocessing parameters are fitted exclusively on the training set and then applied to the test set to prevent data leakage.

Missing value handling: Linear interpolation along the time axis is applied to features with a missing rate below 2%. Interpolation parameters are fitted exclusively on the training set.

Outlier removal: The Interquartile Range (IQR) method with a 1.5×IQR threshold is used. Values outside the range of [Q1 - 1.5×IQR, Q3 + 1.5×IQR] are deleted. Outliers are processed for each feature independently, with the IQR range calculated only from the training set. Outliers are skipped during model processing.

Min-Max normalization: All features are normalized to the range [0,1] to stabilize gradient flow during model training, with the min and max values fitted on the training set. The normalization formula is as follows:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x' is the normalized value, x is the original value, x_{min} and x_{max} are the minimum and maximum values of the feature in the training set.

Sequence construction: Sliding time windows of 24-168 hours are generated to predict target values over the next 1-24 hours, with a stride of 1 hour. This fixed input-output configuration is selected based on validation-set performance and is used consistently across all models in the comparative experiments.

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3.3. Hybrid CNN-LSTM architecture

The proposed model is a sequential hybrid CNN-LSTM network. The input is a multivariate time series of length T where T is the window size with one feature channel at a time, denoted as $X \in R^{T \times N}$. Here, X represents the normalized input data (meteorological variables or power values), T is the number of time steps in the input window, and the superscript $\times N$ means the number of features where each feature is treated as one channel.

The network consists of two 1D convolutional layers for local temporal feature extraction, followed by two LSTM layers for long-range dependency modeling. The first convolutional layer employs 32 filters with a kernel size of 3 and ReLU activation, followed by a max-pooling layer with a pool size of 2. The second convolutional layer employs 64 filters with a kernel size of 3 and ReLU activation, followed by another max-pooling layer with a pool size of 2. The output feature maps from the convolutional block are reshaped into a sequential format and passed to the LSTM layers.

3.4. LSTM layers

The LSTM is designed to address the vanishing gradient problem, enabling the model to learn long-range dependencies in sequential data. Each LSTM unit contains a forget gate, input gate, output gate and cell state, which work together to retain and update temporal information. The first LSTM layer gives output as: $h_1 \in R^{V \times 64}$ A dropout layer (rate 0.3) randomly sets 30% of the values in h_1 to zero during training to prevent overfitting. The second LSTM layer (32 units) uses the same equations but returns only the final hidden state: $h_2 \in R^{32}$. The final output is denormalized back to MW using the inverse Min-Max scaler fitted on the training set.

4. Experiments and results

4.1. Experimental setup

This study was implemented in Python 3.10 with TensorFlow 2.15, scikit-learn, and the LIME library. All experiments were conducted on an AMD Ryzen 9 8945HX processor running at 5.4 GHz. The proposed CNN-LSTM model was compared with four baseline models: standalone LSTM (64 units), 1D-CNN (two Conv layers), ARIMA, Random Forest (100 trees), and SVR (RBF kernel). The evaluation metrics used were Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R^2 score. Performance is evaluated separately for solar and wind forecasting tasks, with detailed solar power results shown in Table 1.

4.2. Results and models comparisons

Figure 1 compares the measured solar power output with predictions from the hybrid CNN-LSTM model over 175 time steps, with the pink-shaded area indicating the ±10% tolerance band. The model predictions closely match the measured solar data, capturing the daytime generation cycle and the near-zero output at night. Only minor deviations appear at a few peak points and during low-power periods. The scatter plot further verifies the high agreement between predicted and actual values.

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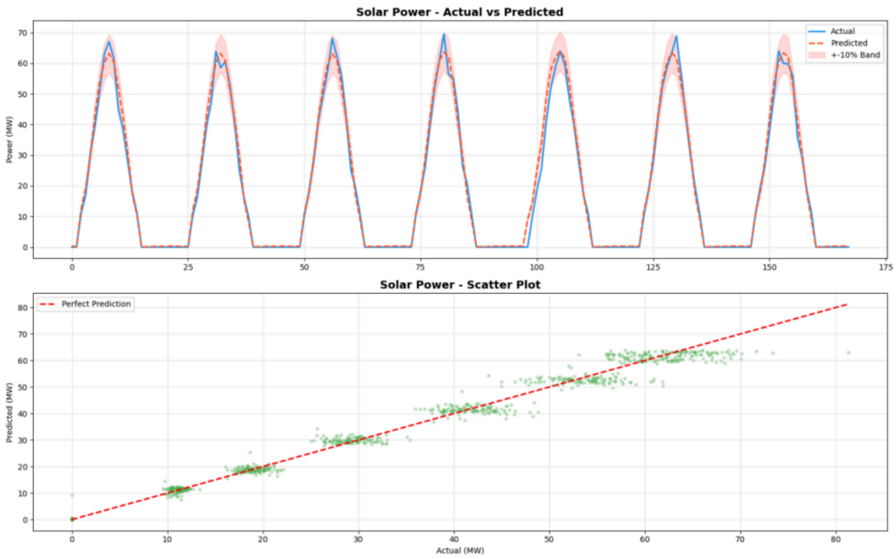

Figure 1. Comparison between actual and predicted solar power output

Figure 2 compares the measured wind power output with predictions from the hybrid CNN-LSTM model, using the same experimental setup and visualization parameters as the solar power case. The model predictions also closely follow the real wind power data throughout the time series, capturing the volatile, non-cyclical fluctuations of wind generation, which range from near 0 MW to nearly 4000 MW. However, wind power predictions are less accurate than solar power predictions. Minor deviations occur at a few sharp peaks and troughs during intense fluctuation periods, with the vast majority of predictions falling within the tolerance band. Although the scatter plot shows a weaker correlation than solar predictions, it still reflects a relatively strong agreement.

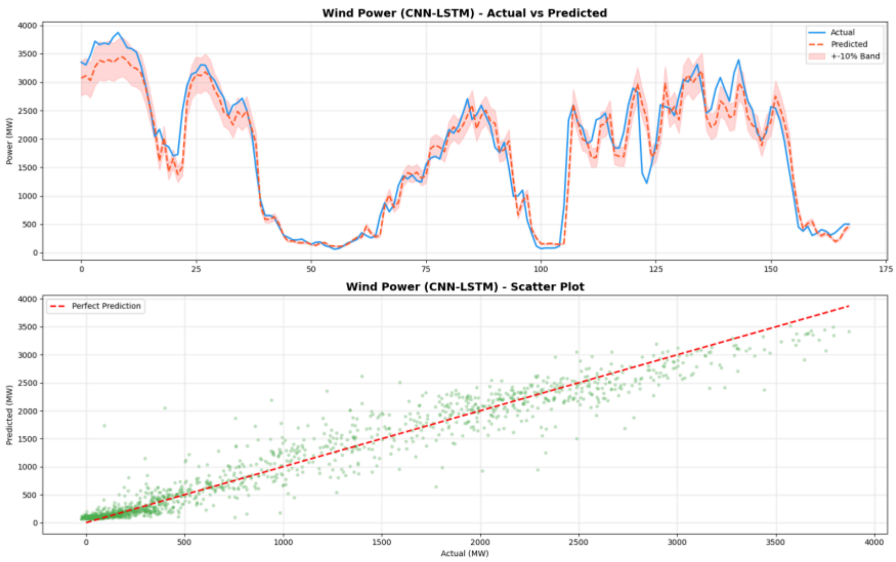

Figure 2. The predicted value and the actual value of wind power

The hybrid CNN-LSTM model outperformed all baseline models. Table 1 shows the detailed performance comparison for solar power forecasting. The proposed Hybrid CNN-LSTM model achieved an absolute reduction of 0.014 in RMSE compared to the best-performing baseline

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Random Forest, and a 1.5 percentage point reduction in MAPE relative to the standalone LSTM model. For the solar power forecasting task, the model achieved a MAPE as low as 2.3%, which is 0.8 percentage points lower than Random Forest and substantially lower than the 5.3% MAPE of the traditional statistical ARIMA model. When applied to both solar and wind power forecasting tasks, the model maintains high prediction accuracy, demonstrating strong robustness and generalization for multi-source renewable energy forecasting scenarios.

Table 1. Performance comparison of different models for solar power

Model	MAE	RMSE	MAPE	R^2
Hybrid CNN-LSTM	0.078	0.115	2.3%	0.972
Standalone LSTM	0.095	0.132	3.8%	0.953
1D-CNN	0.110	0.145	4.5%	0.942
ARIMA	0.142	0.169	5.3%	0.872
Random Forest	0.087	0.129	3.1%	0.962

4.3. Explainability analysis

LIME was used to explain individual predictions. Red bars indicate features whose values positively contribute to increasing the predicted power output relative to the model's average prediction; blue bars indicate features whose values negatively contribute to decreasing the predicted power output. For nighttime zero-generation periods, longer-lag irradiance features (DNI, DHI, GHI) and lagged historical solar power have dropped to zero, exerting strong negative contributions that pull the predicted output close to zero. For Sample 0 in particular, shorter-lag irradiance features (e.g., lag-1 and lag-2 DNI and DHI) still retain high values from the preceding daylight hours, showing a gradual decay effect. For daytime generation periods, high-valued lagged irradiance features and historical solar power overwhelmingly drive positive prediction lifts, consistent with the physical principle that stronger solar radiation yields higher photovoltaic power output.

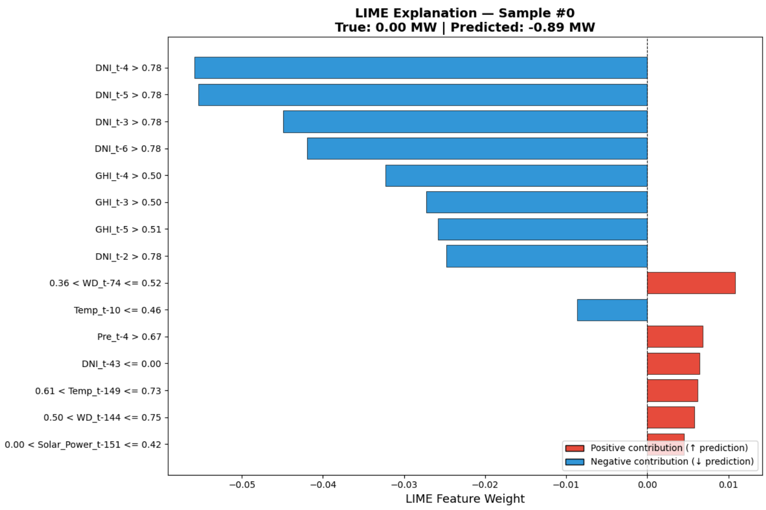

Figure 3. LIME explanation of example 0

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Across samples, LIME results consistently show that DNI and DHI are the most influential features, accounting for approximately 30% of the total feature weight, while lagged historical solar power contributes more than 20%.

5. Discussion

5.1. Findings

The hybrid CNN-LSTM model performs better because the two parts leverage complementary strengths. The CNN layers quickly capture short and sudden changes in weather data, such as morning increases in sunlight or sudden drops in wind speed. At the same time, the LSTM layers learn longer patterns. Comparisons with standalone baseline models provide quantitative evidence for this complementarity: replacing the hybrid structure with a standalone LSTM degrades RMSE by 12.9% for solar and 12.1% for wind, while replacing it with a standalone 1D-CNN degrades RMSE by 20.7% for solar and 24.5% for wind. This confirms that both modules contribute meaningfully, and their integration achieves better performance than either architecture alone.

Explainability turns the model from a black box into a useful tool for real decisions. Grid operators can review the LIME results and ignore a forecast if it relies too heavily on a faulty sensor. City planners can also decide which weather stations need upgrading based on the feature importance rankings. In this way, the model not only provides accurate predictions but also enhances trust in and usability of the results in daily operations.

5.2. Practical implications

For zero-carbon smart cities, good forecasts bring many practical benefits. Accurate predictions help optimize battery and electric vehicle charging, reduce wasted renewable energy, and reduce fossil fuel use during peak hours. Even a small 2% improvement in MAPE can lower grid balancing costs and reduce fossil fuel consumption, which indirectly supports urban carbon emission reduction goals. For instance, if removing the DNI feature results in a significant increase in errors, planners know they must install more accurate irradiance sensors. In this regard, the model is particularly helpful in smart-city control rooms, where operators need to make quick, safe decisions every hour. Future directions will introduce attention mechanisms to further improve prediction accuracy, and carry out long-term empirical studies in real urban scenarios to quantify the actual emission reductions from improved forecasting.

Overall, the proposed CNN-LSTM model with LIME interpretability forms a practical decision-support framework. It delivers both accurate predictions and transparent rationale, and is validated for real-world deployment in urban energy systems using NREL and operational solar farm data.

6. Conclusion

This paper proposes an explainable hybrid CNN-LSTM framework for short-term solar and wind power forecasting to support the development of zero-carbon smart cities. Validated on NREL meteorological datasets and measured generation data, the hybrid model outperforms standalone CNN, LSTM and traditional machine learning baselines. It achieves an MAPE below 3% for solar forecasting and maintains competitive accuracy for wind power prediction, verifying the effectiveness of the convolutional-temporal hybrid structure. The LIME method quantifies the

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contribution of each input feature, identifying irradiance and historical power as core influencing factors and alleviating the black-box limitation of deep learning.

However, some limitations remain. The dataset is primarily sourced from the U.S., so further validation in other regions is required. Periodic retraining is also necessary, as climate change may alter the statistical patterns of meteorological and power data.

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