Electric Vehicle Charging Station Demand Forecasting Using a CNN-LSTM Hybrid Deep Learning Model

Technical track : (7.5) Smart and Micro Grids, EV-Interacting Smart Grid and Electrical Infrastructure

ABSTRACT

With massive growth in Electric Vehicle (EVs), accurate forecasting for charging demand become crucial to support planning and management of charging stations. Conventional forecasting techniques are not effective because of limited EV data along with large uncertainties based on customer behavior, weather conditions, geographical region, etc. To further improve the forecasting accuracy, we proposed a Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM) hybrid deep learning model along with dedicated feature engineering techniques for EV charging satiation demand forecasting. The methodology integrates charging load data from an EV fast-charging station in Pasadena, CA, along with weather data, day and holiday information. We thoroughly compared our method with multiple deep learning forecasting techniques proposed in the literature. Our CNN-LSTM-based method achieved the best predictions in term of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-squared (R2), showcasing its superiority in forecasting EV charging loads.

INTRODUCTION

Electric vehicles (EVs) have witnessed a surge in adoption with the goal of decarbonizing the transportation sector [1], given that transportation remains the highest source of CO_2 emissions in the United States. Effectively managing the implications of the widespread adoption of electric vehicles poses a challenge to power systems, highlighting the essential need for accurate forecasting of EVs' charging loads. An efficient and accurate forecasting model will prove vital for the future of the power grid and the seamless integration of EV charging stations into it. Table 1 provides a literature review approaches to forecasting EV charging loads including the forecasting technique and performance metrics results. These techniques don't provide the level of accuracy needed for short-term forecasting.

This article centers on addressing EV load forecasting challenges through an innovative hybrid approach combining (CNN) and (LSTM). This approach demonstrates superior performance in predicting charging loads for both short-term and long-term forecasting demands. It is designed to forecast EV charging loads at charging stations (CSs) in order to understand the inherent stochastic nature of EV driver behaviors. The approach of CNN-LSTM in EV charging demand forecasting is novel and effective, showing RMSE of 3.28, MAE of 2.195, and R^2 of 0.911 with ~ 40% improvement compared with Recurrent Neural Network (RNN). This technique can be useful for efficient operation and control of CS and power systems.. Further details will be accessible in the full paper.

Table 1: Literature review for various EV load forecasting techniques and their respective performance

Paper	Forecasting Technique	Performance Metrics
[2]	LSTM	RMSE: 28.25 MAE: 16.854
[3]	CNN	RMSE: 26.24738 MAE: 16.23156 MAPE: 3.78%
[4]	LSTM -BDL	RMSE: 4.367 MAE: 2.782 R^2: 0.918
[5]	DNN, RNN, LSTM, GRU	DNN (%): NRMSE: 3.69, NMAE: 0.92 RNN (%): NRMSE: 2.91, NMAE: 0.91 LSTM (%): NRMSE: 3.36, NMAE: 0.9 GRU(%): NRMSE: 2.89, NMAE: 0.77
[6]	EA-LSTM	MAE: 184.74 RMSE: 244.29 R2: 0.883 NRMSE: 8.67%
[7]	LSTM with Mogrifier gating mechanism	MAE: 1996.23 RMSE: 2251.78
[8]	LSTM, SAE (stacked autoencoders)	MSE, 20 min: 4.543 MAE, 20 min: 1.07 RMSE, 20 min: 2.131 MAPE, 20 min: 43.525%
[9]	LSTM with (EMGM)	MAPE: 1.87% MRE: 42.23% RMSE: 6.44
[10]	LSTM-DBN	MAE: 5.84
[11]	LSTM-DBN	MAPE: 0.48% RMSE: 3.44%
[12]	CNN with lion algorithm	RMSE: 2.27% MAPE: 2.14% AAE: 2.086%
[13]	Bidirectional Convolutional LSTM	RMSE: 0.97 MAPE: 260.56% MSE: 0.91
[14]	LSTM	RMSE: 142.72
[15]	Data Fusion with LSTM	MAE: 3.29%
[16]	LSTM	ME: 24 MAE: 4.2 RMSE: 5.9 MAPE: 0.45
[17]	GRU, LSTM, RNN	GRU NMAE: 0.171 GRU NRMSE: 0.028 LSTM NMAE: 0.168 LSTM NRMSE: 0.029 RNN NMAE: 0.169 RNN NRMSE: 0.028
[18]	LSTM +(EMD) +(AOA)	MAE: 0.1083 RMSE: 0.000020628
[19]	MCCNN-TCT	RMSE: 4.92 MAE: 3.49 MAPE: 13.34%
[20]	GRU with GA	RMSE: 2342.92 MAPE: 10.59%

METHODOLOGY

This study explores forecasting for EV fast charging station load in Pasadena, CA by leveraging the weather data available from NREL- SAM tool. The overall approach for forecasting energy generation involves several steps. Initially, input variables

undergo preprocessing through a pipeline. Data attributes are normalized during preprocessing before being fed to the model. The pre-processed dataset is then split into two sets: one for training with validation, and the other for testing. The efficiency of the models is evaluated using RMSE, MAE, and R2 error metrics.

A. Convolutional Neural Networks, CNN

CNN represents a specific category of multilayer perceptron designed for data with an evident grid-like topology. perceptron designed for data with an evident grid-like topology. Time-series data, with a one-dimensional grid topology, is highly compatible with CNNs [21].The model uses convolutions in at least one layer, a distinct form of linear operation, differing from the typical matrix multiplication used in other neural networks, is characteristic of CNNs. CNN models are versatile in handling various input data formats, including 1D, 2D, and nD. The proposed model specifically utilizes the 1D input data shape [22]. The fundamental concept of a CNN is its ability to extract local features from inputs in higher layers and subsequently transfer them to lower layers to construct more complex features [23].

B. Long Short-Term Memory, LSTM

LSTM represents an enhancement over recurrent neural networks (RNNs), addresses the limitations of conventional feed-forward neural networks[24]. It introduces input and output gates to overcome issues like gradient disappearance and gradient explosion. The LSTM model excels in extracting temporal features, making it suitable for various time series applications [25].

C. *Hybrid CNN-LSTM Network*

The proposed CNN-LSTM model employs an encoder-decoder architecture. Local features in time series are extracted by the CNN layer, while the LSTM layer receives these features as input. The input sequence is read and encoded by an encoder model, followed by a decoder model that generates predictions for each individual element in the output sequence through single-step forecasting. The architecture involves an effective CNN structure for the encoder and three LSTM hidden layers for the decoder. This combination allows the model to capture intricate features from the input sequence, making it a robust choice for forecasting applications. Figure 1 shows the flowchart of the proposed approach for predicting EV charging load (details for the full approach will be included in the full paper).

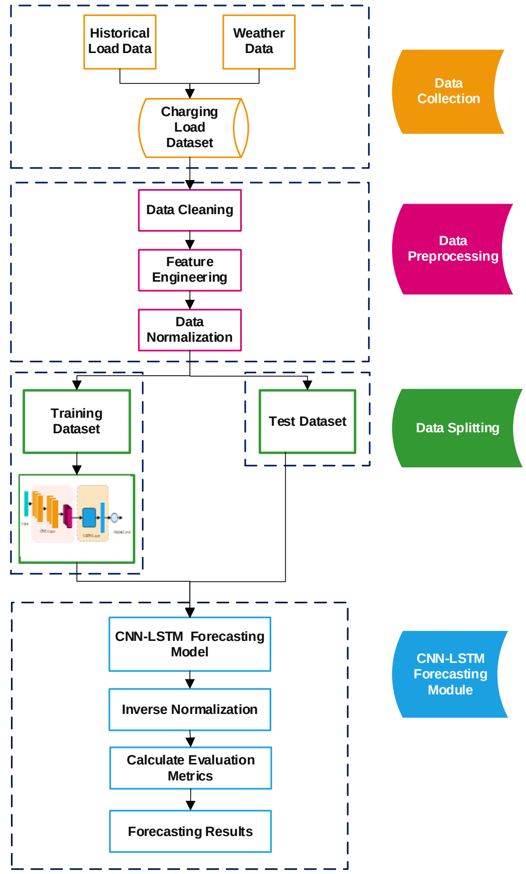

Figure 1: Proposed flow chart for forecasting EV charging load.

SAMPLE RESULTS AND DISCUSSION

The proposed CNN-LSTM forecasting approach was applied for Pasadena, CA fast charging station data. The forecasting results underwent testing for both weekdays and weekends across various seasons. In Figure 2, the weekday forecasting during January is illustrated, showcasing the performance of different forecasting approaches: RNN, CNN, LSTM, and CNN-LSTM. Additionally, the figure tracks the performance of each approach in the form of square prediction error and square accumulated error. The performance metrics, including RMSE, MAE, and R2, for all compared forecasting techniques are detailed in Figure 3 and also presented at Table 2. A comprehensive presentation of the results will be presented in the full version.

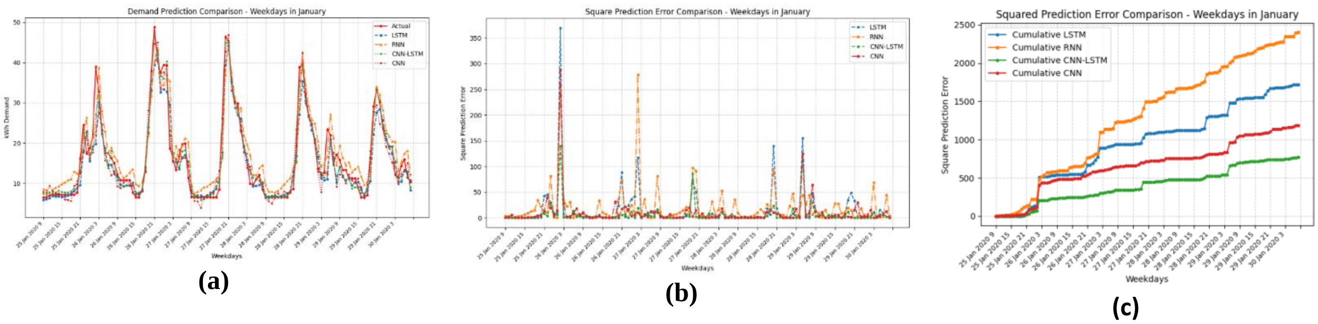

Figure 2: Weekday Forecasting Performance in January: (a) weekdays, (b) square prediction error, and (c) cumulative square prediction error.

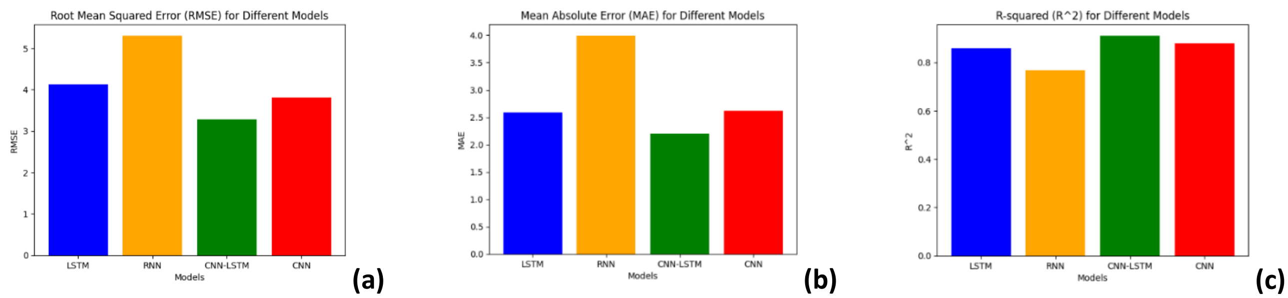

Figure 3: Performance Metrics for Forecasting Approaches. (a) RMSE, (b) MAE, (c) R2.

Conclusions and Future Work

This study introduces a robust and effective CNN-LSTM model for predicting EV charging load. To assess its efficiency, various models, including RNN, CNN, and LSTM, are employed for comparative analysis. The CNN-LSTM model demonstrated superior performance in terms of RMSE, MAE, and R2. Nonetheless, future research endeavors will focus on gathering additional data with features related to customer behaviors to enhance the accuracy of output power forecasting. The complete paper will provide a detailed explanation of the proposed forecasting model.

Table 2: Evaluated performance metrics for the proposed model against other techniques

Approach	RMSE	MAE	R2
RNN	5.3076	3.996	0.76726
CNN	3.812	2.6185	0.8799
LSTM	4.1257	2.581	0.8593
CNN-LSTM	3.282	2.195	0.911

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