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Machine learning-based multivariate forecasting of electric vehicle charging station demand

Najmul Alam,[1] M. A. Rahman,[1]
Md. Rashidul Islam,[1,✉] and M. J. Hossain[2]
[1] *Department of Electrical & Electronic Engineering, Rajshahi University of Engineering & Technology, Kazla, Rajshahi, Bangladesh*
[2] *School of Electrical and Data Engineering, University of Technology Sydney, Ultimo, NSW, Australia*
✉ E-mail: rashidul@eee.ruet.ac.bd

The exponential rise of electric vehicles (EVs) is transforming the global automobile industry, driving a shift towards greater cleanliness and environmental sustainability. EV charging stations (EVCSs) play a pivotal role in this massive transition towards EVs, where accurate forecasting of EVCS demand is crucial for seamlessly integrating EVs into existing power grids. Most of the existing research mainly concentrates on univariate forecasting, neglecting the multiple factors influencing EVCS demand. Hence, this study offers a comparative analysis of different algorithms for univariate forecasting and multivariate forecasting, where the multivariate scheme incorporates metadata such as charging time, greenhouse gas savings, and gasoline savings. The experimental results indicate the superiority of the multivariate scheme over the univariate forecasting. For multivariate forecasting, the gated recurrent unit (GRU) has outperformed other models such as categorical boosting (Catboost), recurrent neural network (RNN), long short-term memory (LSTM), extreme gradient boosting (XGBoost), random forest, convolutional neural network (CNN), CNN + LSTM, and LSTM + LSTM. The results of this study emphasize the significance of using the GRU model for multivariate forecasting with metadata during normal and noisy scenarios to yield more reliable and accurate predictions. This approach enhances decision-making, policy development, and efficient grid integration in the growing EV sector.

Introduction: The invention of the wheel is one of the most impactful milestones in human civilization, which was later elevated with the development of the internal combustion engine vehicle, causing revolutions in the mobilization of people and goods. Nowadays, industrialization and the extensive development of road infrastructure have significantly accelerated the growth of the automobile sector. However, this growth has led to several environmental hazards, including rising global sea levels, increasing temperatures, higher carbon emissions, greenhouse gas (GHG) accumulation, and overall environmental pollution [1]. A promising solution to these problems can be the adoption of electric vehicles (EVs) and the integration of renewable energy sources [2, 3]. Especially, EVs are significantly important due to their potential applications as emergency energy sources to deal with sudden load change, energy storage for renewable energy sources, voltage restorers, and so on [4].

The EV ecosystem relies heavily on the EV charging station (EVCS), which provides the essential infrastructure for the bidirectional energy flow needed for charging the vehicles and supporting EVs' role as energy suppliers. The integration of EVCS with the electrical grid is a significant concern. As the increasing number of EVs contributes to peak load demand, they may cause local shortages and increased grid restrictions issues, as addressed in reference [5]. As an economical and easily implementable solution to these problems, the study in reference [6] has discussed the effectiveness of earlier knowledge of the EVCS demand to help energy authorities use environmentally friendly energy sources and optimize off-peak hours. Hence, several EVCS demand forecasting techniques have been discussed in the existing research works [6–9] to facilitate EVs' grid integration, policy making, infrastructure planning, and management.

Among the notable research works, various deep learning methods have been analyzed in reference [7] for EVCS demand forecasting, where long short-term memory (LSTM) model has been found to be superior to artificial neural networks (ANN), recurrent neural networks (RNN), gated recurrent units (GRU), stacked autoencoders (SAEs), and bidirectional LSTM (Bi-LSTM) models. An improved version of the supervised learning scheme has been discussed in reference [8] to improve the performances of deep learning models in forecasting demand. In another study [9], the classic arithmetic optimization algorithm (AOA) has been discussed for parameter optimization while employing the empirical mode decomposition (EMD) for input data to develop a new deep LSTM (DLSTM) predictor. Although these works are notable, they have explored univariate and multivariate forecasting schemes individually.

Existing research works [10, 11] have addressed the importance of a multivariate forecasting approach in capturing temporal characteristics from more than one critical factor, while highlighting the necessity of incorporating metadata associated with forecasting to improve the accuracy and reliability of predictions. Although a multivariate forecasting approach incorporating metadata may outperform conventional univariate schemes, a comparative analysis is required to verify this concept. To the authors' best knowledge, no comparison has been performed yet between the univariate and multivariate forecasting incorporating metadata to identify the superior one, which is the key objective of this research work. On the other hand, data abnormality can affect the reliability of forecasting schemes [12], which is yet to be addressed for multivariate forecasting. Hence, this research also investigates the forecasting reliability in the presence of noise in the metadata. The contributions of this work are outlined as follows.

- Presenting a comparative analysis of univariate and multivariate forecasting schemes for different models to identify the superior scheme,
- Investigating the reliability of the multivariate forecasting models in the presence of Gaussian noise for data abnormality,
- Selecting an optimum EVCS demand forecasting algorithm under both normal and data abnormality cases.

Methodologies: The methodologies for this investigation include data acquisition and preprocessing as the preprocessing step and model selection and performance evaluation as the execution step. The overall process is presented in Algorithm 1, while the details are presented as follows.

Data acquisition and preprocessing: This research work uses data from an online platform [13] for Palo Alto, a city in the United States. The dataset, spanned from 31 July 2011 to 23 March 2023, consists of 10,000 individual transactions and includes 28 metadata relevant to optimizing EVCS. The data undergoes preprocessing to convert raw data into a structured format suitable for accurate forecasting. These processes include data cleaning and normalization. Initially, missing and null values are removed. Feature selection is then performed, focusing on multiple features such as charging time, GHG savings, and gasoline savings, with demand (kWh) as the target. The dataset is aggregated from hourly to daily, and the charging duration is converted into minutes. Finally, the dataset is normalized, resulting in 602 data points covering 86 weeks. The first 85 weeks of data are used for training, while the last week is reserved for testing.

Model selection and performance evaluation: Various models are evaluated for EVCS demand forecasting to identify an optimum model. Among the models employed here, categorical boosting (Catboost) and extreme gradient boosting (XGBoost) are gradient-boosting models known for their high accuracy and efficiency. Recurrent neural network (RNN), GRU, and LSTM are also used here because of their ability to capture sequential patterns, where RNN may struggle with long-term dependencies. GRU and LSTM models are the updated versions of RNN, with GRU being parameter efficient and LSTM model handling long-term dependencies effectively. As an example of ensemble learning methods, random forest is used here, where random forest combines multiple decision trees to provide robust forecasts. As convolutional neural network (CNN) excels in spatial data analysis, it is considered here. Furthermore, two hybrid models are considered. The first one is CNN + LSTM, which combines CNN for feature extraction with LSTM for sequence modelling. Another hybrid model is LSTM + LSTM, which employs multiple LSTM layers to capture detailed temporal patterns in EVCS demand. The architectures of these models are kept the same while employing each type of model for univariate and multivariate forecasting. Additionally, Gaussian noise is introduced

Algorithm 1 EVCS demand forecasting procedures

Input: Raw data from online

Output: Forecasted value of EVCS demand

Step 1: Data collection.

df = Collect the data from the online source

Step 2: Clean dataset

→ Clean zero and null values

→ Eliminate the undesired fields

df = [Start date, GHG saving, gasoline saving, charging time, energy]

→ Set *Start date* as index

Step 3: Aggregate the raw data

$resampled\_df = df.resample(D).sum()$

```
// Turn hourly data into daily data
```

→ Convert the hourly charging time into minutes

Step 4: Organize the daily data

→ Adjust the data on a weekly basis

```
// The week starts on Sunday and ends on Saturday
```

Step 5: Normalize the data.

$$df_{normal} = \frac{D - D_{min}}{D_{max} - D_{min}} \tag{1}$$

```
// Here D, denotes data point
```

Step 6: Forecast the demand

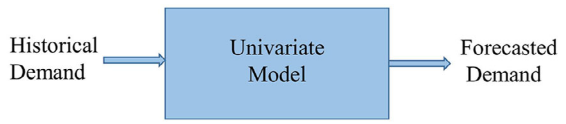
→ Split the dataset into train and test data

→ Forecast using selected model

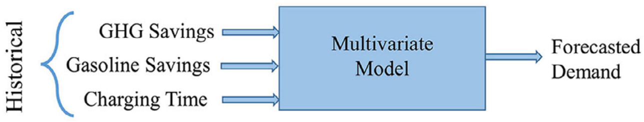
Step 7: Evaluate the forecasted model

→ Evaluate the forecasted model using *MSE, RMSE, MAE*

Return: Forecasted value.



(a) *Univariate scheme*



(b) *Multivariate scheme*

Fig. 1 *Overview of univariate and multivariate electric vehicle charging stations demand forecasting*

into the test data to further assess the effectiveness of these models. As all these models have their distinctive advantages, an optimum model is selected by evaluating their performances using metrics such as mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE). The experiments were carried out using Jupyter Notebook on a computer with an Intel i5 processor and 12GB of RAM.

Model performance analysis: A conceptual overview of univariate and multivariate forecasting is illustrated in Figure 1, presenting the input and output for each scheme. The forecasting accuracies of different machine learning models for univariate and multivariate EVCS demand forecasting are presented in Table 1 and Table 2, respectively, where high error values reflect poor predictive accuracy and reliability. For univariate forecasting, LSTM, CNN + LSTM, LSTM + LSTM, and random forest models have performed competitively better than other models, as presented in Table 1. Especially, the exceptional performance of LSTM-based models underscores the effectiveness of LSTM in capturing long-term temporal patterns in univariate data. As presented in Table 1, the CNN + LSTM model has outperformed others by achieving an MSE of 0.05449 and an RMSE of 0.23343. While the CNN + LSTM model has performed competitively in terms of MAE with a score of 0.20566, the random forest has outperformed others for this performance metric with a score of 0.20305. For other models, CNN and RNN are found to be the least accurate models for univariate forecasting, while Catboost, XGBoost, and GRU models have performed slightly better than those two models, as presented in Table 1. Hence, based on the observations in Table 1, CNN + LSTM is found to be an optimum model for univariate forecasting in terms of all three metrics.

Table 1. Performance comparison of various machine learning and deep learning models for univariate forecasting

Model	MSE	RMSE	MAE
Catboost	0.08922	0.29871	0.28181
GRU	0.08413	0.29006	0.25360
RNN	0.09468	0.30770	0.27161
LSTM	0.06275	0.25049	0.21471
XGBoost	0.08267	0.28752	0.22404
Random forest	0.06691	0.25867	**0.20305**
CNN	0.09431	0.30701	0.29416
CNN + LSTM	**0.05449**	**0.23343**	0.20566
LSTM + LSTM	0.06045	0.24586	0.18784

Bold font – best performance.

Table 2. Performance comparison of various machine learning and deep learning models for multivariate forecasting

Model	MSE	RMSE	MAE
Catboost	6.44531×10^{-5}	0.00802	0.00673
GRU	$\mathbf{8.86864 \times 10^{-6}}$	**0.00297**	**0.00266**
RNN	4.04274×10^{-5}	0.00635	0.00487
LSTM	6.46387×10^{-5}	0.00803	0.00652
XGBoost	4.37881×10^{-5}	0.00661	0.00536
Random forest	7.51699×10^{-5}	0.00867	0.00446
CNN	0.00536	0.07323	0.05994
CNN + LSTM	0.01329	0.11529	0.11166
LSTM + LSTM	0.00015	0.01252	0.01121

Bold font – best performance.

On the other hand, the GRU model has significantly outperformed others for multivariate forecasting, achieving an MSE of 8.86864×10^{-6}, an RMSE of 0.00297, and an MAE of 0.00266, as presented in Table 2. The performance of the GRU model highlights its strong ability to model complex temporal dependencies across multiple variables, resulting in its success in achieving high accuracy. For other models, Catboost, XGBoost, random forest, RNN, and LSTM have performed competitively for multivariate forecasting of EVCS demand, where XGBoost and RNN have performed slightly better than the other three models. However, as presented in Table 2, CNN, CNN + LSTM, and LSTM + LSTM are found to be the least accurate models for multivariate forecasting. Especially, the poor performance of CNN compared to all other models indicates its limitations in handling multivariate data effectively.

From the theoretical aspect, a multivariate scheme is superior due to accommodating charging time, GHG savings, and gasoline savings as input, whereas the univariate scheme uses only demand as input. As presented in Table 2, on comparing the performance of various machine learning and deep learning models for both univariate and

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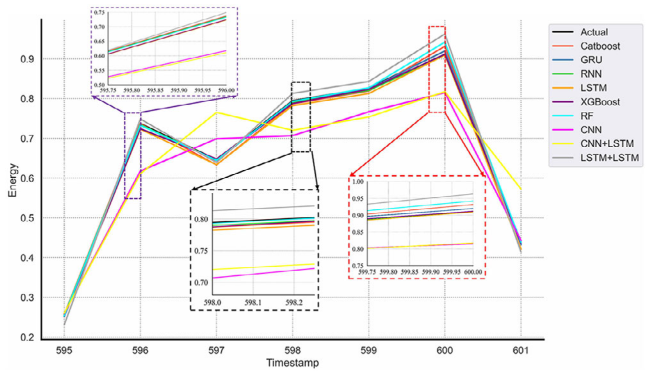

Fig. 2 *Comparison of actual values with predictions for multivariate forecasting models*

Table 3. Performance comparison of multivariate models during Gaussian noise-based data abnormality

Model	MSE	RMSE	MAE
Catboost	0.00013	0.01127	0.00995
GRU	**1.60624×10^{-5}**	**0.00401**	**0.00359**
RNN	4.26052×10^{-5}	0.00652	0.00482
LSTM	6.63348×10^{-5}	0.00814	0.00606
XGBoost	1.41136×10^{-4}	0.01188	0.00963
Random forest	7.89863×10^{-5}	0.00889	0.00625
CNN	0.00574	0.07577	0.06812
CNN + LSTM	0.02044	0.14298	0.12628
LSTM + LSTM	0.00046	0.02147	0.01687

Bold font – best performance.

multivariate time series forecasting, it is evident that multivariate forecasting notably outperforms univariate forecasting in terms of accuracy for all selected models. Figure 2 provides a visual representation of the results from various multivariate forecasting models with a zoomed-in view for enhanced clarity and understanding, highlighting the closeness of the forecasted values with the actual values. Based on the observations in Figure 2 and in Table 2, the GRU model has demonstrated superior performance in multivariate forecasting by achieving the lowest errors across key metrics. These multivariate models are further assessed by adding 5% Gaussian noise in test data, where Gaussian noise represents physical infrastructure-originated data abnormality. As shown in Table 3, the performance is decreased for all models, while the GRU model still maintains its superiority, making it the most effective choice for EVCS demand forecasting. As the forecasting schemes in smart grids are susceptible to cyber attacks [12], further investigation is required to develop robust EVCS demand forecasting schemes.

Conclusion: Accurate EVCS prediction is crucial for policy development, decision-making, and grid integration. Multivariate forecasting incorporating metadata of the EVCS can significantly enhance the charging demand forecasting accuracy. A comparison of ML-based univariate and multivariate forecasting schemes has been performed among nine forecasting models to identify an optimum model. The comparative analysis of univariate and multivariate schemes for the selected models underlines the advantages of using multivariate models for forecasting tasks using the historical metadata charging time, GHG savings, and gasoline savings. The GRU model outperforms others for multivariate forecasting while achieving an accuracy of 8.86864×10^{-6}, 0.00297, and 0.00266 in terms of MSE, RMSE, and MAE, respectively. The GRU model also demonstrates the highest accuracy in the presence of Gaussian noise. The comparison signifies the importance of multivariate models in capturing the complex dependencies among meta-variables to provide better accuracy and reliability for EVCS demand forecasting, contributing to more effective grid management and energy optimization. In the future, this work can be extended to develop a robust and generalized forecasting scheme to estimate EVCS demand.

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