Adaptive Forecasting of Electric Vehicle Charging Load Profiles Using BiLSTM and User Clustering

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Abstract

Effective grid management in urban areas requires accurate forecasting of electric vehicle (EV) charging demand. This paper presents a novel day-ahead EV load prediction method combining deep learning and clustering techniques. We evaluate multiple deep learning architectures, including deep neural networks (DNN), long short-term memory (LSTM), gated recurrent units (GRU), and bidirectional LSTM (BiLSTM), identifying BiLSTM as the most accurate. Using K-means clustering, we group users based on plug-in and plug-out times to capture behavioral patterns. The BiLSTM model is then fine-tuned for each cluster, further enhancing prediction accuracy. Performance metrics confirm that this fine-tuned BiLSTM approach significantly improves forecasting accuracy, underscoring the value of integrating clustering with deep learning for EV load prediction.

Introduction and Motivation

The adoption of EVs supports sustainable transportation by reducing emissions and fossil fuel dependence. However, integrating EVs into urban areas presents challenges for power systems due to unpredictable charging demands, which can strain local grids and increase operational costs [1]. Accurate forecasting of EV demand is essential for effective urban energy management; however, traditional methods may struggle with the complexity of EV behavior shaped by varied user schedules and charging habits. This study addresses these challenges through a deep learning and transfer-learning-based methodology. The key contributions of this study include the following: (1) Address charging behavior variability with K-means clustering on user profiles to enable adaptive forecasting; (2) Develop an EV load forecasting model using cluster-based BiLSTM fine-tuning with greater predictive accuracy.

Applied Method

This study uses residential EV charging data from Norway [2]. The methodology begins with data preprocessing, distributing each charging event's load evenly over 24 h to create a consistent hourly profile and aggregating it to represent the total load daily profile. We chose

30 EVs for the analysis. Several deep-learning models, including DNN, LSTM, GRU, and BiLSTM, were trained and evaluated using error metrics, with BiLSTM achieving the highest accuracy. To capture diverse charging behaviors, K-means clustering grouped profiles by average plug-in and plug-out times. The pre-trained BiLSTM model was fine-tuned for each cluster to enhance prediction accuracy. The overall methodology is illustrated in Fig. 1.

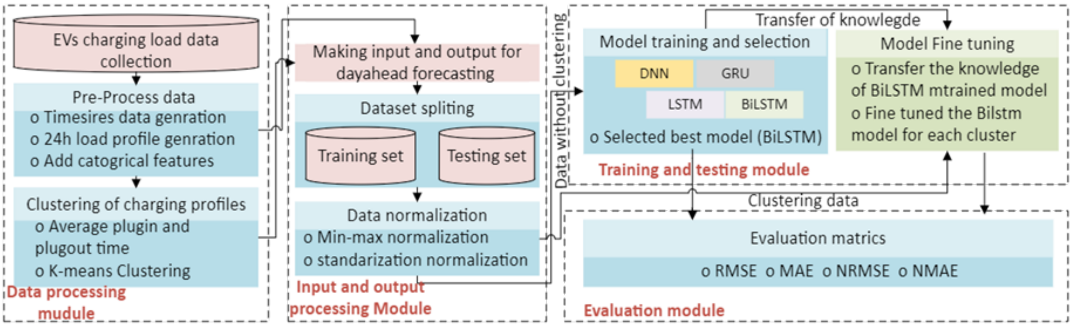

Figure 1.Proposed methodology for day-ahead EV load forecasting

Results

Table 1 shows the BiLSTM model outperforms other models, achieving an accuracy of 13.16% in terms of NRMSE. Table 2 presents the results of the fine-tuned clustering models, indicating that the average performance across all metrics for the clustered models is superior to the BiLSTM model trained on non-clustered data, with an NRMSE of approximately 6.8%.

Table 1. Accuracy comparison of various deep learning models

	RMSE (kWh)	MAE (kWh)	NRMSE (%)	NMAE (%)
DNN	4.3096	3.2079	14.9433	11.1232
GRU	4.78	3.4108	16.5746	11.8269
LSTM	4.3231	3.1877	14.9902	11.0532
BiLSTM	**3.7951**	**2.7018**	**13.1594**	**9.3685**

Table 2.Accuracy comparison of fine-tuned clustered models

	RMSE (kWh)	MAE (kWh)	NRMSE (%)	NMAE (%)
CL1	2.074	1.366	7.193	4.736
CL2	1.931	1.354	6.694	4.694
CL3	1.843	1.395	6.391	4.838
Average	**1.949**	**1.372**	**6.759**	**4.756**

Conclusions

This study demonstrates that combining BiLSTM with K-means clustering significantly improves EV load forecasting accuracy by adapting to diverse user charging behaviors. Fine-tuned models for each cluster yielded lower error metrics compared with the non-clustered data. These findings highlight the effectiveness of clustering integrated with deep learning for precise forecasting of EV demand in urban energy systems.

References

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