Probabilistic Forecasting of Load Demand and Low-Carbon Technologies for Enhancing Flexibility in Energy Communities

DTU PES Summer School 2025
Future Energy Systems: Leveraging
Advanced Optimization, Data Sharing
and AI for Market Design and Operation

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Abstract

The world stands at a critical energy juncture in the third decade of the 21st century. The widespread integration of low carbon technologies (LCTs), with solar photovoltaics (PVs) and electric vehicles (EVs) as key drivers, is posing major challenges to distribution system operators (DSOs). Energy flexibility is crucial for optimising grid operations and balancing energy supply and demand. Increased LCTs integration demands flexible energy systems to manage fluctuating generation and consumption patterns [1]. Properly predicting net load demand and LCTs can significantly contribute to reducing carbon emissions and improving stability [2]. Existing models have been developed for energy load forecasting but lack the consideration of high-resolution data at the local community level, peak-period focusing, and seasonality checking [3]. A local community level refers to a small, defined group of households or buildings—like a neighborhood—working together on shared energy goals, such as using solar power, batteries, or flexible demand. This research proposes a novel CNN-BiLSTM KDE-Monte Carlo Droupout framework to forecast net load demand at the local community level, integrating both deterministic and probabilistic approaches for day-ahead and intra-hour load and LCT predictions. Our hybrid method combines temporal convolutional networks with bidirectional LSTM and, KDE and Monte Carlo dropout for uncertainty quantification.

Introduction

Problem Statement

The intermittent and stochastic nature of renewable generation coupled with increasingly unpredictable consumption patterns from electrified heating and transport creates significant operational challenges for DSOs [4]. Traditional load forecasting methods, typically developed for transmission-level planning, prove inadequate for distribution networks with high LCT penetration.

The primary challenges include:

- ➢ Temporal resolution limitations,
- ➢ Spatial granularity,
- ➢ Flexibility quantification,
- ➢ Peak-period forecasting accuracy,
- ➢ Uncertainty propagation.

Research Objectives and Contribution

This research addresses these challenges by developing a comprehensive framework for forecasting the net load demand at community level. Specifically, this study:

- ➢ Proposes a novel hybrid forecasting approach combining deterministic and probabilistic methods for both day-ahead and intra-hour horizons.
- ➢ Develops an innovative ML architecture to coordinate distributed LCTs while respecting physical and operational constraints.
- ➢ Validates the approach using high-resolution (10-minute and 0.5-h) data from real community deployments across multiple seasons.

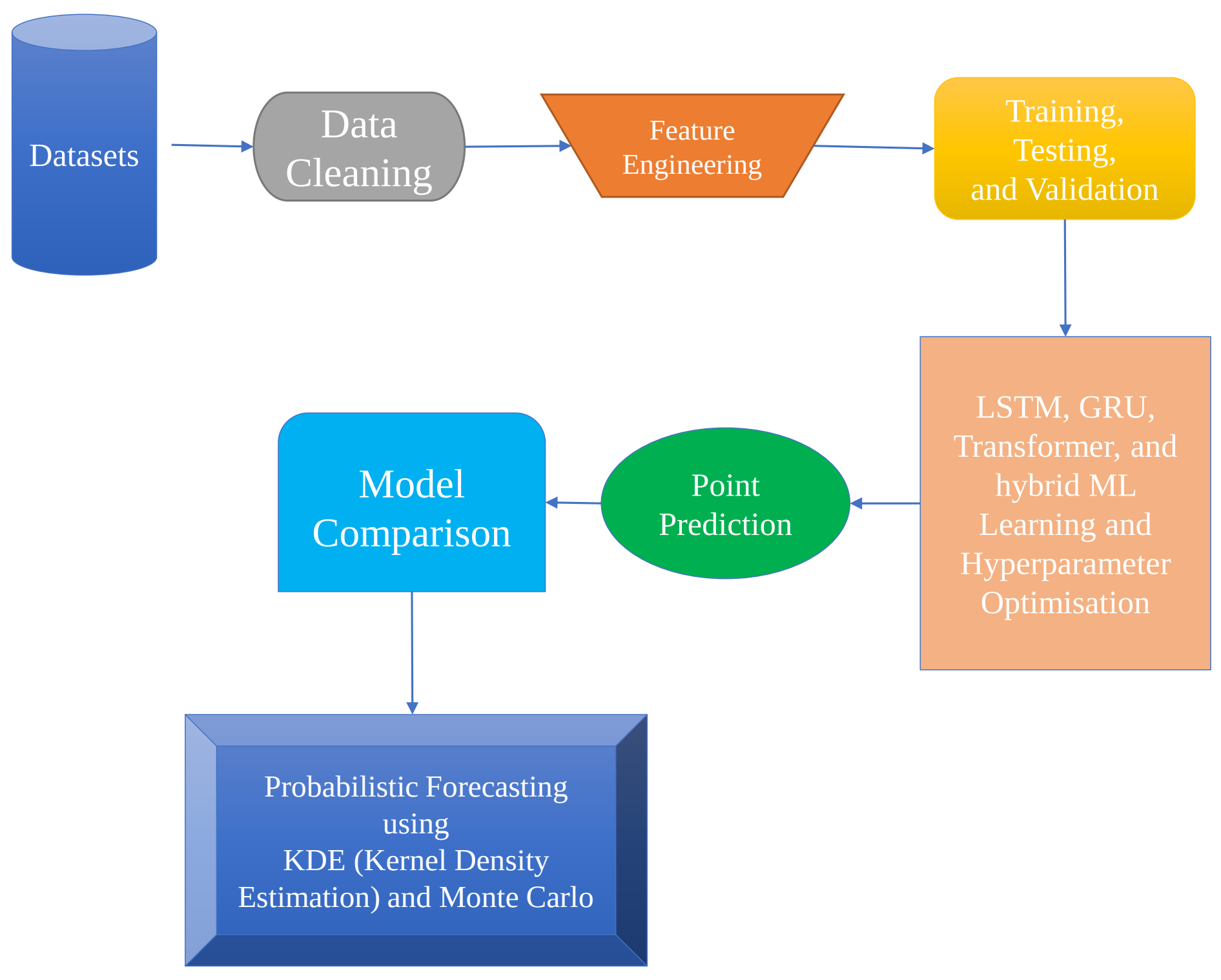

Figure 1. Research Methodology

Methods and Materials

The methodology focuses on forecasting power consumption using a hybrid deep learning framework that combines CNNs, BiLSTM networks, Monte Carlo Dropout, and Kernel Density Estimation (KDE). The approach utilises a dataset of power consumption values recorded at minute-level (resampled to 10-minute and 0.5-hour) intervals during summer and winter times [5].

The pre-processing stage involves transforming raw data into a structured format, deriving additional features to enhance model performance.

Peak consumption periods are identified using a dynamic threshold based on daily statistics. The deep learning stage employs a hybrid CNN-BiLSTM architecture, where CNN layers extract local features, and the bidirectional LSTM captures long-term dependencies in the time series data. The regression stage generates point forecasts and uncertainty estimates, utilising KDE for peak periods and Monte Carlo Dropout for non-peak periods to model prediction uncertainty.

A comprehensive set of metrics is computed for overall, peak, and non-peak periods to provide a holistic assessment of model accuracy, reliability, and bias, ensuring effective communication of results (Table 1 and Figure 2).

Results

Table 1, along with Figures 2 and 3, presents a comparison of deterministic and probabilistic load and PV production forecasting models across time intervals and seasonal variations. The CNN–BiLSTM KDE–Monte Carlo model achieves the highest PICP in both summer and winter peak periods at the 0.5-hour interval (95.16% and 97.50%, respectively), while maintaining narrow PINAW values (≤ 24.29%), indicating strong accuracy and efficient uncertainty capture. In contrast, the Transformer model performs poorly at the 10-minute interval, with a summer non-peak PICP of 56.22% and winter non-peak PINAW of just 10.39%, highlighting its unreliability under high-resolution conditions. Although the naïve and GRU models attain high PICP values (up to 93.55%), they do so with much wider PINAWs, suggesting they overestimate uncertainty to retain coverage.

Table 1. Comparison the probabilistic forecasting models

Time Interval	Prediction Model	Accuracy Evaluation of Probabilistic Forecasting							
		Summer				Winter			
		PICP (%)		PINAW (%)		PICP (%)		PINAW (%)	
		Peak	Non-peak	Peak	Non-peak	Peak	Non-peak	Peak	Non-peak
10-min	Naive	78.07	78.94	44.59	65.58	94.53	90.37	34.55	41.07
	LSTM	90.61	87.48	25.34	36.93	93.75	91.19	27.36	32.01
	GRU	88.08	90.33	23.25	33.69	82.03	89.36	24.84	30.07
	Transformer	81.69	56.22	24.44	39.87	52.34	67.97	24.20	32.78
	LSTM+Attn Layer+RL	91.28	88.94	23.32	31.34	89.01	90.88	23.14	29.63
	CNN-BiLSTM KDE-MC Dropout	91.55	90.94	17.33	14.83	91.41	91.39	21.93	10.39
0.5-h	Naive	93.55	91.59	42.27	39.19	92.05	91.00	27.97	31.96
	LSTM	91.94	92.04	24.30	33.06	91.50	93.50	24.18	29.76
	GRU	93.55	89.82	23.36	34.14	92.50	93.00	34.15	30.70
	Transformer	69.38	45.03	24.29	56.38	64.42	54.33	24.47	32.75
	LSTM+Attn Layer+RL	92.21	91.83	25.02	29.90	93.11	89.68	26.04	31.44
	CNN-BiLSTM KDE-MC Dropout	95.16	92.92	15.67	35.72	97.51	92.50	13.05	11.76

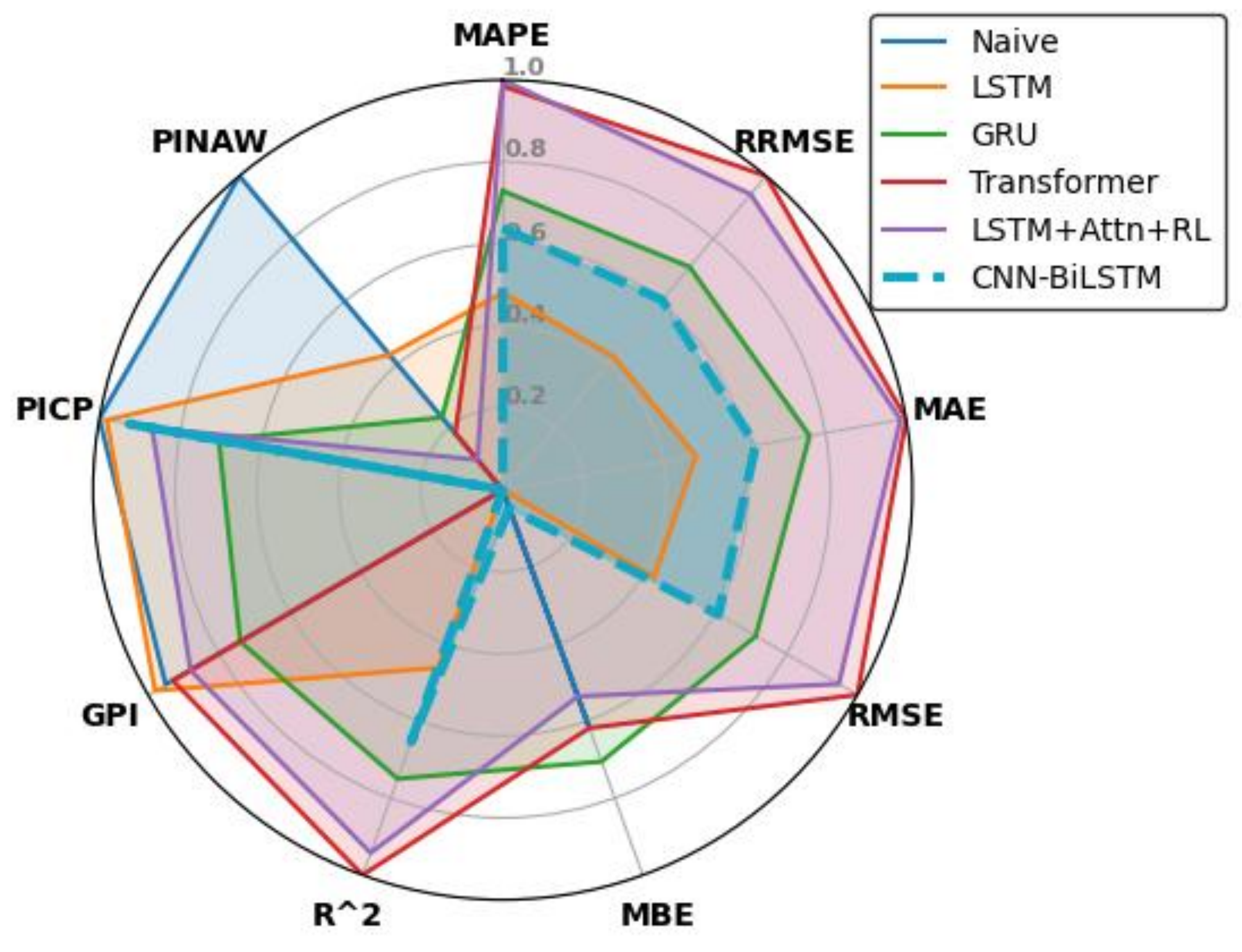

Figure 2. Comparison of the models for Winter time (Peak Period)

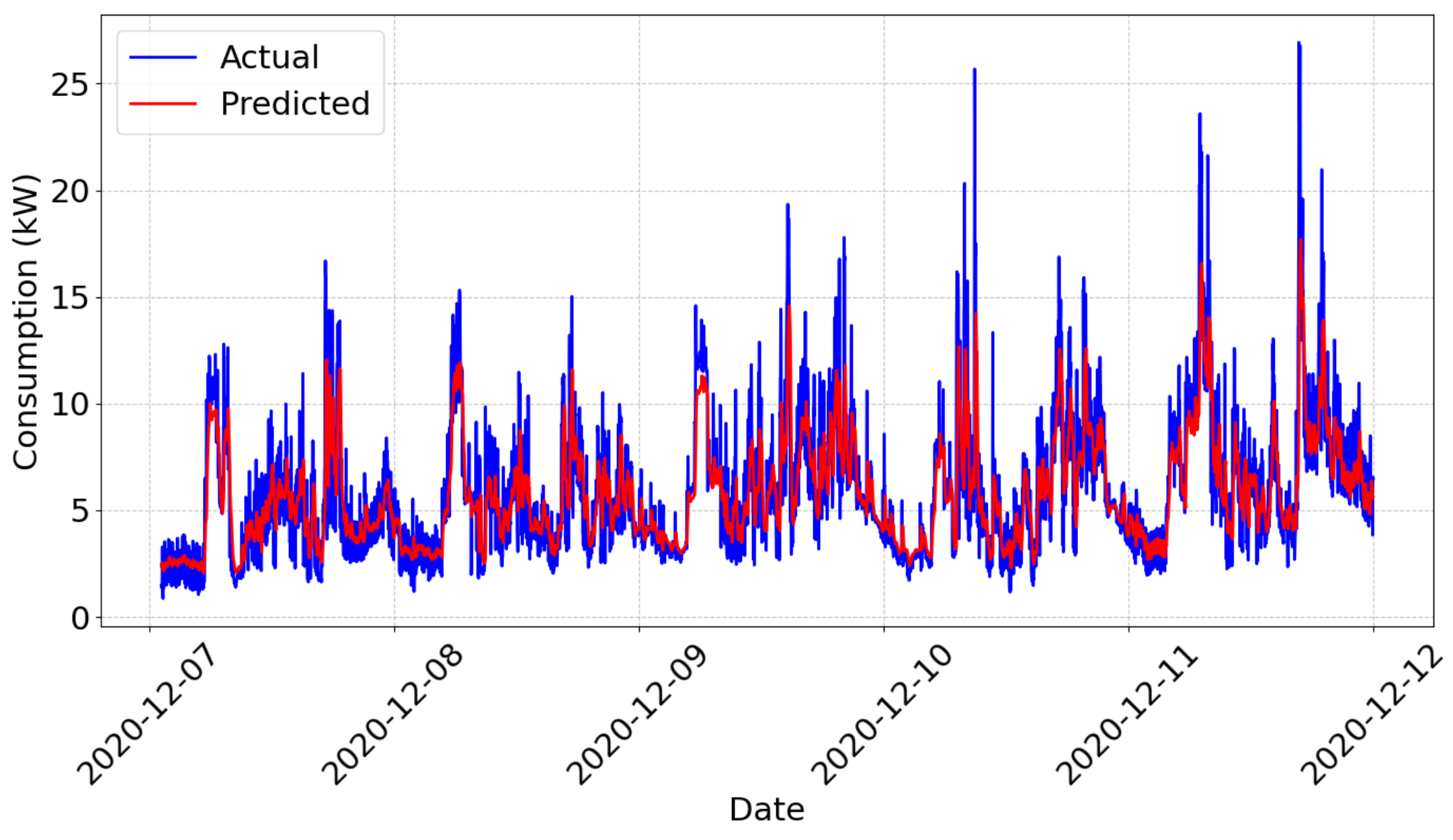

Figure 3.a. Deterministic and Probabilistic Load Forecasting, 10-min Resolution with Hybrid ML Model.

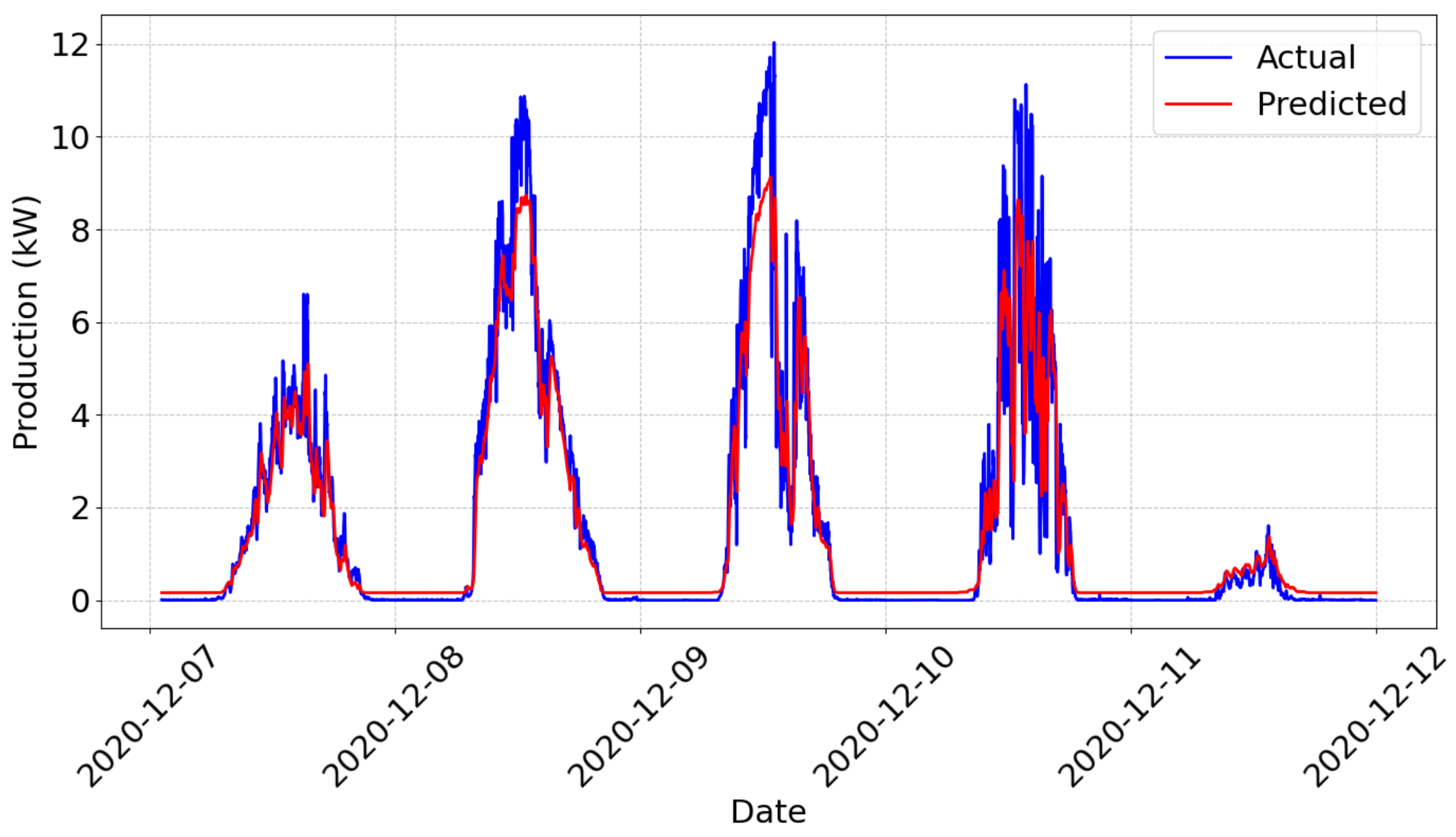

Figure 3.b. Deterministic PV Production Forecasting, 10- min Resolution with Hybrid ML Model.

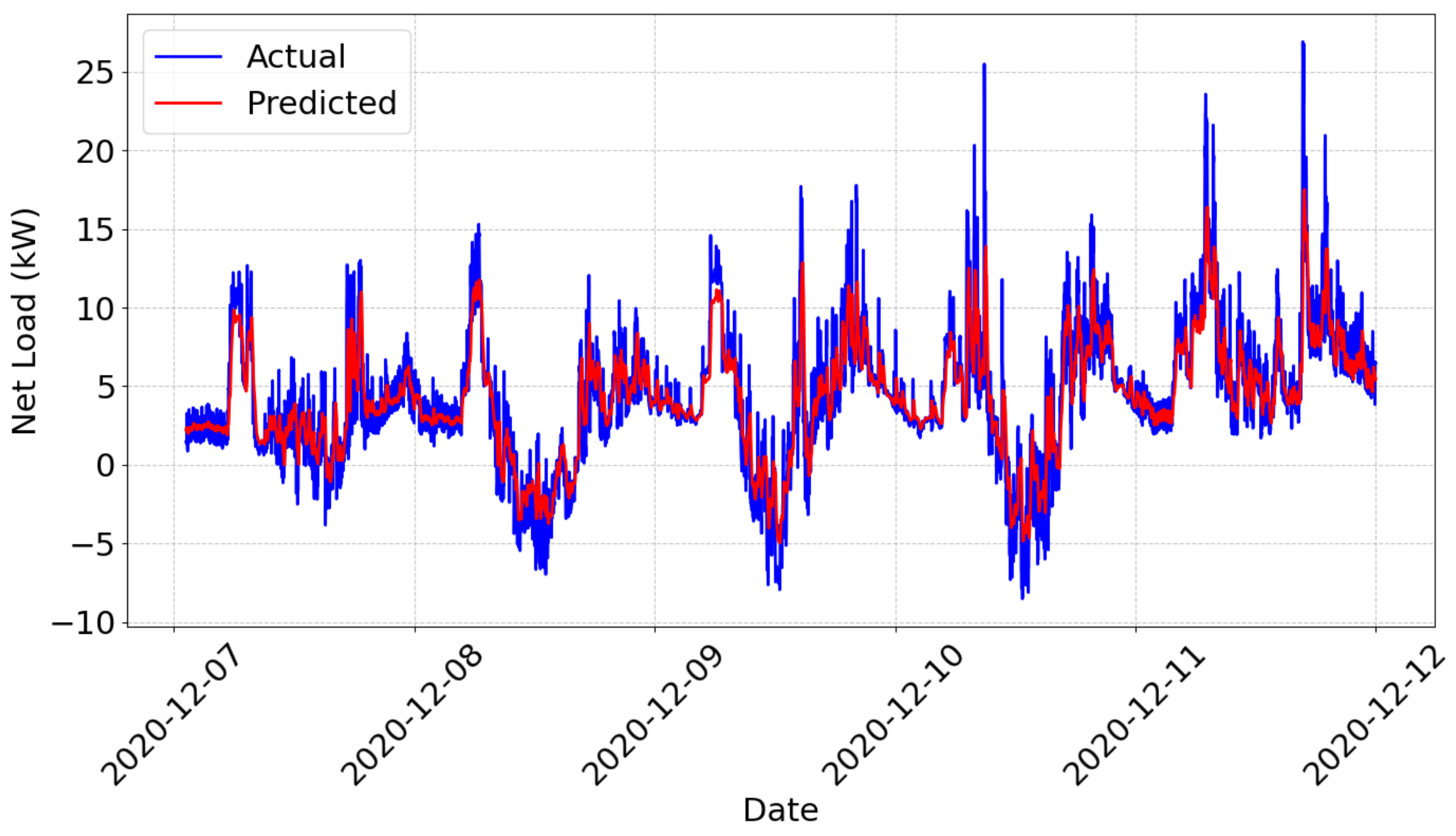

Figure 3.c. Deterministic Net Load Forecasting, 10- min Resolution with Hybrid ML Model.

Discussion

The proposed CNN–BiLSTM KDE–Monte Carlo Dropout model enhances net load forecasting by capturing both local patterns and long-term dependencies, while effectively quantifying uncertainty. It achieved the highest PICP at the 0.5-hour interval—95.16% in summer and 97.50% in winter—while maintaining narrow PINAWs of 15.67% and 13.05%, respectively. In contrast, the Transformer model had lower PICPs (45.03% summer, 54.33% winter) and narrower but less reliable intervals. Naïve and GRU models reached up to 93.55% PICP but required much wider PINAWs (e.g., 42.27% for naïve in summer peak), confirming the hybrid model's superior balance of accuracy and reliability.

Conclusions

This methodology represents an advancement in forecasting net load demand, combining sophisticated pre-processing techniques with state-of-the-art deep learning architectures specifically for peak-period prediction with KDE and non-peak period with Monte Carlo dropout methods.

Next Steps

Local Energy Communities (LECs) are valuable sources of flexibility for energy systems, and accurately forecasting their flexible capacity is key to reducing costs or generating profit. To do this, a robust model combining historical data analysis, deterministic and probabilistic methods, and machine learning should be developed. The model must be validated with real-time data and integrated with local market dynamics to guide energy trading and consumption. Communicating results with community stakeholders will support greater engagement and energy resilience.

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