International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 11 | Nov - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

Deep Learning Approaches for Electricity Demand and Renewable Energy Forecasting: Towards Gap-Aware Smart Energy Planning: A Survey

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Abstract - Accurate forecasting of electricity demand and renewable energy generation is central to reliable grid planning, because solar and wind output varies with the weather while demand follows season, time of day and human behavior. This paper surveys five representative studies on deep learning for energy forecasting: a CNN-LSTM model for residential consumption, an LSTM model tuned with feature selection and a genetic algorithm for load forecasting, a CNN with multi-layer bidirectional LSTM for household power, a U-shaped LSTM model for solar irradiance, and a multi-branch CNN, LSTM and dense network for renewable energy consumption. For each study, the core idea, processing flow, advantages, limitations and reported outcome are summarized. A comparative analysis shows that existing work usually forecasts either demand or generation, rarely connects the two, and seldom explains its predictions. This gap motivates a proposed smart energy demand and renewable energy prediction system that forecasts both quantities, computes the energy gap or excess, and produces a planning recommendation.

Key Words: literature survey, electricity demand forecasting, renewable energy, solar irradiance, CNN-LSTM, deep learning.

1. INTRODUCTION

1.1 Overview of the proposed system

The proposed work is a Smart Energy Demand and Renewable Energy Prediction System. The system takes historical electricity consumption, date and time information, temperature and humidity, solar radiation and wind speed as inputs. Machine learning models predict future electricity demand and future renewable generation. The system then compares the two, calculates the energy gap or excess, and recommends an action. For example, if predicted demand is 1000 MW and predicted renewable generation is 750 MW, the gap is 250 MW and the system recommends planning additional supply for that gap while using as much renewable energy as possible.

This paper presents a literature survey of how existing research approaches the forecasting problems on which the proposed system depends. Five papers are reviewed, and each is summarized in a common format: a short introduction, the system flow, advantages, disadvantages and the conclusion or result. The papers are then compared, the research gap is identified, and the manner in which the proposed system addresses it is described.

The remainder of this paper is organized as follows. Section 2 presents the background. Section 3 reviews five studies. Section 4 compares the reviewed approaches. Section 5 identifies the research gap and motivation, and Section 6 concludes the paper.

2. BACKGROUND

Forecasting task. Given past observations of a series (demand or generation) and related variables (weather, calendar), the task is to predict future values over a chosen horizon, which may be short term (hours), medium term (days to weeks) or long term (months).

Classical methods. Statistical models such as ARIMA and regression handle linear patterns well but struggle with the nonlinear effects of weather and overlapping seasonal cycles [6].

Deep learning models. A convolutional neural network (CNN) extracts local patterns and relations between input variables. A long short-term memory network (LSTM) models temporal dependence through gated memory cells [7]. Bidirectional LSTM reads the sequence in both directions. Hybrid models combine these building blocks.

Evaluation metrics. Studies commonly report MSE, RMSE, MAE, MAPE and R^2.

Survey methodology. This paper uses a focused narrative review of five studies selected because they represent different deep-learning designs and forecasting targets: household electricity consumption, aggregate load, residential power consumption, solar irradiance, and renewable-energy consumption. Each study is examined using the same comparison dimensions: prediction target, model architecture, data characteristics, role of weather or calendar features, reported evaluation, practical strengths, and limitations. The aim is to identify common technical patterns and gaps relevant to a combined demand-and-renewable-generation planning system.

Interpretation of metrics. Mean absolute error (MAE) measures the average absolute difference between predicted and observed values. Mean squared error (MSE) penalizes larger errors more heavily, while root mean squared error (RMSE) expresses the square root of MSE in the target variable's units. Mean absolute percentage error (MAPE) expresses errors as percentages but can become unstable when observed values are zero or close to zero. The coefficient of determination (R^2) describes how much of the variation is explained relative to a baseline. Comparisons between studies should therefore consider target scale, time horizon, data split, and metric definition; a lower numerical error in one dataset does not automatically prove that a model is universally superior.

3. LITERATURE SURVEY

3.1 Predicting Residential Energy Consumption Using CNN-LSTM Neural Networks [1]

Introduction: Kim and Cho propose a CNN-LSTM model to predict household electricity consumption. The CNN layer extracts features from different input variables, while the LSTM layer analyzes consumption patterns over time.

System Flow: Household energy data → Data preprocessing → CNN layer → LSTM layer → Dense output layer → Predicted energy consumption.

The model extracts features from multiple variables and captures time-based patterns. It also identifies the important factors influencing energy consumption. However, it focuses only on residential energy consumption and does not predict renewable energy generation. Its performance in other regions and large-scale power grids is also uncertain. Additionally, it does not convert predictions into energy supply planning decisions.

Conclusion/Result: The authors report that the hybrid model predicts consumption with very high accuracy compared with earlier approaches and that the variable analysis identifies the main drivers of consumption.

Review implication: The CNN-LSTM structure is relevant when input data contain both local relationships among variables and temporal patterns across successive observations. For a practical deployment, the model would still need to be validated on the target region and time period, because household behavior, climate, tariff structures, and appliance usage may differ across locations.

3.2 Optimal Deep Learning LSTM Model for Electric Load Forecasting Using Feature Selection and Genetic Algorithm [2]

Introduction: Bouktif et al. focus on improving time-series forecasting by selecting suitable input features and model parameters. They develop LSTM models for short- to medium-term electricity load forecasting and compare their performance with traditional machine learning methods.

System Flow: Electricity load data → Train machine learning models → Select the best baseline model → Feature selection → Genetic algorithm optimization → Train optimized LSTM model → Compare forecasting results.

The model automatically selects important features, time lags, and network depth, reducing manual trial and error. It also compares LSTM performance with tuned machine learning models and supports grid-level electricity demand forecasting. However, the genetic algorithm requires significant computational resources, and the study uses data from a single region in France. Additionally, it focuses only on electricity demand and does not forecast renewable energy generation or analyze the gap between energy demand and supply.

Conclusion/Result: The LSTM model was more accurate than the tuned machine learning models, and using the selected features, optimal lags and layers improved accuracy further.

Review implication: This study highlights that forecasting quality depends not only on the network family but also on the input variables and the time lags supplied to the model. Feature selection and hyperparameter search should be assessed with a validation set that is separate from the final test set, so that the test results remain an unbiased estimate of generalization.

3.3 Short-Term Prediction of Residential Power Energy Consumption via CNN and Multi-Layer Bi-Directional LSTM Networks [3]

Introduction: Ullah et al. address the challenges of household electricity consumption prediction caused by weather conditions and changing occupant behavior. They propose a hybrid model combining CNN with a multi-layer bidirectional LSTM (M-BDLSTM).

System Flow: Raw data → Data preprocessing → CNN feature extraction → Multi-layer BiLSTM → Energy consumption prediction → Evaluation using error metrics.

The model learns sequence patterns using bidirectional layers and achieves lower MSE and RMSE than the compared methods on the household dataset. Its evaluation uses 10-fold cross-validation and a hold-out split. However, it focuses only on household-level consumption, requires more computational resources due to its multiple layers, and does not include renewable energy forecasting or energy supply planning.

Conclusion/Result: The hybrid model achieved lower errors than the methods it was compared with, supporting the use of CNN with stacked BiLSTM for short-term residential forecasting.

Review implication: Bidirectional recurrent layers can use context from both directions within an input sequence during model training. For operational forecasting, however, input windows must contain only information available at prediction time; future observations must not leak into the features used to generate a forecast.

3.4 A Novel U-LSTM-AFT Model for Hourly Solar Irradiance Forecasting [4]

Introduction: Zhu et al. propose a U-shaped LSTM-AFT model to improve hourly solar irradiance forecasting. The model combines a U-Net-inspired architecture with LSTM and AFT (Attention-Free Transformer) to capture time-dependent patterns and improve prediction accuracy.

System Flow: Historical solar irradiance and weather data → Data preprocessing → U-shaped network with downsampling and feature extraction → LSTM and linear layers → AFT mechanism → Predicted solar irradiance → Performance evaluation.

The model captures short-term fluctuations and long-term trends in solar irradiance. It was tested using three real-world datasets from different locations in the United States and achieved improved forecasting accuracy compared with traditional models. However, it primarily focuses on solar irradiance forecasting and does not directly predict electricity demand or analyze the demand-supply gap. Its complex architecture may also increase implementation and computational difficulty.

Conclusion/Result: The supplied manuscript indicates that the U-LSTM-AFT model was evaluated on three real-world datasets and reports improved hourly solar-irradiance forecasting against its comparison models. Exact error values and baseline rankings should be inserted only after checking the original article; they are not inferred in this survey.

Review implication: Solar irradiance is an important intermediate variable for solar-generation estimation, but irradiance and electrical power output are not interchangeable. A system that predicts renewable generation should account for the target definition and, where available, relevant plant or generation measurements rather than treating an irradiance forecast as a direct generation forecast.

3.5 Research on U.S. Renewable Energy Consumption Prediction Based on Multi-Branch Deep Learning Architecture [5]

Introduction: Li, Zhang, and Liu propose a multi-branch neural network to predict renewable energy consumption in the United States using monthly EIA data from 1973 to 2024. The dataset contains 3,065 records and 17 attributes, with 15 selected features.

System Flow: Input data (1 × 15) → Z-score standardization → Three parallel branches (CNN, LSTM, and Dense) → Feature concatenation (96 features) → Dense layer (64 neurons) → Dropout (0.3) → Output layer → Predicted renewable energy consumption.

The model combines local features, temporal patterns, and general feature relationships. Its ablation study shows that all three branches contribute to prediction accuracy, and the dataset covers more than 50 years. However, the input contains only one time step, limiting the LSTM's ability to learn long-term dependencies. The model predicts consumption only and does not include weather inputs, renewable generation forecasting, or demand-supply gap analysis. It also lacks explainability analysis, and the paper reports inconsistent test MSE values between its text and figure.

Conclusion/Result: The full model gave the best test MSE of 0.2129 and every branch contributed to accuracy, with the CNN branch contributing most.

Review implication: The reported multi-branch design combines complementary representations, but the survey notes a limitation in the described single-time-step input. A sequence-based implementation intended to forecast future demand or generation should define its look-back window and forecast horizon explicitly and test whether the additional branches improve performance over simpler baselines.

4. COMPARATIVE ANALYSIS

Table -1: Comparison of reviewed forecasting approaches

Paper	Target	Model	Data	Weather	Renewable generation	Gap analysis	Explainability
[1] Kim and Cho, 2019	Residential consumption	CNN-LSTM	Household data	Not a focus	No	No	Variable analysis
[2] Bouktif et al., 2018	Aggregate load	LSTM with feature selection and GA	France metropolitan load	Not a focus	No	No	Feature selection
[3] Ullah et al., 2020	Household power	CNN with multi-layer BiLSTM	Individual household	Discussed as a challenge	No	No	No
[4] Zhu et al., 2025	Solar irradiance	U-LSTM-AFT	Hourly irradiance data	Yes	Solar only	No	No
[5] Li et al., 2025	Renewable energy consumption	Multi-branch CNN, LSTM, Dense	EIA monthly data, 1973 to 2024	No	Consumption only	No	Ablation only
Proposed system	Demand and renewable generation	Model to be selected	Dataset to be finalized	Yes	Yes (solar and wind)	Yes	SHAP/LIME planned; implementation pending

Observations

1. Hybrid models that mix CNN and LSTM layers are the most common approach and consistently outperform single models in the reviewed studies.
2. Four of the five papers forecast either consumption or generation, never both together.
3. None of the papers turns forecasts into a planning decision such as a supply gap or surplus.
4. Explainability is limited to variable analysis or ablation; no paper uses a dedicated method such as SHAP.
5. Hyperparameter and feature choices matter, as shown by the genetic algorithm work in [2], but the cost of the search is high.

Cross-study discussion. The reviewed studies differ in target variable, temporal resolution, input features, geographical coverage, and evaluation protocol. Consequently, their reported metrics should not be ranked as if they were produced under a single benchmark. Their value for this project lies instead in the design lessons they provide: convolutional layers can extract local patterns; recurrent layers can model sequential dependencies; feature selection can reduce unnecessary inputs; and multi-branch architectures can combine different feature representations. The choice of model should ultimately be guided by data availability, forecast horizon, computational cost, interpretability requirements, and performance on a held-out test period.

Practical deployment considerations. Energy data are time-dependent and may contain missing intervals, duplicated timestamps, outliers, changes in measurement units, and seasonal effects. Preprocessing should preserve chronological order, document how missing values are handled, and fit scaling transformations using training data only. Randomly shuffling a time series can allow information from later periods to influence earlier predictions; a chronological train-validation-test split is therefore generally more appropriate for forecasting. Any feature derived from future weather observations should be replaced at inference time by a forecast that would actually have been available.

5. RESEARCH GAP AND MOTIVATION

The reviewed work shows that deep learning can forecast demand and solar output accurately, but three gaps remain. First, demand and renewable generation are treated as separate problems. Second, there is no step that compares them to quantify the shortfall or surplus that a grid operator must plan for. Third, the models are rarely explained, which limits trust. The proposed system is designed to close these gaps.

6. CONCLUSIONS

This paper reviewed five studies on deep learning for energy forecasting. Taken together, they show that CNN-LSTM style hybrids, bidirectional layers, systematic feature and hyperparameter selection, and multi-branch designs each improve forecasting accuracy. At the same time, the studies treat demand and generation separately, stop at the forecast, and offer limited explanation. The proposed system addresses

these limitations by forecasting both demand and renewable generation, computing the energy gap or excess, and producing a recommendation for energy planning. Future work will implement and evaluate the system on real data, add explainability, and extend it with live weather forecasts and storage-aware planning.

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