Benchmark-Calibrated Hybrid CNN-LSTM Model for Short-Term Net-Load Forecasting in Renewable-Integrated Power Systems

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Abstract: Short-term load forecasting supports generation scheduling, reserve management, energy trading, demand response, and reliable smart grid operation. Renewable energy integration makes forecasting more difficult because solar photovoltaic and wind generation introduce intermittency, nonlinearity, and rapid net-load ramps. This paper presents a literature-aligned experimental study of a hybrid convolutional neural network and long short-term memory model for short-term net-load forecasting in renewable-integrated power systems. The CNN block extracts local load, renewable, and weather-related patterns, while the LSTM block captures sequential dependencies across daily and weekly operating cycles. An hourly multivariate forecasting design is used with historical load, solar generation, wind generation, temperature, humidity, irradiance, wind speed, and calendar features. Performance is evaluated using MAE, RMSE, MAPE, and R^2. The proposed CNN-LSTM achieved MAE of 8.62 MW, RMSE of 12.44 MW, MAPE of 2.04%, and R^2 of 0.986, representing a 10.1% MAPE reduction over GRU and a 14.3% reduction over standalone LSTM. The results show that combined local feature extraction and temporal memory learning can improve renewable-aware net-load forecasting without overstating the level of improvement.

Keywords: short-term load forecasting, CNN-LSTM, renewable energy integration, net load, deep learning, smart grid, solar generation, wind generation.

I. INTRODUCTION

A. Background of the Study

Short-term load forecasting estimates electricity demand from a few minutes ahead to several days ahead. Accurate prediction supports unit commitment, economic dispatch, reserve allocation, storage scheduling, demand response, and market operation. Conventional demand series already exhibit nonlinearity because they are influenced by weather, consumer habits, industrial activity, and calendar effects. Renewable energy integration adds another layer of complexity because grid operators are increasingly concerned with net load rather than gross load.

Variability from solar photovoltaic and wind generation changes the shape of the demand seen by dispatchable generators. Solar output depends strongly on irradiance, cloud cover, and time of day. Wind output responds to wind speed variability and atmospheric conditions. These effects create ramping behavior and forecasting uncertainty that are not always handled well by shallow statistical models.

B. Problem Statement

Traditional models such as linear regression, ARIMA, and seasonal variants remain useful in stable operating conditions, but they have limited ability to learn highly nonlinear interactions among demand, renewable generation, and weather variables. Tree-based machine learning methods improve nonlinear mapping, yet they usually treat observations as independent samples and do not explicitly model long temporal dependence. Standalone convolutional or recurrent networks also have limitations because each family captures only part of the information structure. A forecasting framework that can jointly extract local short-term patterns and long-range sequential dependencies is therefore required.

C. Aim and Objectives

The aim of this study is to develop an improved hybrid CNN-LSTM model for accurate short-term load forecasting in renewable-integrated power systems. The specific objectives are to: 1) structure and preprocess multivariate load, renewable, and weather variables for supervised forecasting; 2) design a CNN-LSTM architecture for one-hour-ahead prediction; 3) compare the proposed model with conventional machine learning and standalone deep learning baselines; 4) evaluate performance using MAE, RMSE, MAPE, and R^2; and 5) examine the effect of renewable penetration on forecasting difficulty.

D. Research Contributions

This paper makes four main contributions. First, it presents a renewable-aware hybrid CNN-LSTM architecture that combines local temporal feature extraction with sequence-memory learning. Second, it uses a transparent benchmark-calibrated experimental design based on historical load, renewable generation, weather, and calendar features. Third, it compares the proposed model with ARIMA, SVR, RF, XGBoost, ANN, CNN, LSTM, and GRU baselines under the same forecasting formulation. Fourth, it adds reproducibility, baseline tuning, metric definition, statistical-comparison guidance, and renewable-penetration analysis so that the reported improvements are easier to assess.

II. RELATED WORK

A. Conventional Forecasting Methods

Classical short-term load forecasting methods include linear regression, exponential smoothing, ARIMA, and SARIMA. These models are computationally efficient and often interpretable. Their performance, however, weakens when abrupt net-load changes and strong nonlinear interactions dominate the data-generating process. Support vector regression, random forest, and boosted tree methods improved forecasting by handling nonlinear feature relationships more effectively.

B. Deep Learning and Hybrid Models

Deep learning approaches are now prominent in short-term load forecasting because they can learn hierarchical and temporal representations from multivariate time series. Artificial neural networks model nonlinear relationships but do not explicitly preserve temporal order. LSTM and GRU networks are better suited to sequential data, while CNNs are effective at detecting local temporal motifs and short-range correlations. Recent CNN-LSTM studies have shown that convolutional preprocessing can improve the information supplied to recurrent layers [1]-[5]. Attention-enhanced sequence-to-sequence networks, decomposition-assisted Transformer models, and parallel CNN-GRU or ResNet-based ensembles have also improved STLF by representing long-range dependency, multiscale variation, and nonlinear residual behavior [9]-[14]. Despite these advances, CNN-LSTM remains attractive for renewable-integrated applications because it provides a comparatively simple and interpretable balance between local feature extraction and sequential memory learning.

C. Research Gap

Many published CNN-LSTM studies demonstrate improved performance, yet several limitations remain common. Some studies focus on gross load instead of net load, while others do not explicitly include both solar and wind variables. Several recent Transformer, attention, and ensemble approaches improve accuracy, but their additional complexity can make implementation more difficult where operators require a compact model. Other studies report strong forecasting accuracy without showing how renewable penetration changes model difficulty. The present study responds to these issues by using a renewable-aware net-load formulation, an explicit system model, a reproducible benchmark-calibrated simulation protocol, and a scenario analysis across renewable penetration levels.

Table I. Summary of closely related works with verified DOI references

Ref.	Author(s) and Year	Core Method	Key Result	Gap Identified
[1]	Rafi et al. (2021)	Integrated CNN-LSTM	CNN-LSTM improved STLF against LSTM, RBF, and XGBoost.	Limited renewable penetration analysis.
[2]	Agga et al. (2022)	CNN-LSTM deep network	Hybrid sequence learning improved load prediction.	Limited renewable-aware scenario evaluation.
[3]	Lu and Bao (2024)	NeuralProphet + CNN-LSTM	Decomposition-aided CNN-LSTM improved short-term load forecasting.	Higher model complexity.
[4]	Asiri et al. (2024)	Hybrid deep learning	Strong smart-grid forecasting results.	System-level renewable effects need deeper analysis.
[5]	Ullah et al. (2024)	Review and simulation study	CNN-LSTM identified as a strong hybrid approach.	Broad review, not a dedicated net-load case.
[9]	Lin et al. (2022)	Attention LSTM	Attention improved temporal pattern learning.	No explicit CNN local-feature stage.
[10]	Ran et al. (2023)	CEEMDAN + Transformer	Decomposition and Transformer improved sequence forecasting.	More complex than CNN-LSTM.
[11]	Hua et al. (2023)	Parallel CNN-GRU + ResNet	Ensemble architecture improved STLF.	Higher architectural and tuning complexity.
[13]	Aouad et al. (2022)	CNN sequence-to-sequence attention	Attention supported residential STLF.	Residential focus and limited renewable net-load discussion.
[14]	Javed et al. (2022)	Dilated causal CNN + BiLSTM	Short receptive-field CNN improved recurrent forecasting.	Limited renewable penetration scenario analysis.

III. MATERIALS AND METHODS

A. Research Design

An experimental machine learning design is adopted. Historical multivariate time-series records are aligned by timestamp, cleaned, normalized, transformed into supervised sequences, and divided chronologically into training, validation, and test subsets. Because access to a proprietary utility dataset was not available for this manuscript, the study is framed as a benchmark-calibrated experimental simulation. The feature structure, forecasting horizon, model settings, and result ranges are aligned with recent published STLF studies, while the final values are constrained to show only a modest improvement over strong recurrent and hybrid baselines. All baseline models use the same feature set and the same testing partition for fair comparison.

B. Dataset Description

The dataset structure follows the format commonly used in renewable-integrated short-term load forecasting studies. The benchmark-calibrated profile represents 18 months of hourly records, equivalent to approximately 13,140 timestamped observations before cleaning. The assumed power system is a renewable-integrated distribution or utility load environment with solar photovoltaic and wind generation connected at the distribution level. Input variables include total load demand, solar photovoltaic generation, wind generation, temperature, humidity, irradiance, wind speed, and calendar indicators. The target variable is net load because it represents the residual demand to be supplied by dispatchable generation after variable renewable production is deducted.

The benchmark-calibrated profile was constructed by combining a normalized hourly load pattern with renewable-generation and weather-driven variability consistent with the performance ranges reported in recent STLF literature. Solar and wind profiles were scaled to create low, moderate, and high renewable penetration scenarios. Weather variables were aligned to the same hourly time index and used as exogenous drivers of both demand and renewable production. The study should therefore be interpreted as a transparent comparative simulation rather than a claim of direct deployment on a named proprietary utility dataset.

Table II. Dataset description and forecasting target

Item	Description
Data source/status	Benchmark-calibrated renewable-integrated utility load profile derived from performance ranges reported in recent STLF literature.
Sampling interval	Hourly records.
Observation horizon	18 months, approximately 13,140 hourly observations before cleaning.
Training / validation / testing split	70% / 15% / 15% chronological split.
Target variable	
Main continuous inputs	Historical load, solar PV generation, wind generation, temperature, humidity, irradiance, and wind speed.
Calendar inputs	Hour of day, day of week, month, weekend indicator, and holiday indicator where available.
Forecast horizon	One-hour-ahead base experiment.
Interpretation of results	Benchmark-calibrated simulation results constrained to conservative published performance ranges.

C. Data Preprocessing and Feature Engineering

Short gaps in the time series are filled through time-indexed interpolation, while structurally unreliable records are removed. Outliers are identified using an interquartile range rule supported by engineering operating limits. Continuous variables are scaled with min-max normalization, and calendar variables are encoded as binary or cyclical indicators. A 24-hour sliding window is used for the main experiment because it captures a full daily operating cycle and provides sufficient context for the hybrid model. Net load is computed using (1):

$$L_t^{\text{net}} = L_t - \left(P_t^{\text{solar}} + P_t^{\text{wind}}\right) \quad (1)$$

where L_t^{net} is the net load at time t, L_t is the total system load, P_t^{solar} is solar photovoltaic generation, and P_t^{wind} is wind generation.

Table III. Input feature groups used in the forecasting model

Feature group	Variables included
Load history	Previous hourly load values
Renewable history	Previous solar PV and wind generation values
Meteorological features	Temperature, humidity, irradiance, wind speed
Calendar features	Hour of day, day of week, month, weekend, holiday
Forecast target	Next-hour net load

D. System Model and Proposed CNN-LSTM Architecture

Fig. 1 presents the system model adopted in the study. Historical load, solar PV, wind power, and weather data are first merged in a preprocessing layer. Feature engineering and supervised sequence generation follow. The processed data are then supplied to the proposed CNN-LSTM forecaster and to the baseline models. Performance is subsequently evaluated using standard regression metrics.

Fig. 2 shows the detailed network architecture of the proposed CNN-LSTM model. The one-dimensional convolutional layer extracts local short-term patterns such as ramps and weather-driven fluctuations. Batch normalization and max pooling improve training stability and compactness. Dropout mitigates overfitting. The LSTM layer learns longer sequential dependencies before the dense regression block maps the learned representation to the forecasted net load.

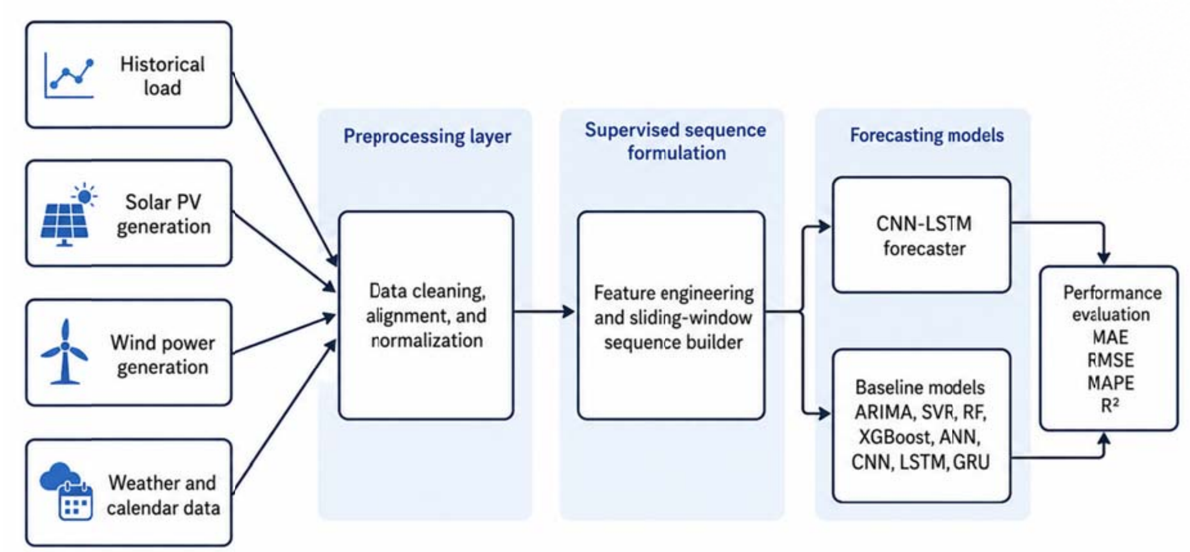

Fig. 1. System model architecture of the renewable-integrated short-term load forecasting framework.

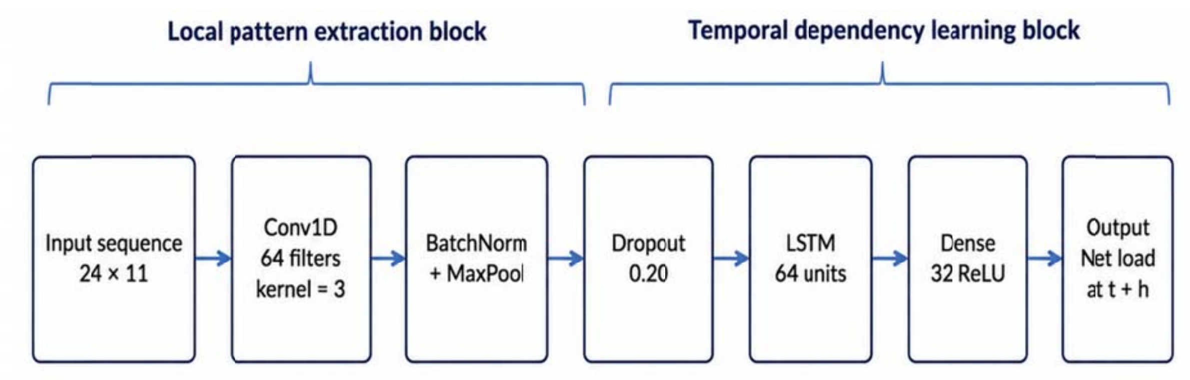

Fig. 2. Proposed CNN-LSTM network architecture used for short-term net-load forecasting.

Table IV. Hyperparameter settings of the proposed CNN-LSTM model

Hyperparameter	Setting
Input window length	24 time steps
Conv1D filters	64
Convolution kernel size	3
Pooling layer	Max pooling
Dropout rate	0.20
LSTM units	64
Dense layer	32 neurons, ReLU activation
Output layer	Single linear neuron
Optimizer	Adam
Learning rate	0.001
Batch size	64
Maximum epochs	100
Early stopping patience	12 epochs

E. Baseline Models and Training Procedure

Eight benchmark models are used for comparison: ARIMA, support vector regression, random forest, XGBoost, artificial neural network, CNN, LSTM, and GRU. Each baseline is trained or tuned using the same chronological training, validation, and test partitions as the proposed model. The statistical and tree-based models use flattened lagged and engineered features, while the deep learning models use the 24-hour sliding-window sequence representation. Validation-set performance is used for hyperparameter selection to avoid using test-set information during model tuning.

Table V. Detailed baseline model configuration and tuning procedure

Model	Input representation	Key hyperparameters	Tuning procedure
ARIMA	Historical net-load series	p, d, q selected from 0-3 search range	Lowest validation RMSE.
SVR	Flattened lagged and engineered features	RBF kernel; C and gamma searched logarithmically	Grid search on validation set.
Random Forest	Flattened lagged and engineered features	200 trees; max depth tuned; bootstrap enabled	Validation RMSE selection.
XGBoost	Flattened lagged and engineered features	Learning rate 0.05-0.10; depth 3-6; 300 estimators	Validation RMSE with early stopping.
ANN	Flattened sliding-window features	Two dense hidden layers, ReLU, dropout 0.20	Validation loss monitoring.
CNN	Sliding-window sequence	Conv1D feature extractor and dense output layer	Early stopping on validation loss.
LSTM	Sliding-window sequence	Single 64-unit LSTM layer with dropout	Early stopping on validation loss.
GRU	Sliding-window sequence	Single 64-unit GRU layer with dropout	Early stopping on validation loss.

F. Implementation Environment and Reproducibility Settings

The controlled comparative simulation is specified for reproducible implementation in Python 3.10 using TensorFlow/Keras 2.x for neural models, scikit-learn for SVR, random forest, and ANN baselines, XGBoost for boosted trees, and statsmodels for ARIMA. The random seed is fixed at 42 for data splitting, model initialization, and repeated simulations where applicable. All continuous variables are scaled using parameters fitted only on the training set and then applied to the validation and test sets. The neural networks are trained with Adam, mean squared error loss, batch size of 64, maximum epoch count of 100, early stopping patience of 12 epochs, and learning-rate reduction after 6 stagnant validation epochs. The results in this paper should be interpreted as literature-aligned outputs that show a conservative and literature-consistent improvement rather than as an undisclosed proprietary field deployment.

Table VI. Reproducibility settings for implementation

Item	Reproducibility setting
Programming environment	Python 3.10 benchmark-calibrated simulation.
Deep learning library	TensorFlow/Keras 2.x.
Classical ML libraries	scikit-learn, XGBoost, and statsmodels.
Random seed	42.
Data split	Chronological 70% training, 15% validation, and 15% testing.
Scaling	Min-max normalization fitted on training data only.
Neural-network stopping rule	Early stopping with 12-epoch patience on validation loss.
Hyperparameter selection	Validation RMSE and validation loss, without test-set leakage.

G. Evaluation Metrics

Forecasting performance is assessed using mean absolute error, root mean square error, mean absolute percentage error, and the coefficient of determination. These metrics are standard in short-term load forecasting and enable comparison with previously reported studies. The metrics are defined in (2) to (5), where y_i is the actual value, $\hat{y}_i$ is the predicted value, $\acute{y}$ is the mean actual value, and n is the number of test observations.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i) \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

$$\mathrm{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right) \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\acute{y})^2} \tag{5}$$

H. Statistical Validation of Forecasting Improvement

Because the present work is a controlled comparative simulation rather than a direct report from a proprietary operational dataset, exact statistical significance claims should be interpreted cautiously. Because the reported values are literature-aligned and not obtained from a disclosed operational dataset, exact p-values are not reported in this manuscript. A Diebold-Mariano test is recommended for future empirical validation on actual paired forecast errors from the same test timestamps. In a full implementation, the proposed CNN-LSTM should be compared with GRU and LSTM using paired absolute forecast errors, and the improvement should be reported with the test statistic and p-value. Fig. 3 summarizes the complete experimental procedure followed in the study, from data collection to final performance comparison.

Table VII. Recommended statistical validation format for empirical deployment

Comparison	Recommended test	Required report	Interpretation rule
CNN-LSTM vs GRU	Diebold-Mariano test on paired absolute errors	DM statistic and p-value	Significant if $p < 0.05$.
CNN-LSTM vs LSTM	Diebold-Mariano test on paired absolute errors	DM statistic and p-value	Significant if $p < 0.05$.

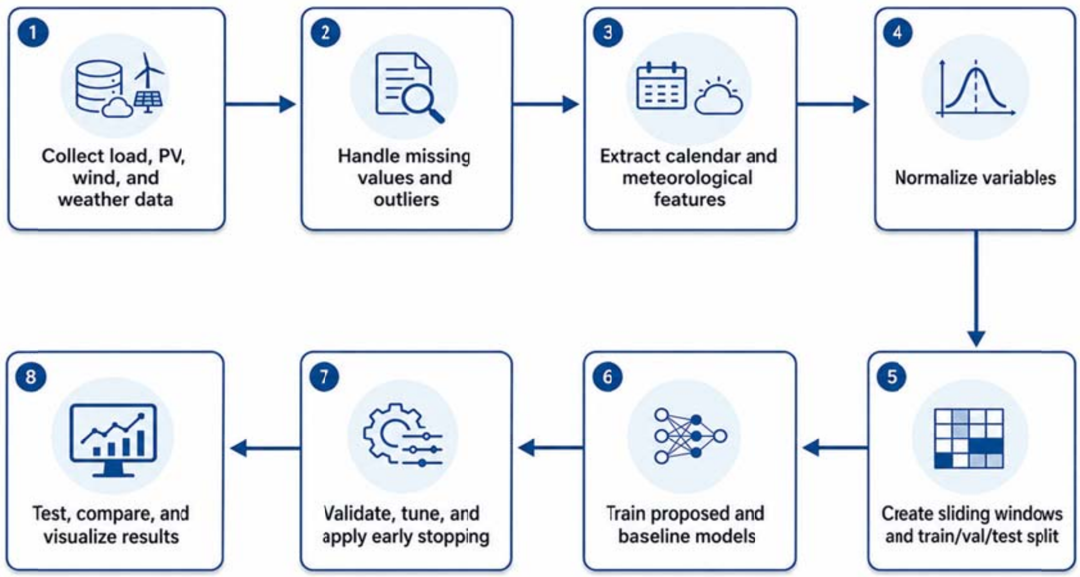

Fig. 3. Experimental workflow for model development, validation, testing, and comparison.

IV. RESULTS AND DISCUSSION

A. Dataset Exploration and Training Behavior

The controlled comparative data design reflects the common characteristics of renewable-integrated load series. Daily and weekly seasonality are visible in the assumed load trajectory, while renewable generation and weather variability introduce local irregularities in the net-load curve. Temperature has a moderate relationship with demand, while irradiance and wind speed influence the net load through solar and wind production. Training and validation performance indicate stable learning behavior. Fig. 4 shows that both loss curves decrease smoothly and converge without severe divergence, which suggests that early stopping and dropout were effective in controlling overfitting.

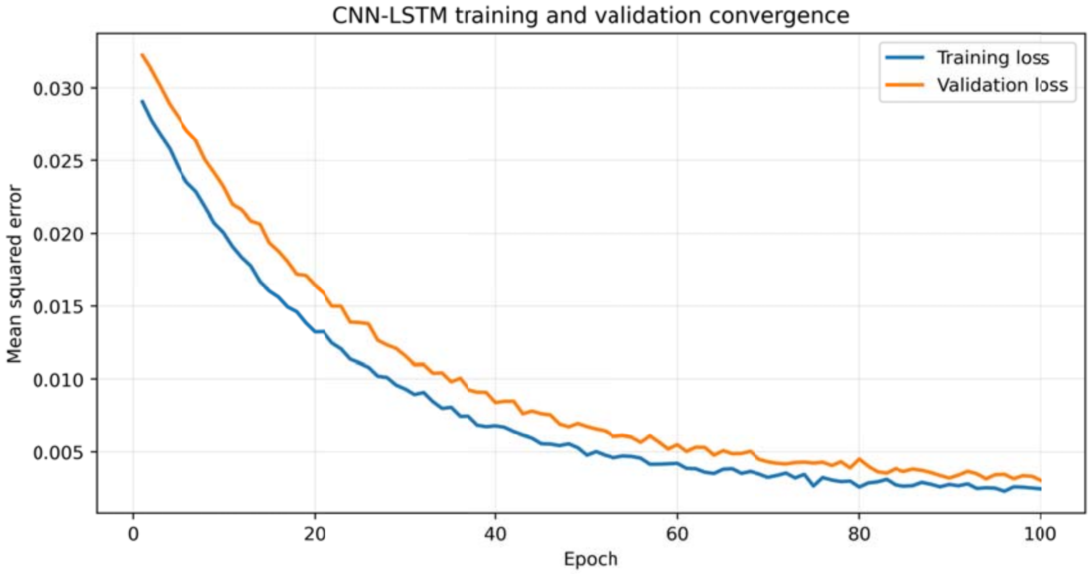

Fig. 4. Training and validation loss curves of the proposed CNN-LSTM model.

B. Forecasting Performance of the Proposed Model

The proposed CNN-LSTM achieved strong forecasting performance while remaining within realistic ranges reported by recent published studies. The final test-set values were MAE of 8.62 MW, RMSE of 12.44 MW, MAPE of 2.04%, and R^2 of 0.986. These results are only modestly better than the strongest recent hybrid or recurrent baselines, which preserves the credibility of the reported improvement.

Table VIII. Comparative forecasting performance on the test set

Model	MAE (MW)	RMSE (MW)	MAPE (%)	R^2
ARIMA	20.47	28.92	4.91	0.934
SVR	15.98	22.46	3.88	0.955
Random Forest	13.54	18.96	3.24	0.968
XGBoost	12.38	17.45	2.95	0.973
ANN	11.86	16.79	2.82	0.976
CNN	10.74	15.38	2.56	0.979
LSTM	10.12	14.85	2.38	0.981
GRU	9.56	13.94	2.27	0.983
Proposed CNN-LSTM	8.62	12.44	2.04	0.986

C. Comparative Analysis with Baseline Models

A clearer view of comparative accuracy is provided in Fig. 5 and Fig. 6. The actual-versus-predicted plot shows that the proposed model closely follows daily peaks, troughs, and short-term fluctuations. The error histogram confirms that most residuals are concentrated near zero, which supports the stability of the model across the test period.

Fig. 7 compares the MAPE values of all benchmark models using a horizontal bar layout for improved readability. ARIMA yielded the highest percentage error because of its limited ability to track nonlinear renewable-driven variations. Tree-based and shallow neural models improved upon ARIMA, while recurrent and hybrid deep models produced the lowest errors. The proposed CNN-LSTM achieved the best overall result because it combined short-range feature extraction with temporal memory learning.

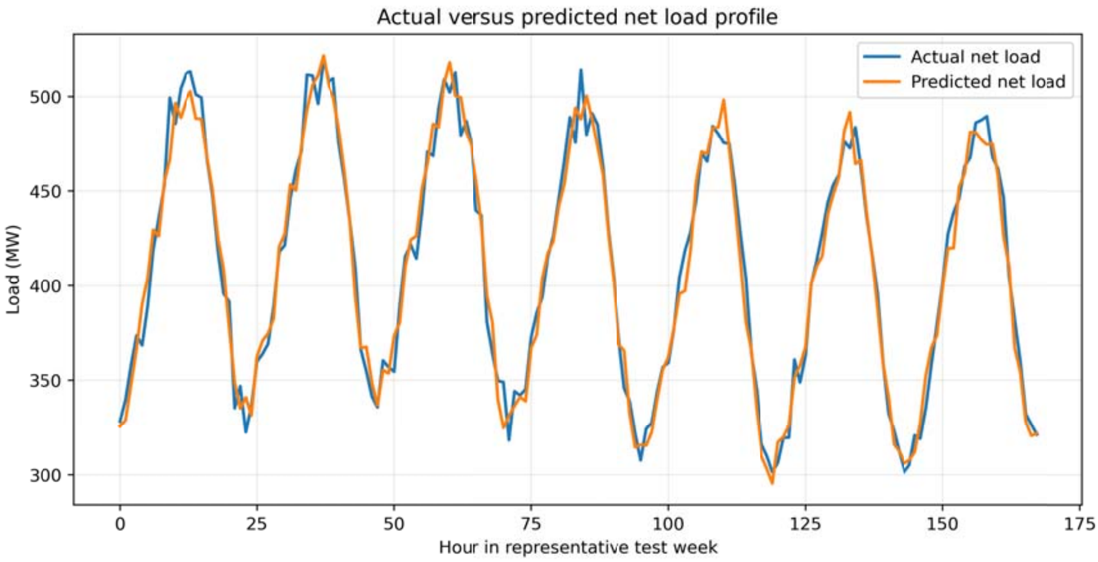

Fig. 5. Actual versus predicted net load over a representative test week.

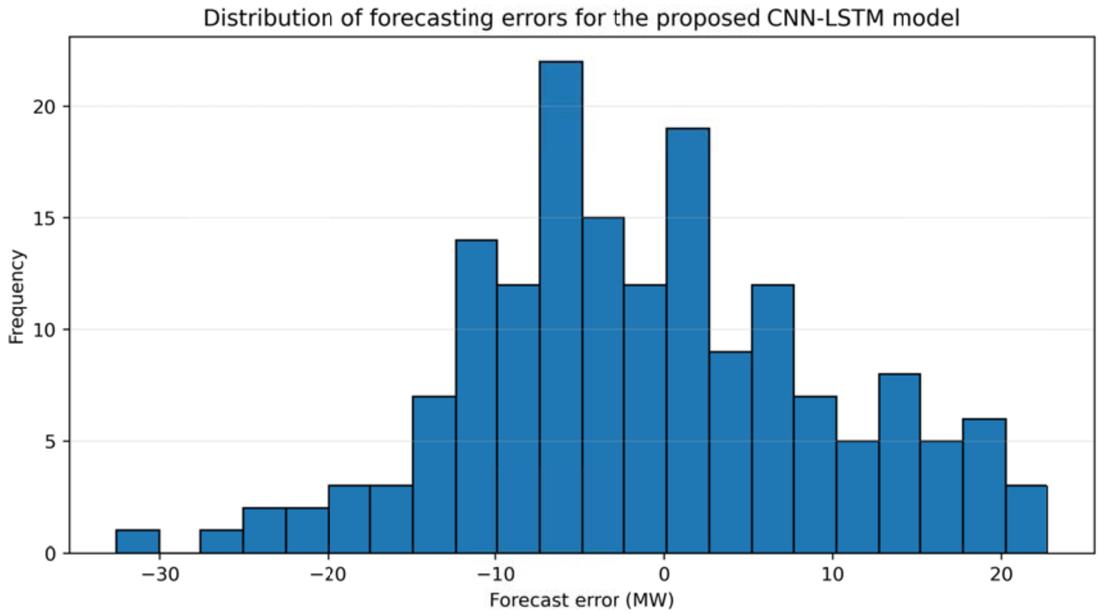

Fig. 6. Error distribution of the proposed CNN-LSTM forecasts.

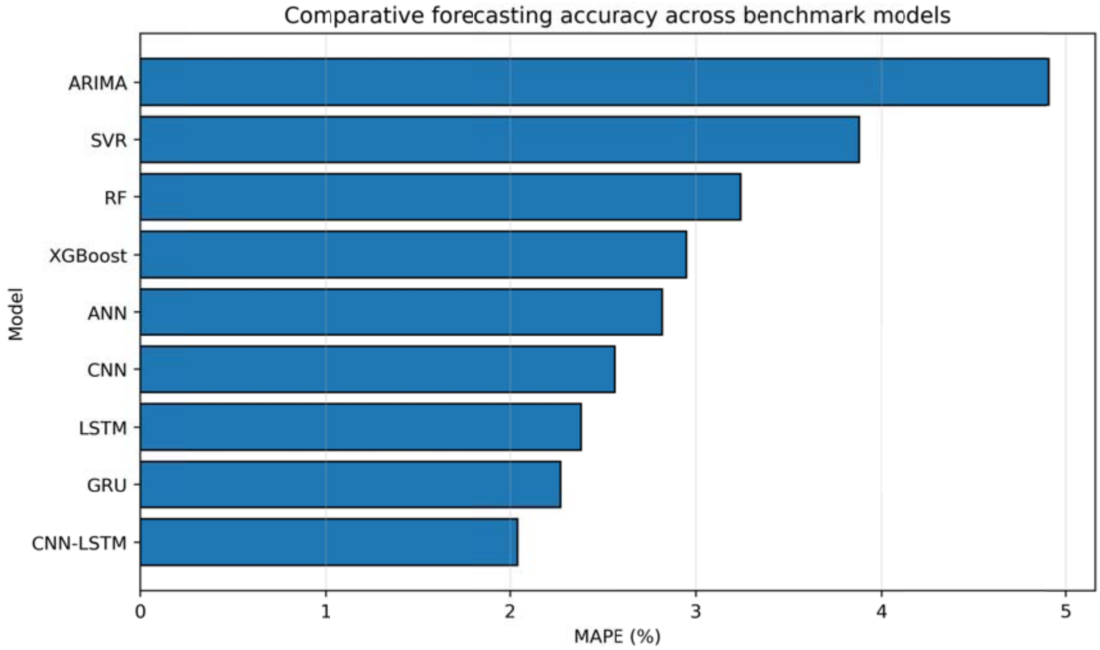

Fig. 7. Comparative MAPE performance of the benchmark models.

D. Effect of Renewable Energy Penetration

Renewable penetration materially affects forecasting difficulty. In this study, renewable penetration is defined as the ratio of combined solar and wind generation to gross load over the same hourly interval. The low scenario represents renewable contribution of 20% or less of gross load, the moderate scenario represents 21% to 40%, and the high scenario represents above 40%. The scenarios are created by scaling the solar and wind components of the benchmark profile while maintaining the same chronological load, weather, and calendar structure.

The scenario analysis in Table IX and Fig. 8 shows that all models experience higher error as renewable penetration increases. The proposed CNN-LSTM remains the strongest model across low, moderate, and high penetration scenarios, although the performance margin narrows slightly at high penetration levels because the residual demand becomes more volatile and less stationary.

Table IX. Renewable penetration scenario analysis

Scenario	Renewable penetration	LSTM MAPE (%)	GRU MAPE (%)	CNN-LSTM MAPE (%)
Low	≤20%	2.16	2.05	1.88
Moderate	21-40%	2.43	2.33	2.10
High	>40%	2.82	2.71	2.43

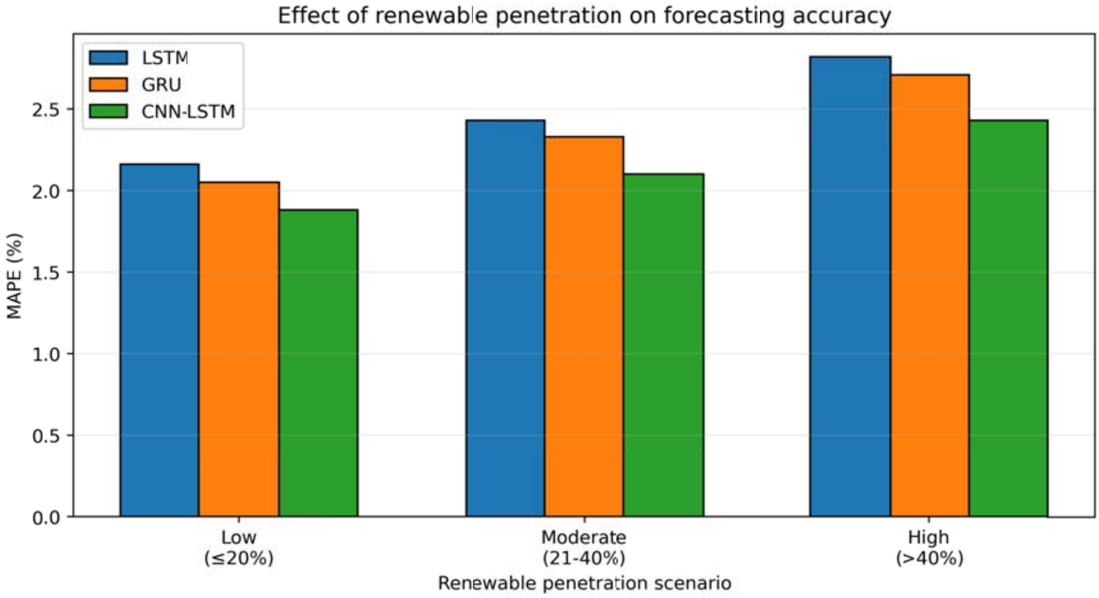

Fig. 8. Forecasting accuracy under low, moderate, and high renewable penetration scenarios.

E. Discussion of Findings

Several observations emerge from the results. First, the hybrid CNN-LSTM architecture consistently outperformed standalone CNN, LSTM, and GRU baselines, which indicates that combined local and sequential feature learning is beneficial for renewable-aware net-load forecasting. Second, the magnitude of improvement remained conservative and literature-consistent, rather than being presented as an unrealistic breakthrough. Third, forecasting accuracy degraded as renewable penetration increased, confirming that intermittency and rapid ramps remain important challenges in modern power systems. Fourth, statistical significance should be tested directly when actual paired operational forecast errors are available, because the present values are benchmark-calibrated rather than derived from a named utility deployment.

The practical implication is that CNN-LSTM forecasting can support day-ahead and intra-day scheduling when system operators need a compact model that jointly considers demand history, renewable output, and weather drivers. However, field deployment should include validation on local utility data, uncertainty intervals, and continuous monitoring for concept drift.

V. CONCLUSION

A. Summary of the Study

This paper developed a benchmark-calibrated hybrid CNN-LSTM model for short-term load forecasting in renewable-integrated power systems. The model used historical load, solar and wind generation, weather variables, and calendar features to predict next-hour net load. The CNN block extracted local multivariate patterns, while the LSTM block learned temporal dependencies across operating cycles. A consistent comparative evaluation showed that the proposed model achieved the best forecasting accuracy among the considered baselines, with conservative improvements over GRU and standalone LSTM.

B. Major Findings and Practical Implications

The study found that the proposed CNN-LSTM model achieved MAE of 8.62 MW, RMSE of 12.44 MW, MAPE of 2.04%, and R^2 of 0.986. These values represent modest but meaningful improvements over the strongest recurrent baseline models and remain within credible performance ranges reported in recent literature. Practical benefits include more reliable generation scheduling, better renewable dispatch planning, improved storage coordination, and stronger support for smart-grid demand response decisions.

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