Electric Vehicle Charging Load Forecasting with an integrated DeepBoost approach

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Introduction: The Problem

1. The transportation sector is a major contributor to greenhouse gas emissions, particularly in urban environments, which raises serious concerns about environmental sustainability and public health.

2.Widespread adoption of Electric Vehicles (EVs) presents a promising solution to mitigate these emissions and promote a more sustainable transportation ecosystem for a greener future.

3.EV introduction brings substantial additional load to the existing power grid, potentially leading to operational challenges and requiring careful management to ensure stability.

4.Accurate forecasting of EV charging load is crucial for effective grid management, resource allocation, and strategic planning to handle the increasing demand from electric vehicles.

GHG Emissions & EVs

1.Greenhouse Gas (GHG) emissions are the primary driver of climate change, posing a significant threat to global ecosystems and human well-being, demanding immediate and impactful action.

2.The transportation sector significantly contributes to these emissions, especially in urban areas, highlighting the urgent need for cleaner and more sustainable transportation alternatives.

3.Widespread adoption of Electric Vehicles (EVs) offers a viable pathway to substantially reduce emissions, promoting a transition towards environmentally friendly transportation systems.

4.EVs can significantly contribute to mitigating climate change and fostering sustainability by decreasing reliance on fossil fuels and reducing the carbon footprint of transportation.

Impact on Existing Grids

1.The increased adoption of Electric Vehicles (EVs) introduces additional load on the existing power grid, potentially straining its capacity and impacting its stability and reliability seriously.

2.Unmanaged EV charging can lead to peak demand issues, causing overloads, voltage drops, and potential damage to grid infrastructure, requiring strategic planning and mitigation.

3.Effective forecasting of EV charging load is essential for proactive grid management, allowing utilities to optimize resource allocation and ensure a stable power supply for all consumers.

4.Advanced forecasting techniques can enable smart charging strategies, which balance EV charging with grid capacity, minimizing negative impacts and maximizing efficiency.

Motivation and Contributions

1.The primary motivation is addressing climate change by reducing GHG emissions through EV adoption, recognizing the urgent need for sustainable transportation solutions globally.

2.The study identifies and aims to solve the problem of increased load on power grids due to EV charging, seeking to prevent adverse effects on grid operation and stability effectively.

3.Development of a novel **DeepBoost** approach, integrating **CatBoost, XgBoost, LSTM, and LR models**, to improve the accuracy of day-ahead EV charging station load forecasting.

4.Comprehensive performance comparison of DeepBoost against conventional and hybrid methodologies, showcasing its potential as a superior forecasting technique for practical applications.

Literature review & limitations

Model / Approach	Description	Limitations
ARIMA & SARIMA (Statistical Models)	Time-series models based on linear assumptions to forecast load, using historical data. ARIMA forecasts total load; decoupled ARIMA forecasts electric and EV loads separately.	Assumes linearity; struggles with non-linear relationships; limited ability to incorporate external factors; cannot effectively model complex temporal dependencies.
Clustering + Monte Carlo (MC)	Clusters data based on user behavior; uses MC for load forecasting.	Computationally intensive; limited generalizability; not designed to directly model temporal dependencies.
Classical Machine Learning Models (XgBoost, CatBoost, LSTM, Informers)	Non-linear models capturing complex relationships; LSTM models sequences, boosting trees are ensemble methods.	Require extensive hyper-parameter tuning; computationally demanding; LSTM has limitations handling long-term dependencies; hybrid models add complexity.
Hybrid Deep Learning Models (e.g., LSTM + GBDT)	Combines temporal deep learning with gradient boosting to leverage model strengths.	High computational complexity; potential overfitting; integration challenges.
DeepBoost (Proposed in the Paper)	Layered approach combining LSTM, GBDT (XgBoost, CatBoost) and Linear Regression in a stacking architecture.	Increased computational requirements; real-time deployment challenges; demands parallel processing frameworks.

Proposed Model: “DeepBoost”

The paper proposes DeepBoost to address several gaps identified in the literature:

- **Enhanced Accuracy & Robustness**: By integrating diverse models (LSTM for temporal dependencies and GBDTs for complex non-linear patterns), DeepBoost achieves superior forecasting performance, outperforming individual and other hybrid models.
- **Overcoming Limitations of Individual Models**: Traditional models like ARIMA are limited in handling non-linear and complex patterns. DeepBoost combines the strengths of deep learning and ensemble methods to overcome these limitations.
- **Addressing Generalizability**: The layered architecture improves the model's ability to perform consistently across different datasets, enhancing its practical applicability.
- **Reducing Model Shortcomings**: The stacking approach mitigates the overfitting and interpretability issues of complex models by leveraging meta-learning (LR) and parallel training.
- **Facilitating Real-world Application**: Despite computational challenges, the approach aims at providing more accurate day-ahead load forecasts, facilitating energy scheduling and grid stability, ultimately contributing to sustainable EV infrastructure development.

In summary, DeepBoost is designed as a comprehensive, hybrid approach to improve the accuracy, robustness, and scalability of EV charging station load forecasting compared to previous models.

Dataset and Methodology

The study utilizes a comprehensive dataset of EV charging station load data, including historical charging patterns, weather conditions, and other relevant factors affecting charging demand trends.

Table 1
Datasets description.

Datasets	Fields
ACN data	Connection and disconnection time, weekend, arrival, idle duration, parking duration, KWh delivered
Palo Alto	Connection and disconnection time, MAC address, port number, KWh delivered, plug number, GHG and gasoline saving, port type
Perth	Connection and disconnection time, arrival, park duration and KWh delivered

Data availability The datasets available at the github repository: https://github.com/Ubaid014/DeepBoost-for-EVs-charging-station-load forecasting.

Methodology-Steps

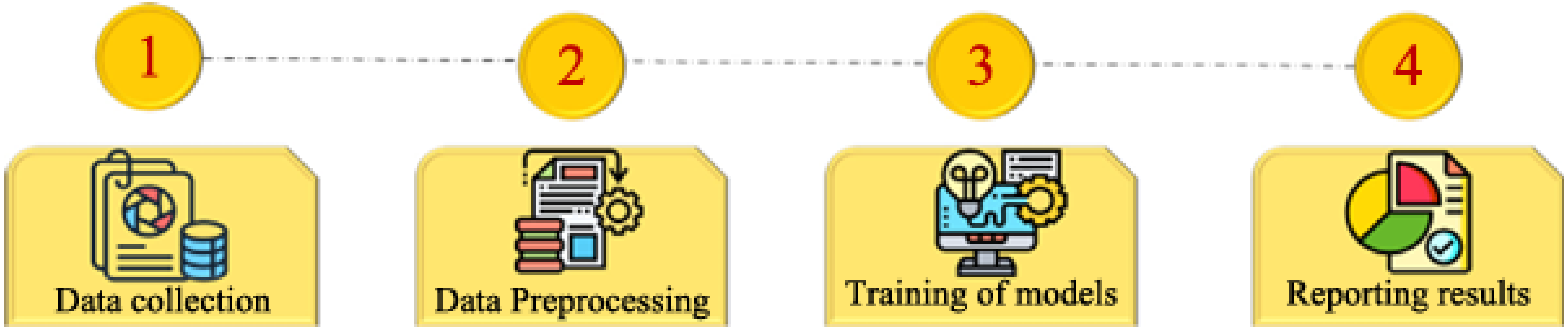

Fig. 1. Methodology steps for the proposed study.

Methodology & Approach

The methodology involves training and validating the DeepBoost model and its component models using appropriate evaluation metrics, ensuring robust and unbiased performance assessment.

The performance of the models is evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) for rigorous comparison.ure.

- Layer 1: LSTM, CatBoost, XgBoost - parallel training.
- Layer 2: Linear Regression combines outputs.

DeepBoost Approach Overview

1.The DeepBoost approach is a novel integrated method for forecasting day-ahead EV charging station load, designed to improve accuracy and reliability in predictions effectively.

2.DeepBoost combines the strengths of multiple models, including Categorical Boosting (CatBoost), Extreme Gradient Boosting (XgBoost), Long Short-Term Memory Network (LSTM), and Linear Regression (LR).

3.By integrating these diverse models, DeepBoost leverages their individual capabilities to capture various patterns and dependencies in the EV charging load data effectively.

4.The ensemble approach enhances robustness and reduces the risk of relying on a single model, leading to more accurate and stable forecasting results in diverse operating conditions.

DeepBoost Approach Overview

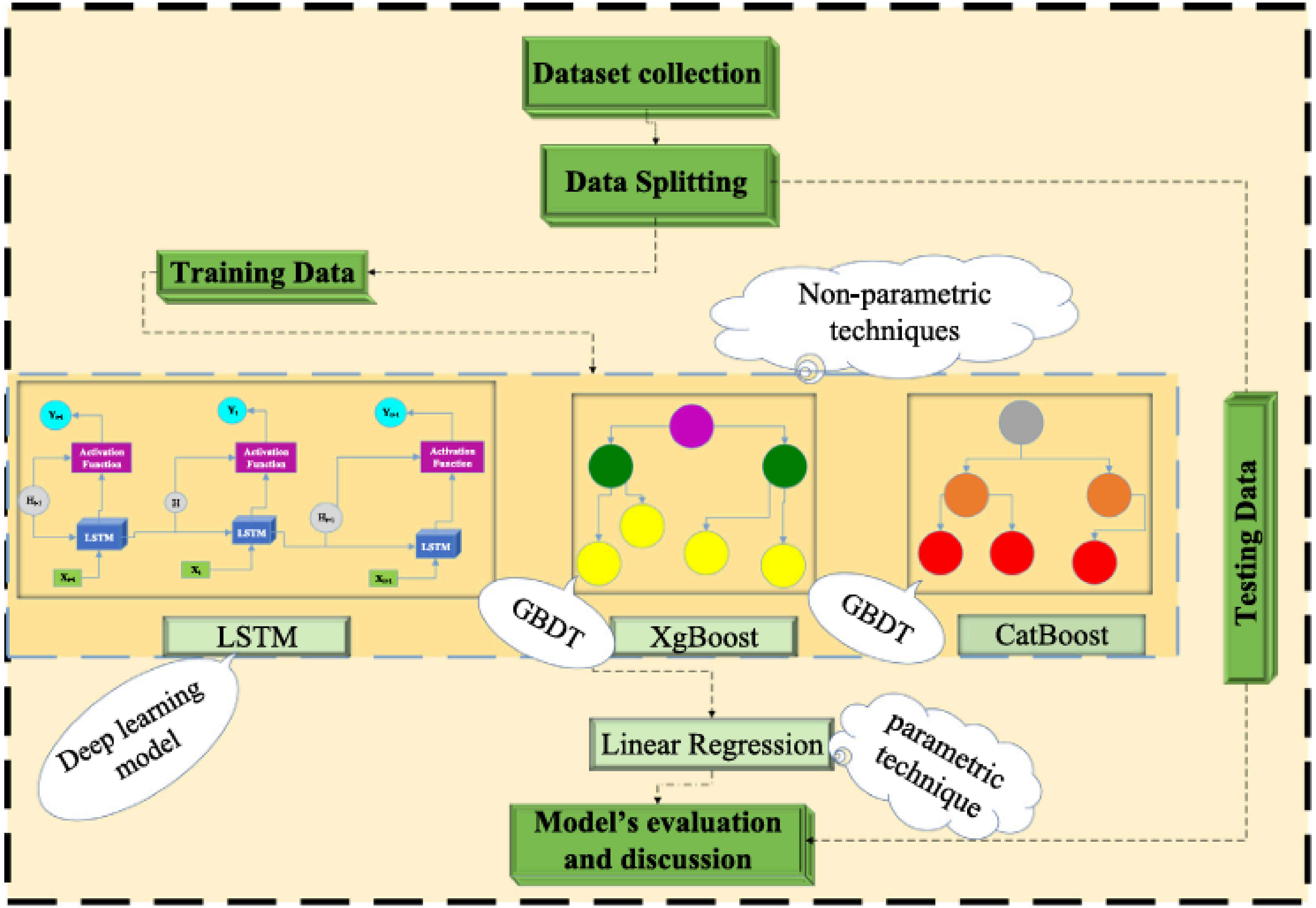

Fig. 3. Workflow of the proposed approach.

Component Models

1.Long Short-Term Memory Network (LSTM)

Long Short-Term Memory Network (LSTM) is included to capture temporal dependencies in the EV charging load data, leveraging its ability to model sequential patterns and long-range dependencies.

- Handles long-term dependencies.
- Uses forget, input, and output gates.

2.Extreme Gradient Boosting (XgBoost)

Extreme Gradient Boosting (XgBoost) is employed for its efficiency and accuracy in gradient boosting, enabling the model to capture complex relationships and patterns in the data effectively.

- Efficient, handles missing data.
- Regularized learning to avoid overfitting.

3.Categorical Boosting (CatBoost)

Categorical Boosting (CatBoost) is utilized for its ability to handle categorical features directly and its robust performance with default parameters, simplifying model development and deployment.

- Handles categorical features.
- Fast and scalable gradient boosting.

4.Linear Regression (LR)

4.Linear Regression (LR) serves as a base model for capturing linear relationships and providing a stable baseline, contributing to the overall stability and accuracy of the DeepBoost approach.

- Combines Layer-1 predictions.
- Trains on outputs from LSTM, CatBoost, XgBoost.

Metrics Used

4.4. Performance metrics

In this study, we used four error metrics: RMSE (KWh), MAE (KWh), MSE $(KWh)^2$ and NRMSE (%) to evaluate models' performances and the following equations defined these metrics.

$$RMSE = \sqrt{\frac{1}{N}\sum_{I=1}^{N}(A_I - B_I)^2} \tag{10}$$

$$NRMSE = \frac{RMSE}{max(B_I) - min(B_I)} * 100 \tag{11}$$

$$MAE = \frac{1}{N}\sum_{I=1}^{N}|A_I - B_I| \tag{12}$$

$$MSE = \frac{1}{N}\sum_{I=1}^{N}(A_I - B_I)^2 \tag{13}$$

where A_I and B_I denote observed and forecasted points, correspondingly. Whereas, N corresponds to a total number of values.

Performance Comparison

1.The DeepBoost approach is rigorously compared against conventional models such as CatBoost, XgBoost, and LSTM to evaluate its performance improvement and effectiveness comprehensively.

2.Comparison includes Informers, a state-of-the-art time-series forecasting model, to benchmark DeepBoost against advanced deep learning techniques for time-series forecasting.

3.Hybrid deep learning methodologies are also used for comparison, ensuring a thorough assessment of DeepBoost's performance relative to other integrated forecasting methods currently available.

4.Performance metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) are used to quantitatively evaluate the forecasting accuracy of each method.

Performance Comparison

Dataset	Model	RMSE (KWh)	MAE (KWh)	MSE $(KWh)^2$	NRMSE (%)
	CatBoost	3.01	1.98	9.07	0.49
	XgBoost	4.09	2.69	16.76	0.61
	LSTM	18.58	15.13	345.21	3.15
	GRU	14.87	10.96	221.35	2.37
	RNN-GRU	15.5	14.89	240.36	2.23
ACN	RNN-LSTM	11.72	11.01	137.53	1.71
	CNN-LSTM	15.78	15.04	249.03	2.38
	CNN-GRU	17.01	15.24	289.44	2.63
	Informers	16.88	10.48	284.93	2.76
	DeepBoost	**2.61**	**1.81**	**6.82**	**0.39**

Dataset	Model	RMSE (KWh)	MAE (KWh)	MSE $(KWh)^2$	NRMSE (%)
	CatBoost	13	4.06	169.16	0.77
	XgBoost	13.37	4.18	178.9	0.79
	LSTM	30.14	25.86	908.54	1.58
	GRU	19.71	17.38	388.33	1.09
	RNN-GRU	45.91	42.1	2107.3	2.44
Palo Alto	RNN-LSTM	40.62	28.7	1649.91	2.46
	CNN-LSTM	30.85	25.04	951.44	1.75
	CNN-GRU	21.98	20.88	483.13	1.17
	Informers	25.94	18.23	672.88	1.41
	DeepBoost	**7.63**	**2.94**	**58.29**	**0.39**

Dataset	Model	RMSE (KWh)	MAE (KWh)	MSE $(KWh)^2$	NRMSE (%)
	CatBoost	27.45	9.05	753.63	2.26
	XgBoost	27.36	9.58	748.74	2.26
	LSTM	32.36	28.35	1047.43	2.32
	GRU	34.92	31.08	1219.27	2.59
	RNN-GRU	40.16	32.92	1612.69	2.86
Perth	RNN-LSTM	35.83	23.49	1283.46	2.79
	CNN-LSTM	20.06	16.21	402.42	1.42
	CNN-GRU	29.51	22.01	870.85	2.24
	Informers	30.51	16.71	930.86	2.17
	DeepBoost	**13.83**	**8.04**	**191.42**	**0.96**

Results and Analysis

1.The results demonstrate that DeepBoost outperforms conventional CatBoost, XgBoost, and LSTM models, achieving higher accuracy and lower error rates in day-ahead EV charging load forecasting.

2.DeepBoost exhibits superior performance compared to Informers and other hybrid deep learning methodologies, showcasing its effectiveness as a competitive forecasting technique overall.

3.Analysis reveals that DeepBoost leverages the strengths of its component models, capturing both linear and non-linear patterns in the EV charging load data effectively and adaptively.

4.The improved forecasting accuracy of DeepBoost has practical implications for grid management, enabling better resource allocation and more efficient operation of EV charging infrastructure.

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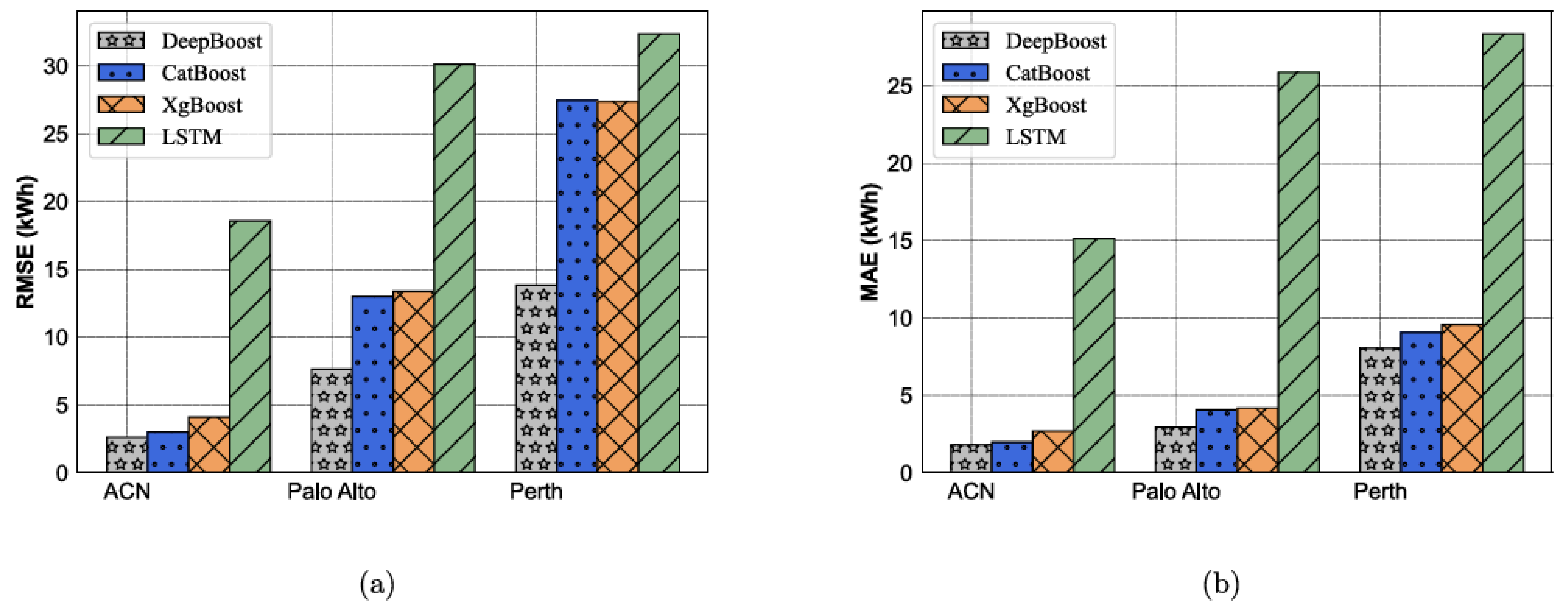

Fig. 4. Errors demonstration through bar plots. (a) RMSE (b) MAE.

Results and Analysis

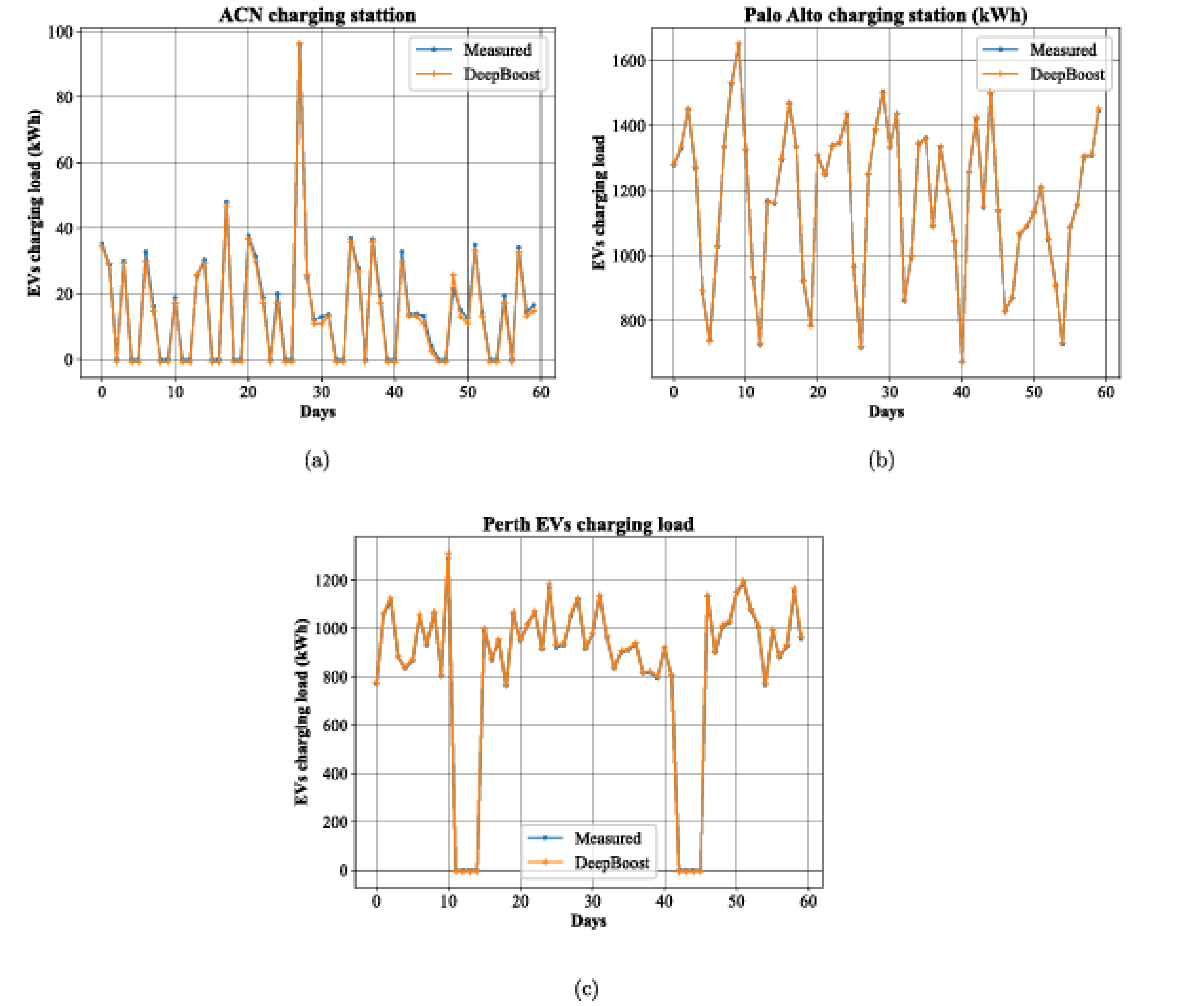

Fig. 5. Measured and predicted curves. (a) ACN (b) Palo Alto (c) Perth.

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\# The improved forecasting accuracy of DeepBoost has practical implications for grid management, enabling better resource allocation and more efficient operation of EV charging infrastructure.

Conclusion & Future Work

1.The DeepBoost approach offers a robust and accurate solution for forecasting day-ahead EV charging station load, addressing the increasing demand and grid impact from electric vehicles.

2.By integrating CatBoost, XgBoost, LSTM, and LR models, DeepBoost leverages their individual strengths to achieve superior forecasting performance compared to conventional methods.

3.Future work includes exploring the integration of additional data sources, such as real-time grid conditions and user behavior patterns, to further enhance forecasting accuracy dynamically.

4.Further research will focus on optimizing the DeepBoost architecture and exploring adaptive learning techniques to improve its adaptability to changing EV charging patterns in real-world scenarios.

Thank You

If you have any question you can ask