EV Load Forecasting using a Refined CNN-LSTM-AM

Detailed Presentation Based on Elsevier Paper, 2024

1. Introduction

- EV load forecasting is critical to smart grid operations.
- China relies heavily on coal; accurate EV prediction reduces emissions.
- Hybrid neural networks can improve load forecasting accuracy.
- Paper Section Indications :
  - Section 1: Introduction
  - Section 2: Related Work / Literature Review
  - Section 3: Proposed Model Architecture
  - Section 4: Experiments & Dataset
  - Section 5: Conclusion

2. Related Work

- Previous models: ANN, LSTM, GRU, Transformer.
- Limitations: short-term focus, insufficient accuracy, no interval-awareness.
- CNN and attention mechanisms have shown improvements in time-series tasks.

Work	Methodology	Limitations
[5] G. Vishnu et al. (2023)	Short-term EV load forecasting using various ML and DL techniques	Limited to short-term forecasts; may not capture long-term patterns effectively
[6] A. Agga et al. (2022)	CNN-LSTM hybrid for photovoltaic power prediction	Power-specific; may require adaptation for load forecasting; computational complexity
[31] Qiming Sun et al. (2016)	Support Vector Regression (SVR) for EV station load prediction	Susceptible to noise; performance degrades with complex data and nonlinearity

2. Related Work

Work	Methodology	Limitations
[32] P. Ray et al. (2016)	Artificial Neural Network (ANN) for short-term load forecasting	Struggles with complex, nonlinear patterns; may require extensive tuning
[33] M. Imani (2021)	CNN-based residential load forecast incorporating temperature data	Focus on residential loads, less on EV; environmental data may limit generalization
[35] H. Zang et al. (2021)	LSTM fused with self-attention mechanism	Increased computational demand; primarily residential loads, not EV
[36] X. Chu et al. (2021)	Dual-attention convolutional LSTM for univariate time series	High model complexity; potential overfitting; specialized to univariate data
[37] Li et al. (2021)	Wavelet packet decomposition + LSTM for solar power forecasting	Possible information loss during decomposition; limited to solar PV data

Methodology

3. Problem Formulation

- Formulate load forecasting as a multi-step time series problem.
- Goal: Predict EV charging load ŷ from input Xt with multiple intervals.
- Use MIMO strategy for multi-output prediction.

y1, y2, …, yn denote the values of n time points in the predicted future,

x1, x2, …, xT denote the time series sampled at fixed time intervals at moment T, and f denotes the network model that can be used for pre diction.

Xt=concat(xl,xs)

[y^1, y^2. . . y^n]= f(X1,X2…XT)

4. Dataset Description

- Dataset: ACN data from Caltech & JPL.
- Over 30,000 charging sessions, Apr 2018 – Jan 2021.
- Granularity: 1-minute and 15-minute intervals.

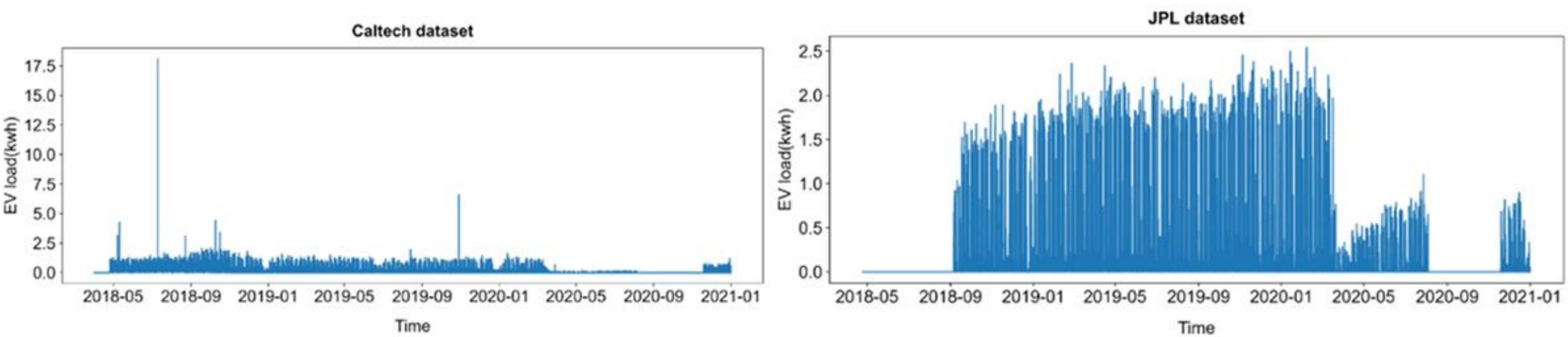

Fig. 5. Caltech (a) and JPL (b) dataset.

Table 1
Dataset division.

Dataset	Train set	Val set	Test set
Caltech	2018.4.25~2019.8.31	2019.9.1~2019.12.31	2020.1.1~2020.3.31
JPL	2018.9.1~2019.8.31	2019.9.1~2019.12.31	2020.1.1~2020.3.31

5. Model Overview

- Architecture: CNN → LSTM → Attention Mechanism.
- Input: Hybrid interval-aware time series (short + long intervals).
- Output: Multi-step EV load forecasts.

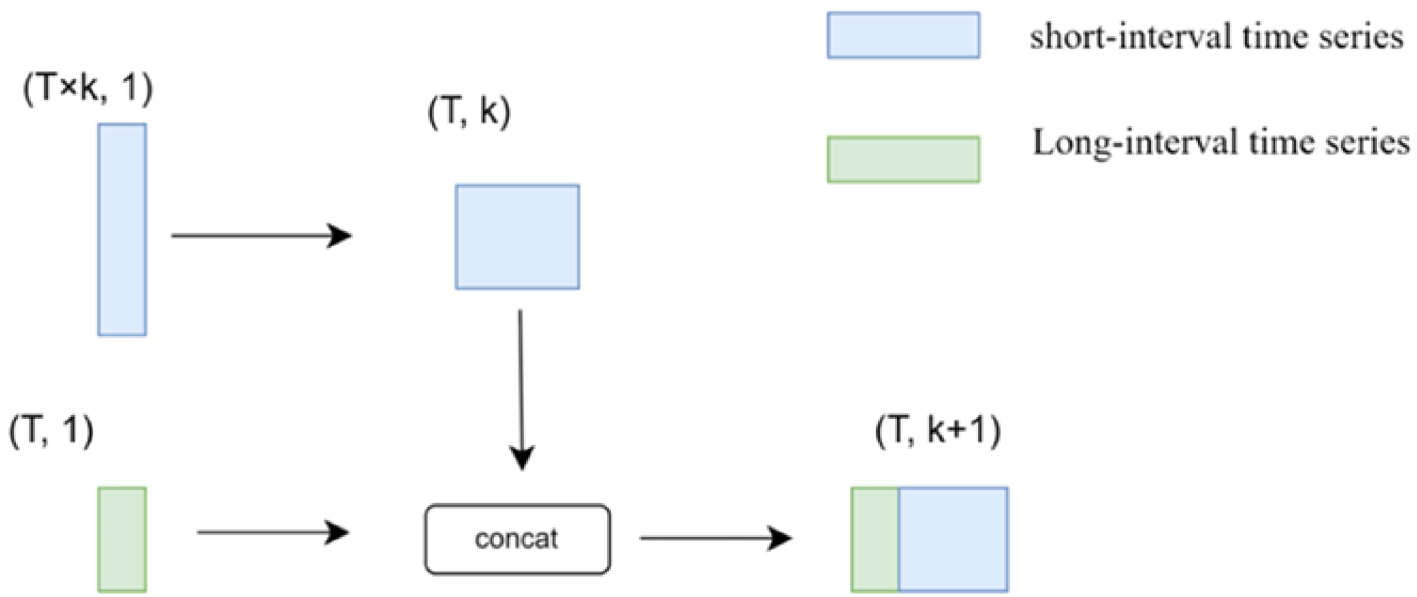

Fig. 2. Input matrix.

Model Overview

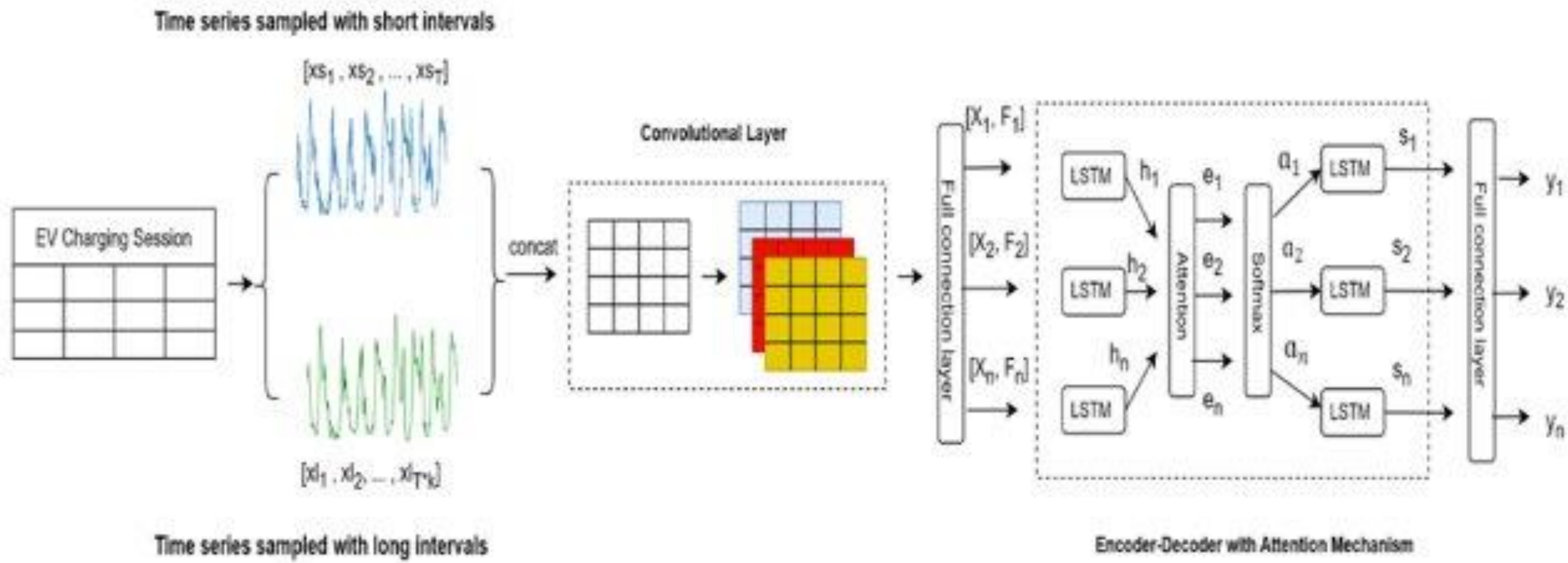

Fig. 1. The overall framework for EV Load Forecasting applying CNN-LSTM-AM.

6. CNN Block

- 3-layer 1D convolution with ReLU & dropout.
- Expands features, captures time dependencies.
- Output reshaped for LSTM input.

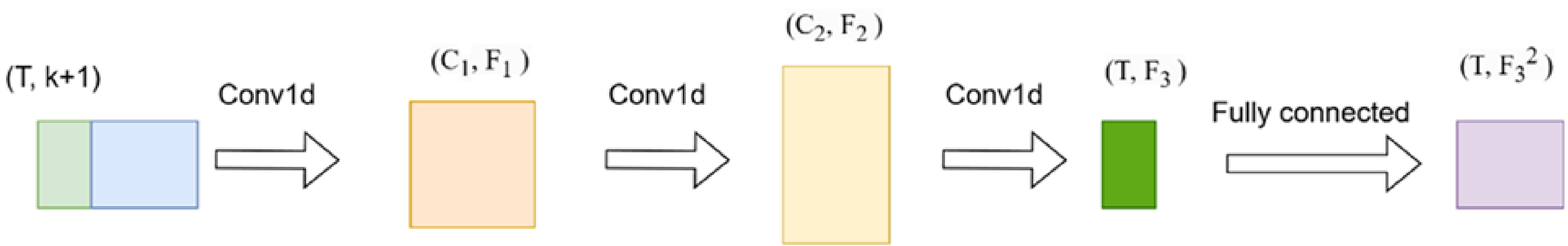

Fig. 3. Convolution layer.

7. LSTM Block

- Encoder-decoder LSTM models sequential dependencies.
- Enables memory of past values across long sequences.
- Bidirectional encoding improves representation.

8. Attention Mechanism

- Applies self-attention over decoder hidden states.
- Weights important time steps for accurate forecasting.
- Improves multi-step predictions.

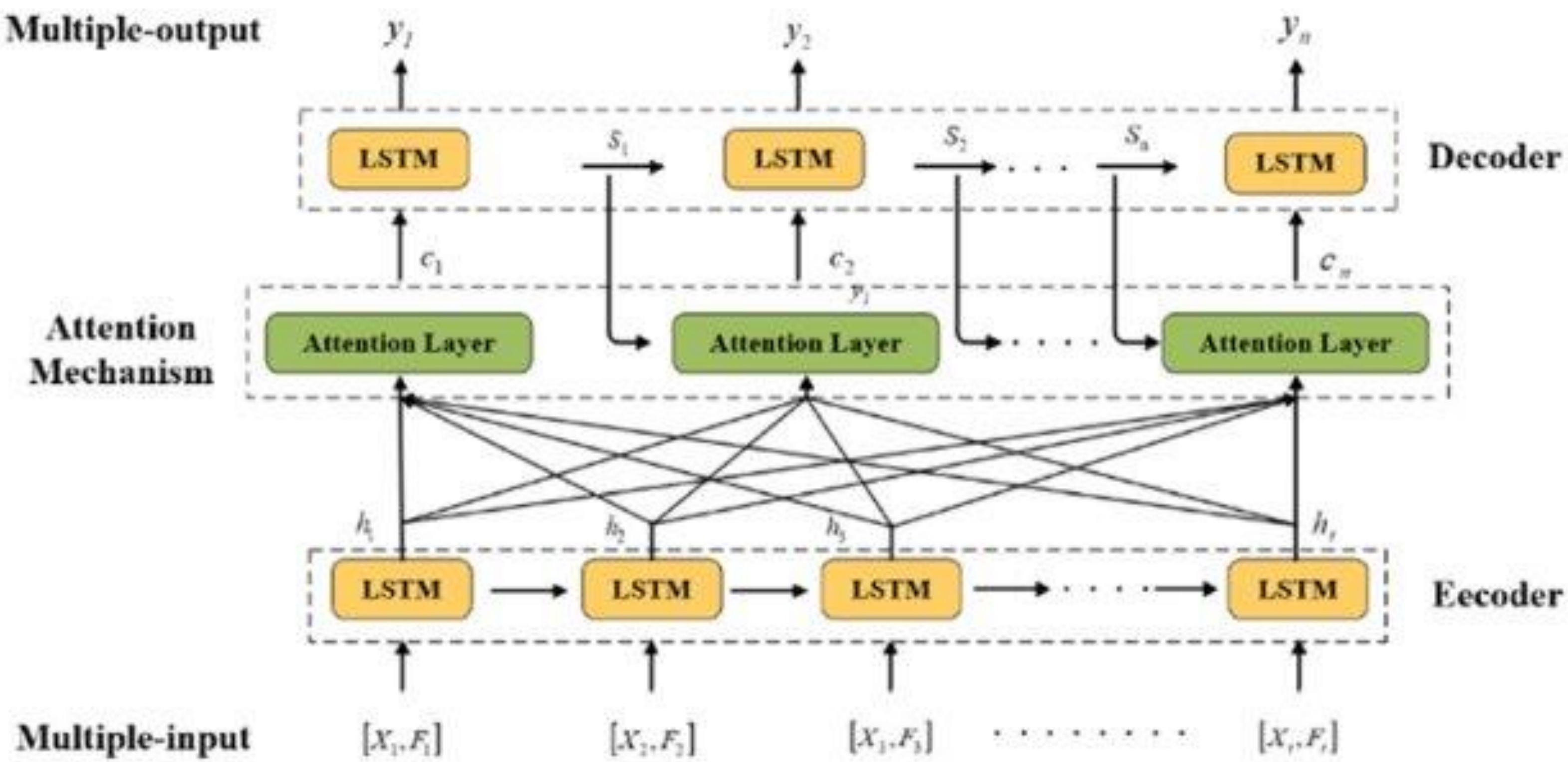

Fig. 4. Attention-based encoder-decoder LSTM networks.

9. Model Training Elements

- Framework: PyTorch 1.10.2.
- Loss Function: Mean Squared Error (MSE).
- Optimizer: Adam |
- Split: Train-Validation-Test.

10. Forecasting Horizons

- Evaluated for 4-step, 8-step, ..., 96-step predictions.
- Model tested on both Caltech & JPL datasets.

11. Evaluation Metrics

- MAE: Mean Absolute Error.
- RMSE: Root Mean Square Error.
- R^2: Coefficient of Determination.

we use the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE) and the coefficient of determination (R^2) to evaluate the performance of the proposed model.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2} \quad (8)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y}_i| \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2}{\sum_{i=1}^{n}\left(y_i - y_\mu\right)^2} \quad (10)$$

12. Baseline Models

- ANN, LSTM, Transformer, LSTNet, TCN.
- CNN-LSTM-AM outperformed all baselines in RMSE, MAE.
- Best performance on both Caltech and JPL.

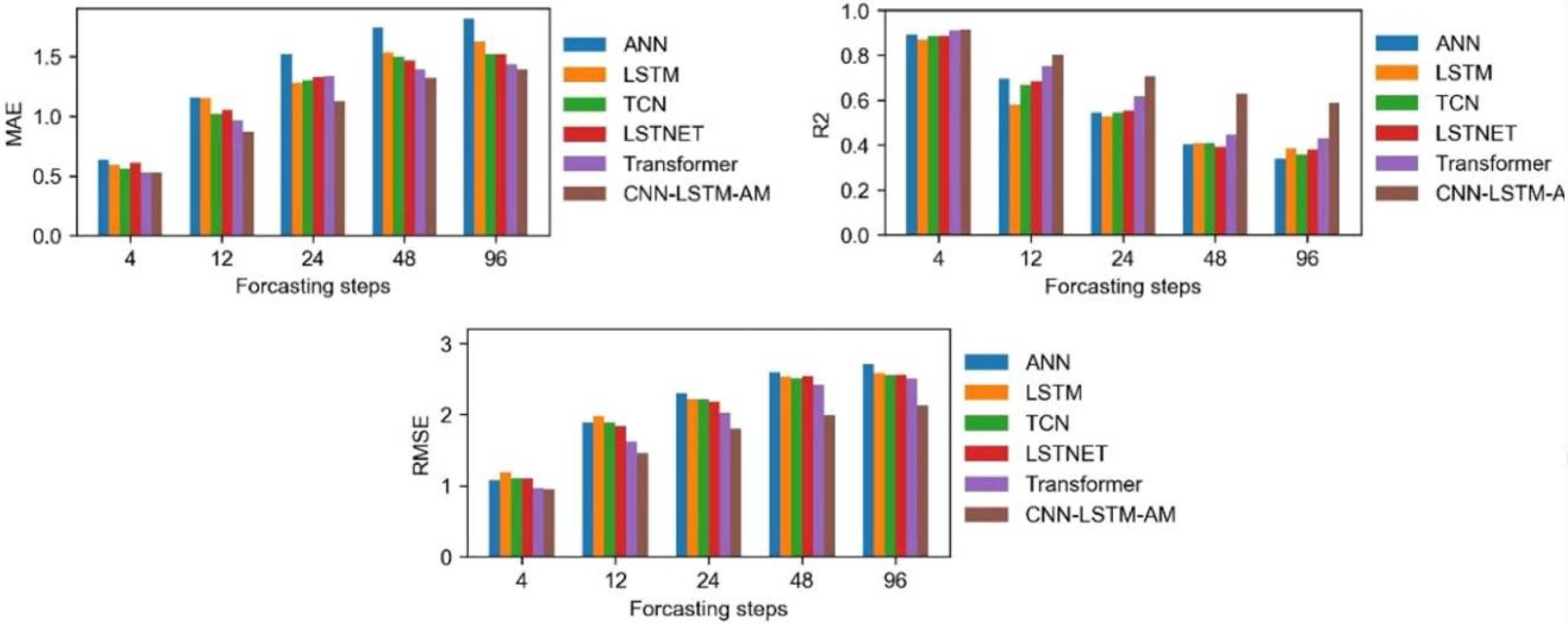

Fig. 9. Error values for Caltech dataset.

13. Caltech Results

- 4-step: RMSE=0.95, MAE=0.52, R^2=0.91.
- 96-step: RMSE=2.13, MAE=1.38, R^2=0.58.
- Consistent accuracy at different prediction depths.

14. JPL Results

- Similar pattern to Caltech observed.
- Accuracy higher on shorter steps (4),
- Accuracy drop on longer steps (48, 96).
- Model generalizes well across locations.

15. Interval Analysis

- 1-min and 10-min interval combo gave best results.
- Long intervals help with trend; short for fine changes.
- Hybrid input improves generalization.

Table 4
Compares the single and multiple sequences at 10 min intervals and 20 min intervals.

Step	Metric	10Min	1–10Min	5–10Min	20Min	1–20Min	5–20Min
4	RMSE	0.5806	**0.5756**	0.5789	1.6854	1.4269	1.4251
	MAE	**0.3026**	0.3284	0.3380	0.9107	0.8546	0.7909
	R^2	0.9286	**0.9294**	0.9288	0.8477	0.8908	0.8910
12	RMSE	1.1363	**0.9343**	1.0249	3.0284	2.3476	2.3723
	MAE	0.5975	**0.5631**	0.5470	1.7516	1.4268	1.4561
	R^2	0.7272	**0.8153**	0.7765	0.5120	0.7093	0.7056
24	RMSE	1.7929	**1.2771**	1.2992	3.2765	2.4075	2.5830
	MAE	1.0496	**0.7530**	0.7829	2.1357	1.5927	1.7431
	R^2	0.3197	**0.6570**	0.6506	0.4369	0.6933	0.6528
48	RMSE	1.8826	**1.3357**	1.4087	3.6093	2.7378	2.7627
	MAE	1.3132	**0.8756**	0.9403	2.5471	1.8137	1.8590
	R^2	0.2749	**0.6175**	0.5914	0.3399	0.6047	0.6078
96	RMSE	1.9140	**1.4411**	1.4472	4.0150	2.9506	3.3374
	MAE	1.3427	**0.9309**	0.9710	3.0523	1.9560	2.2585
	R^2	0.2365	**0.5663**	0.5768	0.2276	0.5457	0.4210

- In the advance 4-step forecasting, the predictions of 1–10 min sequence achieved a RMSE of 0.5736, a MAE of 0.3284 a R2 of 0.9294.

16. Univariate vs Multivariate

- Univariate CNN with interval awareness outperformed multivariate.
- Multivariate models caused overfitting and noise.
- Simpler models yielded better generalization.

Table 6
Comparison input sequence.

Step	Metric	Multivariate input sequence	Our input sequence
4	RMSE	0.5712	0.5756
	MAE	0.3354	0.3284
	R^2	0.9135	0.9294
12	RMSE	0.9546	0.9343
	MAE	0.5579	0.5631
	R^2	0.7926	0.8153
24	RMSE	1.3637	1.2771
	MAE	0.8735	0.7530
	R^2	0.5824	0.6570
48	RMSE	1.5636	1.3557
	MAE	1.0963	0.8756
	R^2	0.4358	0.6175
96	RMSE	1.6219	1.4411
	MAE	1.2369	0.9309
	R^2	0.3981	0.5663

17. Forecasting Visualization

- Plots show prediction closely follows actual data.
- Deviation increases with horizon but trend preserved.
- CNN-LSTM-AM provides interpretable trends.

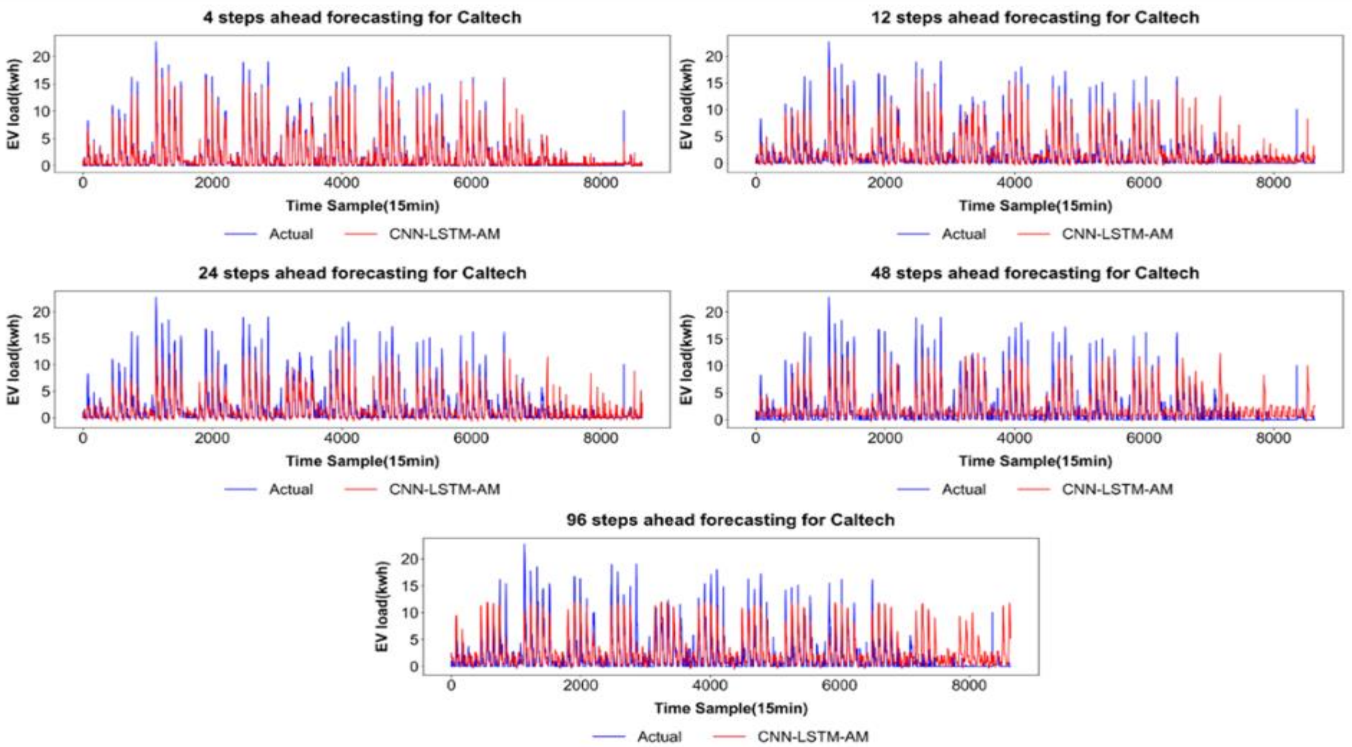

Fig. 7. 4-,12-,24-,48- and 96-step-ahead forecasting of the CNN-LSTM-AM model in the Caltech dataset.

17. Forecasting Visualization

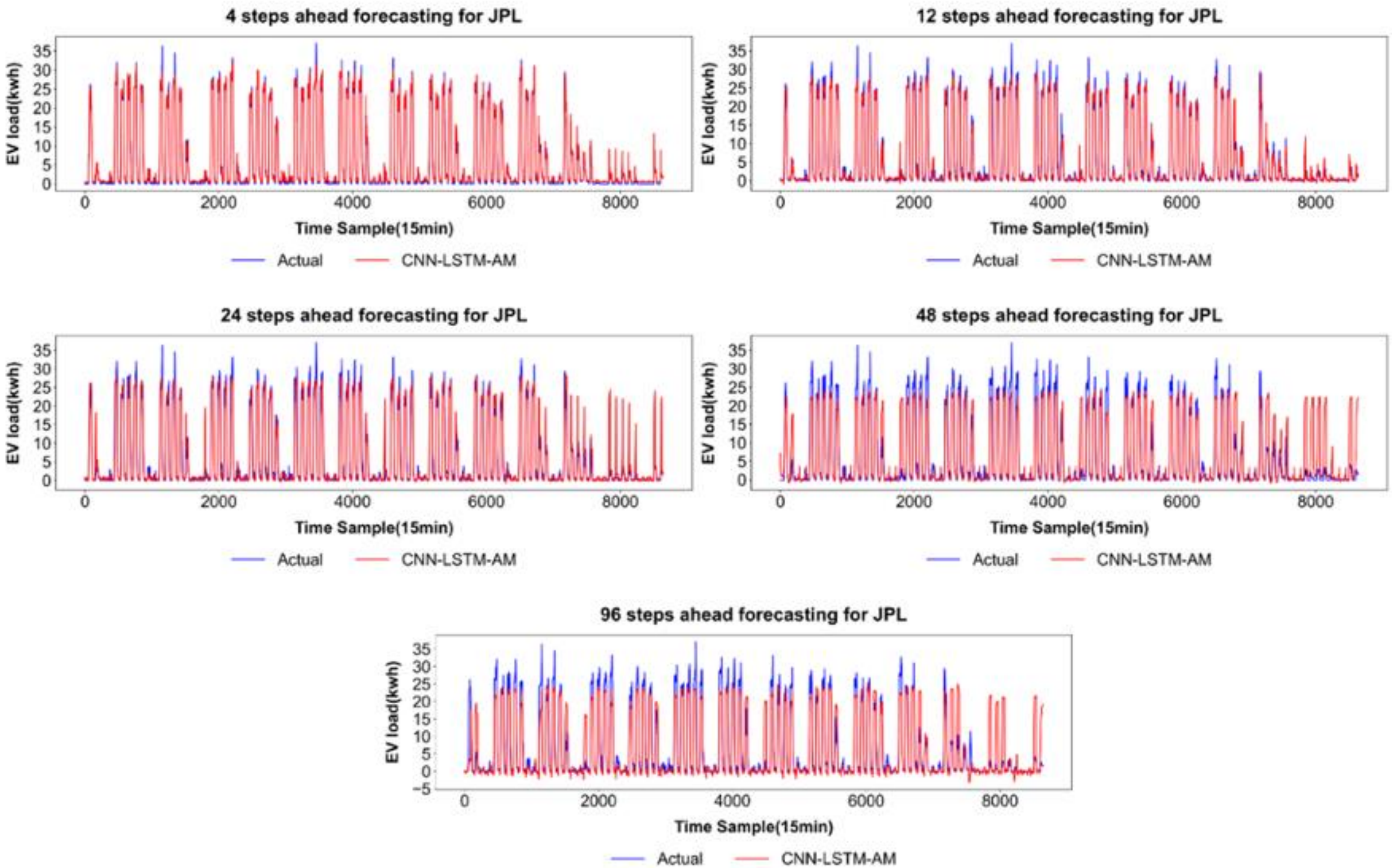

Fig. 10. 4-,12-,24-,48- and 96-step-ahead forecasting of the CNN-LSTM-AM model in the JPL dataset.

18. Model Comparison Table

- CNN-LSTM-AM lowest RMSE & MAE across steps.
- Transformer models underperformed on longer horizons.
- Hybrid model has best short & long-term tradeoff.

Table 7
Multi-step-ahead Load results on Caltech.

Step	Metric	ANN	LSTM	TCN	LSTNet	Transformer	Ours model
4	RMSE	1.0757	1.0720	1.1060	1.1026	0.9670	**0.9519**
	MAE	0.6371	0.5973	0.5621	0.6109	0.5274	**0.5268**
	R^2	0.8911	0.8918	0.8850	0.8855	0.9120	**0.9138**
12	RMSE	1.8956	1.7425	1.8577	1.8324	1.6270	**1.4529**
	MAE	1.1583	1.0227	0.9953	1.0573	0.9651	**0.8665**
	R^2	0.6966	0.7147	0.6776	0.6843	0.7508	**0.8013**
24	RMSE	2.2976	2.2188	2.2103	2.1805	2.0213	**1.7991**
	MAE	1.5217	1.2824	1.3030	1.3304	1.3361	**1.1230**
	R^2	0.5460	0.5725	0.5454	0.5531	0.6193	**0.7043**
48	RMSE	2.5995	2.5299	2.5145	2.5395	2.4263	**1.9896**
	MAE	1.7442	1.5356	1.5018	1.4671	1.3964	**1.3253**
	R^2	0.4042	0.4064	0.4087	0.3931	0.4469	**0.6303**
96	RMSE	2.7100	2.5815	2.5519	2.5628	2.5145	**2.1325**
	MAE	1.8166	1.6253	1.5211	1.5208	1.4341	**1.3898**
	R^2	0.3389	0.3842	0.3867	0.3827	0.4301	**0.5871**

18. Model Comparison Table

Table 8
Multi-step-ahead Load results on JPL.

Step	Metric	ANN	LSTM	TCN	LSTNET	Transformer	Ours model
4	RMSE	1.1267	1.1250	1.0764	1.0642	1.1893	**0.9852**
	MAE	0.6697	0.5847	0.6132	0.6267	0.7431	**0.6032**
	R^2	0.9864	0.9864	0.9875	0.9863	0.9848	**0.9879**
12	RMSE	2.2367	1.9629	1.9978	1.9533	2.1266	**1.8604**
	MAE	1.5085	1.1648	1.1242	1.1521	1.2428	**1.0575**
	R^2	0.9464	0.9587	0.9573	0.9591	0.9516	**0.9629**
24	RMSE	4.1169	3.9758	3.9986	3.9345	3.9811	**3.1329**
	MAE	2.3978	2.3045	2.2774	2.1617	2.2120	**1.5658**
	R^2	0.8185	0.8309	0.8287	0.8345	0.8305	**0.8948**
48	RMSE	6.1271	6.0088	5.7747	5.6707	5.6673	**4.6711**
	MAE	4.0749	3.7631	3.5839	3.1120	3.0922	**2.5193**
	R^2	0.6155	0.5988	0.6434	0.6566	0.6599	**0.7665**
96	RMSE	6.5138	6.1602	6.2052	6.1045	6.1600	**5.0243**
	MAE	4.3854	3.6739	3.8107	3.2432	3.4892	**2.5042**
	R^2	0.5642	0.5946	0.5881	0.6033	0.5843	**0.7303**

19. Ablation Study

- Without CNN: Loss of temporal pattern capture.
- Without attention: Forecasting variance increases.
- Full model performs best with all components.

20. Contributions & Limitations

Contributions :

- Interval-aware hybrid forecasting model.
- Better multi-step accuracy vs baselines.
- New approach for hybrid feature matrix (1-min + 10-min).

Limitations:

- Doesn’t consider external variables (e.g. weather, events).
- Only tested on two datasets.
- Computational overhead for deep layers.

21. Future Work & Conclusion

Future Work :

- Include external inputs: holiday, temperature, user profile.
- Apply transfer learning to new locations.
- Real-time load forecasting integration.

Conclusion:

- CNN-LSTM-AM shows robust multi-step EV load forecasting.
- Hybrid feature matrix with interval awareness is key innovation.
- Work lays ground for scalable, smart EV grid planning.

THANK YOU

Thank You for keeping patience

If you have any questions you may proceed .