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Electric Vehicle charging station load forecasting with an integrated DeepBoost approach

Joveria Siddiqui [a,1], Ubaid Ahmed [a,1], Adil Amin [a], Talal Alharbi [b], Abdulelah Alharbi [b,*], Imran Aziz [a], Ahsan Raza Khan [c], Anzar Mahmood [a,*]

[a] Department of Electrical Engineering, Mirpur University of Science and Technology (MUST), Mirpur, 10250, Azad Jammu & Kashmir, Pakistan
[b] Department of Electrical Engineering, College of Engineering, Qassim University, Buraydah, Qassim, 52531, Saudi Arabia
[c] Department of Computer Science, University of York, Heslington, YO105GH, United Kingdom

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ABSTRACT

The emission of Greenhouse Gases (GHGs) is the main cause of climate change and the transportation sector, especially in urban areas, is among the major contributors to these emissions which are putting a big question mark on sustainability. A significant reduction in emissions is possible through widespread adoption of Electric Vehicles (EVs) which can help in addressing the issues of climate change and sustainability. However, the introduction of EVs brings additional load on the existing grid and can adversely affect its operation. Therefore, we presented a novel DeepBoost approach for forecasting day-ahead EVs charging station load. The proposed approach consists of Categorical Boosting (CatBoost), Extreme Gradient Boosting (XgBoost), Long Short-Term Memory Network (LSTM) and Linear Regression (LR) models. The performance of DeepBoost is compared with conventional CatBoost, XgBoost, LSTM, Informers and different hybrid deep learning methodologies and other techniques reported in the literature. The results demonstrate the effectiveness of the DeepBoost over other models. For the dataset of Adaptive Charging Networks (ACN), the Mean Absolute Error (MAE) of DeepBoost improves by 9.4%, 32.7% and 88% as compared to CatBoost, XgBoost and LSTM networks, respectively.

1. Introduction

To address the alarming issue of climate change, a landmark event was witnessed in December 2015 as the Paris Agreement. The core objectives of the agreement were to reduce Greenhouse Gases (GHGs) emissions to limit the increase in global temperature and provide financial support to developing countries for initiating different measures to eradicate the causes of climate change [1]. The GHGs emissions have far-reaching effects on the environment, health and sustainability. 7 million premature deaths every year are due to air pollution, according to World Health Organization (WHO) report [2]. Different sectors contribute to the emission of GHGs. According to the report of California GHGs inventory, the transportation sector is the largest source of GHGs emissions, contributing 38% of the total global GHGs emissions from 2000 to 2020 [3]. The widespread adoption of Electric Vehicles (EVs) has great potential to significantly reduce the transportation's sector role, especially in urban areas, in contributing to GHGs emissions. Moreover, the use of EVs helps to mitigate reliance on fossil fuels, leading to a cleaner environment [4].

In recent years, many countries have introduced various initiatives to promote the widespread adoption of EVs. According to the report of the International Energy Agency (IEA), global sales of EVs reached 10 million in 2022 and it is projected to increase by 35% in 2023 [5]. According to the study [6], the world now has 16.5 million EVs and this number is projected to be 30 million in 2025. The findings of the study [7] report that unplanned integration of 20% market share of EVs will increase the peak demand of the traditional grid by 35.8%. Moreover, the Global EV Outlook 2022 states that the EVs charging load will increase to 780 terawatt hours by 2030 [8]. EVs can be charged either at homes or at public charging stations. However, the simultaneous integration of large numbers of EVs with the electrical grid has adverse effects such as voltage and frequency instability, injection of harmonics and demand–supply mismatch. These issues can be overcome by using a robust EVs charging load forecasting model [9,10]. The efficient forecasting models estimate the future EVs charging load and help in maintaining the stability of the grid.

In the literature, different models are reported for EVs charging station load forecasting. In recent years, due to the advancement in

* Corresponding authors.
E-mail addresses: ALY.Alharbi@qu.edu.sa (A. Alharbi), anzar.ee@must.edu.pk (A. Mahmood).
[1] Equal contribution.

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computing technologies, hybrid methodologies have been studied extensively. These hybrid methodologies combine different techniques and provide better forecasting results. A hybrid model consisting of Variational Mode Decomposition (VMD), Lion Swarm Optimization (LSO) and Bi-directional Long Short-Term Memory (BiLSTM) is proposed for forecasting the load of EVs charging stations located in Southern China in [11]. For the decomposition of the data, VMD is used whose parameters are optimized by LSO. The decomposed data is then fed to BiLSTM for short-term charging load forecasting. The performance of the proposed model is compared with Deep Neural Network (DNN), LSTM and Gated Recurrent Unit (GRU) through Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). Findings illustrate that VMD-LSO-BiLSTM produces better forecasting results. Two encoder–decoder-based models: Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) and Bi CNN-LSTM are proposed in [12]. In this proposed study, four EVs charging station load datasets are used. Moreover, the performances of the proposed approaches are compared with conventional LSTM, CNN and BiLSTM models. For forecasting Leeds Council EVs fleet charging load, a hybrid BiLSTM model is presented in [13]. Multiple decomposition strategies consisting of Swarm Decomposition (SWD) and Complete Ensemble Empirical Mode Decomposition Adaptive Noise (CEEMDAN) are implemented for decomposing the dataset. In the subsequent state, the decomposed data is fed to BiLSTM to estimate future charging load. Moreover, the comparative analysis of the CEEMDAN-SWD-BiLSTM is also performed with different state of art models through Mean Square Error (MSE), R-squared (R^2), Mean Absolute Error (MAE) and RMSE.

1.1. Motivation and contributions

The adoption of EVs can help in reducing GHGs emissions, particularly in the transport sector. However, the high-scale integration of the EVs into the existing system can negatively impact the performance of the grid. By implementing EVs charging load forecasting model, the reliability and stability of the grid are ensured. The statistical models can offer computationally efficient forecasting but the inability to handle data non-linearities hinders their application. The LSTM reported superior performances in sequential tasks among the deep learning networks. However, the LSTM network requires a large volume of data points with external features for effective learning of temporal dependencies. Moreover, it also requires effective hyper-parameters tuning to avoid underfitting and overfitting problems. The boosting algorithms can be trained on fewer data points but suffer from generalizability and scalability. Their performance degrades with changing data distributions, limiting their real-world application in data variability scenarios where scalability is critical for reliable performance. Therefore, this study presented a novel approach, DeepBoost, integrating LSTM with LR and state-of-the-art boosting algorithms: Extreme Gradient Boosting (XgBoost) and Categorical Boosting (CatBoost). This unique integration overcomes the limitations of the individual models. The combination of LSTM network overcomes the generalizability issues of boosting algorithms. The final forecast is generated through LR which learns from the level 1 learners' outputs, overcoming the limitation of data scarcity for the LSTM network. The main contributions of the paper are listed below:

1. An integrated learning algorithm, DeepBoost, consisting of LSTM, XgBoost, CatBoost and LR is proposed for day-ahead forecasting of EVs charging stations load. The DeepBoost level 1 contain learner LSTM, XgBoost and CatBoost algorithms while LR is implemented in level 2 which combines the intermediary forecasts of the level 1 learners by adjusting the weights.
2. The DeepBoost compared with the conventional LSTM, XgBoost, CatBoost and Informers and different hybrid methodologies of deep learning networks using RMSE, MAE, MSE and NRMSE. Moreover, a comparative analysis of the DeepBoost with the other techniques reported in the literature for forecasting charging station load is also performed

1.2. Paper organization

The remaining of this work is organized as follows: Section 2 reports the literature review, Section 3 discusses the methods and preliminaries, Section 4 describes the simulation setup, Section 5 reports results and literature comparison of the proposed DeepBoost, Section 6 discusses the model's scalability and real-world implementation challenges and Section 7 summarizes the conclusions.

2. Literature review

Efficient forecasting of EVs charging load can be achieved using different approaches reported in the literature. These methods can broadly classified into statistical time series and Artificial Intelligence (AI) models [14].

2.1. Statistical models

In [15], Auto Regressive Integrated Moving Average (ARIMA) is proposed for forecasting electric and EVs charging load. The EVs charging demand, daily pattern and distance travel are used as input features. Initially, a couple ARIMA model is implemented to forecast the total load consisting of conventional electric load and EVs charging load then decoupled ARIMA is used which forecasts electric and EVs charging load separately. The results indicate that the decoupled ARIMA produces better forecasting results than the couple ARIMA model. For short-term forecasting of EVs charging station load, Seasonal Auto-Regressive Integrated Moving Average (SARIMA) is proposed in [16]. The real-world datasets are collected from the charging stations of San Diego, California and Washington. For evaluating the model's performance MSE and MAPE are used. A clustering-based Monte Carlo (MC) approach is presented in [17]. The data is first clustered based on user behavior patterns, followed by the implementation of MC approach to forecast Adaptive Charging Networks (ACN) data collected from California. The proposed algorithm is also compared with "Persistence" and LSTM models.

2.2. Deep learning models

In recent years, different deep learning models have been developed. These AI models learn the hidden patterns in the dataset more accurately and produce better forecasting results. The LSTM network is proposed in [18] for forecasting of EVs charging load using exogenous variables. In the first step, three predictions are generated by the LSTM model. These initial predictions are then optimized by the Dempster-Shafer (DS) evidence theory. The MAE is used for performance evaluation and the results indicate that the utilization of DS theory improves the MAE of LSTM network. In [19], a comparative analysis of LSTM, GRU and CNN hybridized with LSTM and GRU is presented for short and medium-term forecasting of multiple charging station loads. To improve the performance of LSTM, the novel gating mechanism "Mogrifier" is integrated into the LSTM model in [20]. Moreover, Generative Adversarial Network (GAN) is used to overcome the data scarcity issue which degrades the forecasting performance of LSTM. A comparative analysis of Artificial Neural Network (ANN), Recurrent Neural Network (RNN), LSTM and GRU for Morocco EVs charging station power demand forecasting is presented in [21]. The RMSE and MAPE are used as performance indicators. The GRU network achieved RMSE of 0.76 and MAPE of 2.90%. In [22], an attention-based LSTM network is exercised for Shenzhen charging station load estimation. In the proposed study, data up-scaling and down-scaling algorithms are used to obtain high-resolution input data. Moreover, the attention-based LSTM network is compared with ANN, LSTM and RNN for short-term load forecasting of charging stations. The RMSE, MAE, R^2 and Normalized Root Mean Square Error (NRMSE) are used to evaluate the models' performances. For a short-term load forecasting of the charging station situated in Southern China Propet Bidirectional Long Short-Term Memory (PBiLSTM) model is presented in [23]. The Propet algorithm is used for selecting suitable features. Moreover, Propet-BiLSTM is compared with LSTM, ANN, CNN-LSTM and Transformers networks. The Propet-BiLSTM reports better forecasting results than other models.

A comparative analysis of six Deep Neural Networks (DNNs): RNN, LSTM, BiLSTM, GRU, CNN and Transformers is performed in [24] for charging load forecasting. The historical data of Boulder, Colorado, USA is used in the proposed study. The models' performances are evaluated through RMSE and MAE. Findings illustrate that for daily, weekly and monthly forecast Transformers model outperforms other networks. A comparative analysis of LSTM with K-Nearest Neighbors (KNN), Random Forest (RF), SVM, and Decision Tree (DT) algorithm is presented in [25]. The MSE, gradient loss and action error are used for the model's comparison. Results indicate that LSTM network records MSE of 0.258. For 7, 30, 60 and 90 days-ahead load forecasting of Boulder EVs charging station, Transformers model is proposed in [26]. Moreover, the performance of the Transformers model is compared with ARIMA, SARIMA, RNN and LSTM networks. The findings indicate that for a 7 days-ahead forecast LSTM outperforms other models. While for 30, 60 and 90 days-ahead forecasting the Transformers network gives the least errors. A sequence-to-sequence (Seq2Seq) model is proposed for forecasting single and multi-step charging load of Utah and Los Angeles stations in [27]. The proposed Seq2Seq is compared with Historical Average (HA), LSTM, ARIMA, Propet and XgBoost models. Findings demonstrate that for single-step ahead forecasting Seq2Seq and LSTM network have similar performance while for multi-step ahead forecasting Seq2Seq produces better results than other models.

2.3. Hybrid models

In the literature, hybrid models are also reported for forecasting of EVs charging station load. The hybrid models consist of multiple approaches that work in conjunction to give better forecasting outputs. A hybrid LSTM approach with Bayesian Deep Learning (LSTM-BDL) is proposed for forecasting Caltech EVs charging station load in [28]. The performance of LSTM-BDL is compared with Multiple Linear Regression (MLR), LSTM, Support Vector Regression (SVR) and Quantile Regression (QR) using RMSE, MAE and R^2. Results demonstrate the superiority of the proposed LSTM-BDL over other approaches. A hybrid Multi-Channel CNN (MCCNN) and Temporal CNN (TCNN) are proposed for forecasting the load of Northern China charging station in [29]. The fluctuation trend of the dataset is extracted using MCCCN while TCNN is implemented for forecasting load using temporal dependencies. Moreover, the MCCNN-TCNN network is compared with ANN, LSTM and CNN-LSTM networks. In [30], the LSTM network is hybridized with XgBoost for forecasting charging load. The hyper-parameters of LSTM and XgBoost are optimized by the "Bayesian" algorithm. The LSTM with residual collection Grey Model (GM) is put forward in [31]. In the first step, different external factors are analyzed using GM to reduce cumulative error. The GM-LSTM is compared with conventional GM and LSTM. Findings demonstrate that the GM-LSTM records the least error. The authors in [32], proposed a Back-Propagation Neural Network (BPNN) for EVs charging station load forecasting. The input data is collected from the Qingpu District, Shanghai and contains environmental, societal and economic external parameters. In the first step of the proposed study, the authors implemented Least Absolute Shrinkage and Selection Operator (LASSO) for the selection of the suitable external parameters that have more predictive power regarding the target variables. The superiority of the LASSO-BPNN is demonstrated through its comparative analysis with different state-of-the-art algorithms. For the short-term forecasting of EVs charging station load, the Multiscale Spatio-Temporal Enhanced Model (MSTEM) is proposed in [33]. The proposed model utilizes the Graph Neural Network (GNN) for learning the non-linear temporal dependencies of the dataset. For learning the spatial pattern, the residual fusion mechanism and recurrent learning component are hybridized with GNN. The proposed methodology is also compared through RMSE, MAE and MSE with different networks for 6, 12, and 24 hours-ahead load forecasting. However, the results demonstrate that the performance of the proposed approach is not very generalizable and for some cases, the Dlinear model outperforms the proposed MSTEM.

A comparative analysis of different RNN models is presented in [34] for 24 hours-ahead EVs load forecasting. The dataset of ACN is used to train the model. Findings demonstrate that the LSTM network with an attention mechanism records better performance than other networks. The RMSE, MAE and MSE recorded by the attention-based LSTM network are 19.70, 10.33 and 388.10, respectively. A hybrid methodology consisting of BiLSTM and CNN is proposed in [35]. The CNN layer in the proposed model architecture is used to extract the suitable feature from the input data matrix and BiLSTM layer processes the temporal dependencies of the data. Moreover, the authors also implemented the Improved Dung Beetle Optimization Algorithm (IDBO) for the effective hyper-parameter optimization of the CNN-BiLSTM network. Results indicate that the proposed model tuned by IDBO outperforms the individual models of CNN and BiLSTM approaches. The authors in [36] presented a clustering-based hybrid approach for EV charging load estimation. The dataset is collected from the charging station of Pukou District, Nanjing. The dataset is recorded at intervals of 5 min. To avoid data scarcity, the authors first implemented the Monte Carlo (MC) algorithm to generate an extensive dataset. In the next step, data is divided into groups using spectral clustering. For finding the optimal clusters number Davies–Bouldin and silhouette coefficient indexes are used as performance indicators. Lastly, the CNN-LSTM network is exercised to forecast the load demand of EV charging stations. The study also reported a comprehensive comparative analysis of the proposed technique with baseline models. A comparative analysis of conventional LSTM, stacked-LSTM and attention mechanism-based stacked-LSTM is presented in [37]. The dataset, consisting of five different charging stations in Wahun City, China, is used to evaluate the model's performance. Findings demonstrated that the attention stacked-LSTM recorded the least error compared to other models. The authors also implemented PCC to find the correlation between the charging pattern of EVs and other external factors. For privacy-preserving EV charging load forecasting, the authors in [38] presented a BiLSTM network with Blockchain-based Federated Learning (FeDL). The blockchain strategy is used for the aggregation of the clients' model weight in a decentralized manner. The updating of weights is performed through Federated Averaging (FedAvg). The author also compares the performance of the proposed algorithm with centralized techniques using RMSE, MAE and MSE as performance indicators.

The accurate forecasting of EVs charging load helps in energy management and scheduling which ensures the grid's stability. From the above discussion, we can conclude that various methodologies have been reported in this regard. The statistical models are computationally efficient and easy to implement. However, these models are unable to learn the non-linearities of the data. Different machine learning and deep learning models are also reported. The above literature review also summarizes that among the deep learning algorithms LSTM and its variants have superior performance than other algorithms. However, the LSTM and other deep learning algorithms require a huge amount of data for efficient training. Moreover, these algorithms require high computational power and are sensitive to hyper-parameters optimization. The gradient boosting algorithms can be efficiently trained with a small dataset. However, Gradient Boosting Decision Tree (GBDT) algorithms have generalizability issues and are sensitive to hyper-parameter optimization. The hybrid methodologies are also reported with deep learning algorithms. The integration of attention mechanisms, VMD and meta-heuristic algorithms with deep learning improves the forecasting

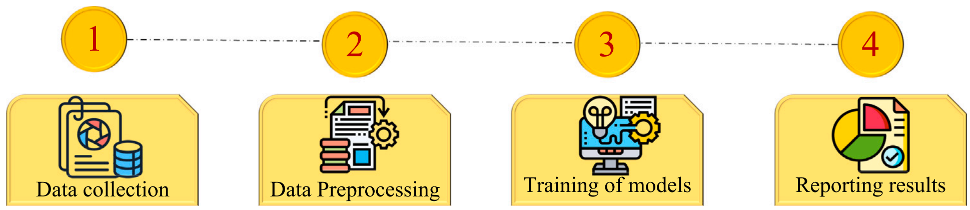


Fig. 1. Methodology steps for the proposed study.

performance. However, the hybrid methodologies also require higher computational power.

There is very limited work performed with GBDT algorithms for EVs charging station load forecasting. Moreover, the above literature review also concludes that no such methodologies that integrated the deep learning networks with GBDT algorithms are proposed. Therefore we proposed a novel DeepBoost approach that combines the LSTM network with CatBoost, XgBoost and LR algorithms. The hybrid methodology leverages the strength of each algorithm and overcomes the shortcomings of individual models. DeepBoost has the deep learning algorithm in its architecture which will help in overcoming the generalizability issues with GBDT algorithms. At the same time, the GBDT algorithms and LR model have low computational requirements and this aspect makes the DeepBoost computationally efficient than other hybridized methodologies. The DeepBoost aims to provide a more accurate 24 hours-ahead EVs charging load forecast with balanced computational efficiency and generalizability.

3. Methods and preliminaries

The workflow of the proposed study is comprised of subsequent steps and depicted in Fig. 1.

1. The first step is to collect EVs charging stations load datasets. In this study, we collect three charging station datasets for scalability analysis of proposed approach.
2. In the data preprocessing step, the resolution of the datasets is set to 24 hours interval to forecast next day EVs charging load. Moreover, feature selection and data normalization are also performed.
3. The DeepBoost and the algorithms used for comparative analysis are trained on the training dataset and forecast day-ahead EVs charging load.
4. In the last step, the performance of the proposed approach and other models is evaluated through error metrics and the results and conclusions are reported.

3.1. Long Short-Term Memory (LSTM) network

The LSTM network is designed to overcome the problems associated with RNN such as vanishing gradient due to the backpropagation, exploding gradients and long-term dependency issues [39]. It comprises different memory cells and three layers namely the forget gate layer, multiplicative input gate layer and multiplicative output gate layer. The gates are introduced to prevent perturbation by limiting the information passed through a cell and manipulating the stored information [40]. The forget gate removes the unwanted information from the cell states using the sigmoid activation function as a filter and multiplies the output to the cell state for performance optimization of the LSTM network. The output of the forget gate is 0 or 1, while 0 is used to discard a particular feature and 1 to keep a particular data. The forget gate layer can be modeled by the following equation.

$$u_t = \sigma(M_u(h_{t-1}, a_t) + n_u) \tag{1}$$

The input gate layer adds new data to the cell state using the sigmoid activation function as a filter and tanh activation function to determine the new possible values to be added. The output range of tanh activation function is −1 or +1. The output of these two filters is first multiplied and then added to update the hidden cell state. The input gate layer can be modeled as in the Eqs. (2)–(4)

$$v_t = \sigma(M_v(h_{t-1}, a_t) + n_v) \tag{2}$$

$$c' = \tanh(M_c(h_{t-1}, a_t) + n_c) \tag{3}$$

$$c_t = u_t * c_{t-1} + v_t * c' \tag{4}$$

The output gate layer uses tanh function for cell state filtration and sigmoid function for input data filtration. The result of these two functions is multiplied and the product obtained is considered as output data. The output gate layer can be modeled as follows [41].

$$o(t) = \sigma(M_o(h_{t-1}, a_t) + n_o) \tag{5}$$

where u_t is the forget gate, v_t is the input gate, o_t represent output gate, σ is sigmoid activation function, M_v, M_u, M_c M_o are corresponding weights of gates, $h_{(t-1)}$ is an output of previous block at timestamp $t-1$, a_t is an input at current time stamp and n_v, n_c, n_o and n_u are the biases for the respective gates.

3.2. Extreme Gradient Boosting (XgBoost)

The XgBoost is a tree-based GBDT algorithm. The main goal of this algorithm is to enhance the computational speed and increase the efficiency of the predictive model [42]. It iteratively optimizes the parameters of training models by performing gradient descent to minimize the cost function. It minimizes the loss function MSE to improve the overall performance of the system and find the best tree model. The second-order Taylor expansion, described through Eqs. (6)–(8), is used to calculate the XgBoost's loss function [43].

$$A(t) \approx \sum_{o=1}^{k} A(z_o, z'_{(o-1)} + b_o f_o(x_o) + 1/2 c_o h_o^2(x_o)) \tag{6}$$

$$b_i = h'(t) = \frac{\partial A(z_o, z'^{(t-1)})}{\partial z'^{(t-1)}} \tag{7}$$

$$c_o = h''(x) = \frac{\partial^2 A(z_o, z'^{(t-1)})}{\partial z'^{(t-1)}} \tag{8}$$

The symbols b_o and c_o denote the loss function's first and second-order gradient statistics, respectively. XgBoost model has an end-to-end tree-boosting system which makes it computationally efficient for handling sparse and big data.

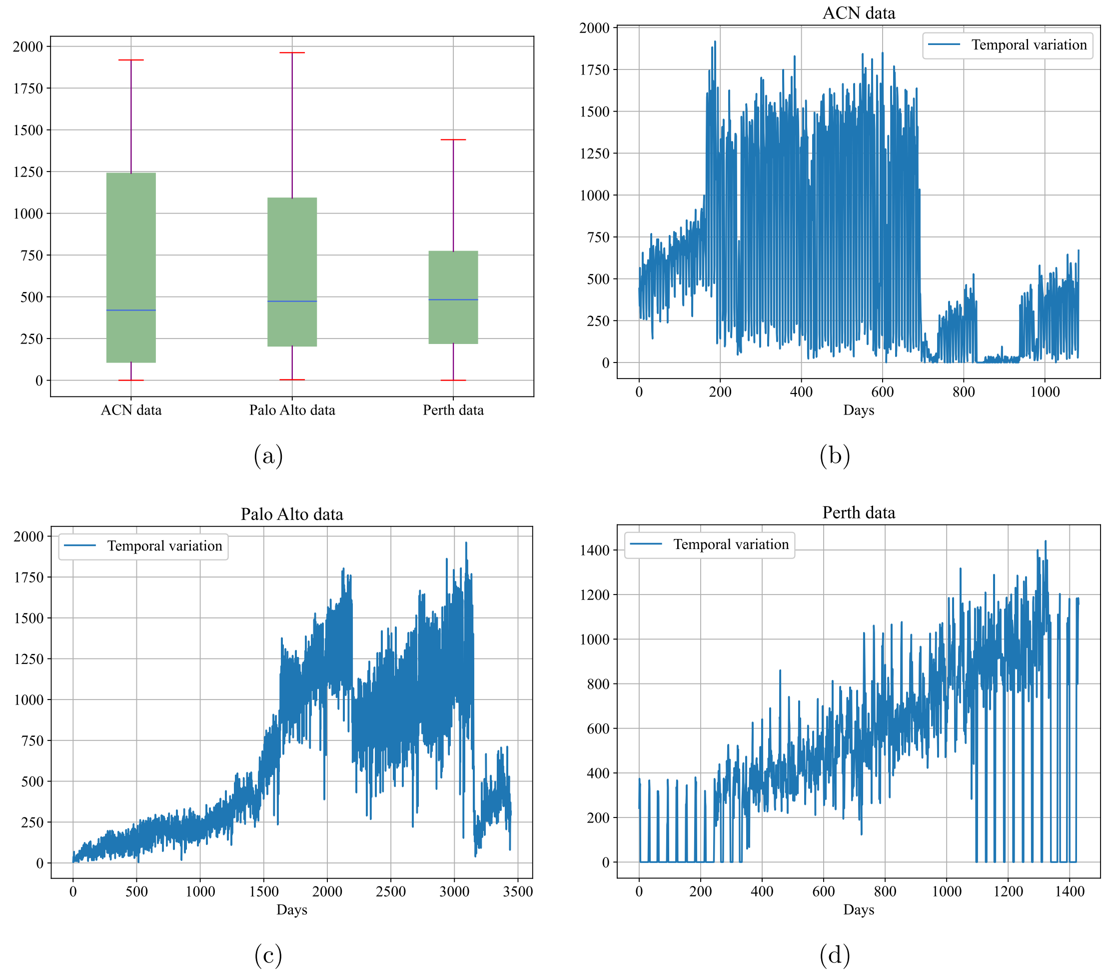


Fig. 2. Data visualization: (a) Box plot representation of three datasets, (b) Temporal variation within ACN dataset, (c) Temporal variation within Palo Alto dataset, (d) Temporal variation within Perth dataset.

3.3. Categorical Boosting (CatBoost)

CatBoost is an implementation of GBDT to process the categorical features of a dataset having a large number of independent features. It transforms the categorical features into numerical features using a combination of target encoding and ordered statistics. The number of features are reduced to the specific features required by the model for high cardinality data to improve the performance of the model [44]. It uses an effective strategy named ordered target-based statistics (TBS). It builds symmetric trees and grows them level by level using the same split for all of the nodes. To determine the direction of flow, one just needs to know the current level that corresponds to a feature and its corresponding value. Then it performs the vectorization i.e., creates a vector of thresholds and a vector of values is used for prediction and performing element-wise comparison in parallel [45].

3.4. Linear regression (LR)

LR is the supervised machine learning algorithm that is used for predicting demand, trend estimation, etc. LR aims to minimize the sum of MSE by understanding the linear relationship between input and target variable [46]. The following equation describes LR model:

$$b = \beta_0 + \beta_1 a_1 + \cdots \ldots + \beta_p a_p + \varepsilon \tag{9}$$

The input and predicted output are represented by a and b, respectively. The intercept, coefficient and error are represented by β_0, β_p and ε, respectively. The symbols a and b are used for input and forecasted values, correspondingly.

4. Simulation setup

4.1. Dataset description and preprocessing

In this study, three different EVs charging stations datasets are used collected from different resources. The ACN dataset is collected from the charging sites located at Caltech campus, California [47]. This dataset is gathered from 54 Electric Vehicle Supply Equipment (EVSE) and it ranges from 25 April 2018 to 12 April 2021. The second dataset is attained from the Palo Alto charging station [48]. The dataset contains historical EVs charging load data with other features from 29 July 2011 to 31st of December 2020. The third dataset is collected from Perth and Kinross station [49]. This dataset ranges from September 2016 to 12 August 2019. All these datasets also contain other features like EVs arrival and departure time, parking duration, MAC address, etc.

The aim of the proposed study is to estimate day-ahead EVs charging station load using univariate time series forecasting. Therefore, we first change the resolution of the data to 24-hour interval keeping the information regarding historical EVs charging load and removing all other features from the data. For data normalization, the “MinMax” scaler is used which scales the data between 0 and 1. The datasets are split into training and testing sets using the 80 : 20 rule, where 80% of the data is used for training purposes and 20% for evaluating the models’ performances. In Fig. 2, the box plot is presented to visualize the distribution of the data (see Table 1).

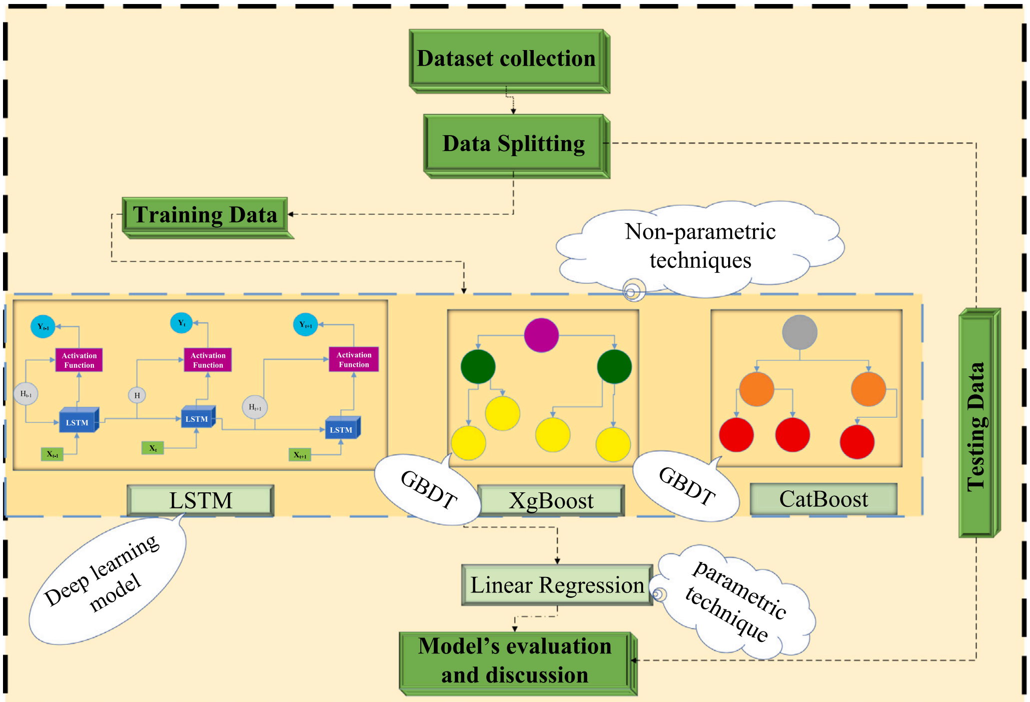


Fig. 3. Workflow of the proposed approach.

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

4.2. DeepBoost

The proposed DeepBoost is an integrated approach with different layered models. Layer 1 of the DeepBoost has LSTM, XgBoost and CatBoost models. The LSTM network utilizes hidden layers and memory cell architecture to learn data patterns, while XgBoost and CatBoost implement boosting strategies that minimize the error iteratively. The input training data is fed to LSTM, CatBoost and XgBoost models simultaneously to provide parallel computing at layer 1. The LSTM, XgBoost and CatBoost interpret the training data according to their hidden layer and tree-based functionality. The LSTM uses the gating mechanism to learn the long-term data pattern in the sequence of events. The LSTM has three gates, memory cells and hidden layers and uses second-generation neurons for learning the time-series intrinsic patterns. Different activation functions are also implemented in the LSTM network for handling the non-linearities of the data. The CatBoost provides the order boosting to the DeepBoost algorithm. It develops the decision trees sequentially, which simplifies the structure and improves the mechanism of combining the output of multiple decision trees. In the DeepBoost framework, XgBoost provides a histogram-based boosting mechanism to learn the data pattern effectively. This histogram learning speeds up the training process. Moreover, the regularization parameters used in XgBoost also avoid the overfitting of the curve. After parallel training of models at layer 1, the intermediary forecasts are fed to layer 2 rather than acting as a standalone prediction. In layer 2, the DeepBoost has LR, which interprets the training data and the intermediary forecast of LSTM, XgBoost and CatBoost algorithms by learning the linear relationship between them and updating the weight and biases. The LR works as a meta-learner, combines the output of models at layer 1 and adjusts the weight and biases to minimize the objective function, which is, in the present case, minimizing the MSE between observed and predictive values.

With this integration of different algorithms, DeepBoost leverages the advantages of layered network and boosting iterative techniques for providing more robust and scalable forecasting outcomes. This novel architecture of DeepBoost overcomes the limitations of the individual techniques and provides accurate fitting of the curve. The proposed DeepBoost is depicted in Fig. 3.

# Step 01	*Calling level 1 models: XgBoost, CatBoost and LSTM* *Training of level 1 models* *level 1= list ()* *level 1. append (XgBoost, CatBoost and LSTM)* *level 1. fit (training data)*
# Step 02	*Generating and storing intermediary forecasts* *intermediary_forecasts = []* *for each model in [level 1]:* *intermediary_forecasts. append (level 1. predict (training_data))*
# Step 03	*level 2 model: Linear Regression* *level 2 = LR ()* *level 2. fit (intermediary_forecasts, training_data)*
# Step 04	*Stacking level 1 and level 2* *model = StackingRegressor(estimators=level0, final estimator=level1)*
# Step 05	*forecasting of EVs charging station load* *output = model. predict (testing_data)*

Table 2
Hyper-parameters setting with defined search space.

Models	Hyper-parameters	Exploration space	Optimized setting
XgBoost	Estimators	[100, 200, 300]	200
	Learning rate	[0.01, 0.03, 0.1, 0.5]	0.5
	Tree method	[“gpu hist”, “approx.”]	“approx”
	Colsample bytree	[0.6, 0.8, 0.9, 1]	0.6
	Maximum depth	[6, 9, 12]	6
	Subsamples	[0.7, 0.8, 0.9, 1]	1
CatBoost	No. of estimators	[1000, 1250, 1500]	1000
	Maximum depth	[2, 4, 6, 8]	8
	Learning rate	[0.1, 0.3, 0.01, 0.05]	0.05
	L2 leaf regularization	[0.2, 0.5, 1, 3]	3
LSTM	No. of layers	[2, 3, 4, 5]	6
	Optimizers	[“Adam”, “RMSprop”, “SDG”]	Adam
	Learning rate	[0.0001, 0.001, 0.01, 0.1]	0.01
	No. of units	[32, 64, 96, 128]	128
	Dropout	[0.05, 0.1, 0.2]	0.2
	Batch size	[16, 32]	16

4.3. Hyper-parameters tuning

A random search algorithm optimizes the hyper-parameters of LSTM, XgBoost and CatBoosts. The random search algorithm involves the random sampling from the predefined search space set of the hyper-parameters. Unlike the grid search algorithm, in which every combination of the hyper-parameters is evaluated, the random search algorithm runs for the defined trails. In the proposed study, the random search algorithm is executed for 10 trials and during each trial, hyper-parameters are selected randomly and evaluated through MSE on the validation set. When the stopping criterion is met, the best combination of the hyper-parameters that record the lowest MSE is selected. Maximum depth, learning rate, number of estimators, subsamples, colsample bytree and tree method are XgBoost hyper-parameters optimized in this study. In the case of CatBoost, the number of estimators, L2 leaf regularization, number of iterations, maximum depth and learning rate are the hyper-parameters that were studied. The LSTM network parameters: units, optimizers, number of layers, learning rate, batch size and dropout are also optimized. Moreover, these parameters are optimized on the ACN dataset and these parameter settings are implemented for other datasets. Table 2 presents the hyper-parameters setting with defined search space.

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.

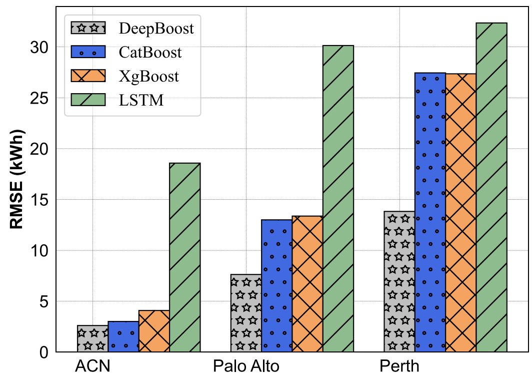
5. Results

Findings of DeepBoost and other models implemented for day-ahead EVs charging station load forecasting are reported in this section. Machine having specifications of Intel(R) 235Core (TM) i5-7200U CPU @ 2.50 GHz 2.71 GHz processor with “Python” language is used for simulation purposes. Table 3 findings indicate that the DeepBoost forecasts day-ahead charging station load with the least error for each dataset than other models. The RMSE, MAE, MSE and NRMSE of the DeepBoost are 2.61, 1.81, 6.82 and 0.39%, respectively, for ACN dataset. The proposed hybrid technique records RMSE, MAE, MSE and NRMSE of 7.63, 2.94, 58.29 and 0.39%, respectively, in case of Palo Alto charging station. The recorded values of RMSE, MAE, MSE and NRMSE for the Perth charging station dataset are 13.83, 8.04, 191.42 and 0.96%, respectively.

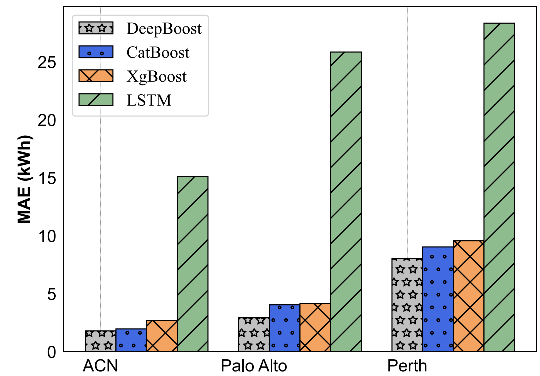
In Fig. 4, the bar plots depict the models' RMSE and MAE. Fig. 5 illustrates the charging load forecasted curves of the proposed DeepBoost and the measured curves. These graphical analyses demonstrate that the proposed DeepBoost outperforms other models in forecasting day-ahead charging station load.

Table 3
Model's error measurements.

Dataset	Model	RMSE (KWh)	MAE (KWh)	MSE $(KWh)^2$	NRMSE (%)
ACN	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
	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**
Palo Alto	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
	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**
Perth	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
	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**

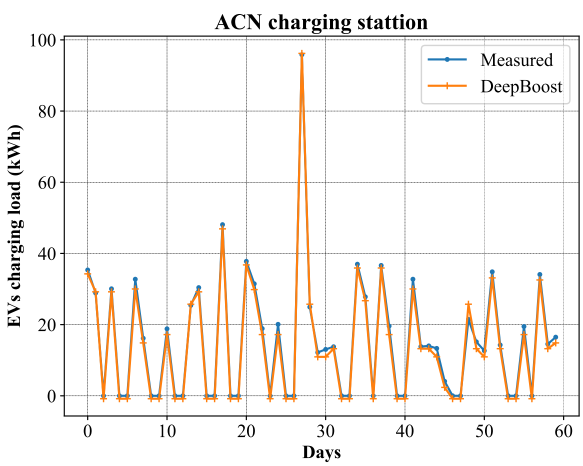


(a)

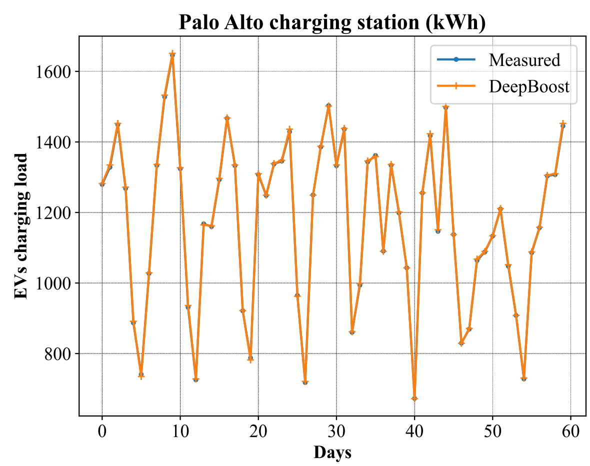


(b)

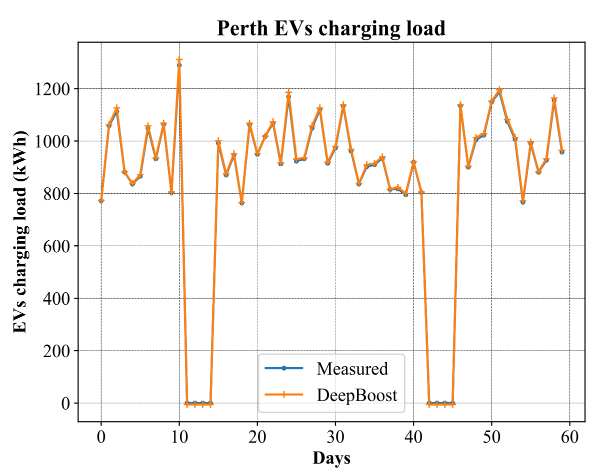
Fig. 4. Errors demonstration through bar plots. (a) RMSE (b) MAE.



(a)



(b)



(c)

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

5.1. Literature comparison

Comparative analysis of the DeepBoost approach with the techniques for day-ahead forecasting of EVs charging station load already reported in the existing is performed for generalizability purposes. In [28,34,50,51]. the GRU, LSTM-BDL, LSTM-EMD and seq-seq attention LSTM networks are proposed for forecasting ACN load data, respectively. In Table 4, the DeepBoost is compared with these models for forecasting the day-ahead charging load of ACN. The authors in [50] proposed a conventional GRU network for the dataset of ACN.

Table 4
DeepBoost comparative analysis with existing techniques.

Ref	Journal	Dataset	Model	RMSE (KWh)	MAE (KWh)
[50]	Electronic	ACN	GRU	60.53	46.83
[28]	Energies	ACN	LSTM-BDL	4.367	2.782
[51]	Forecasting	ACN	LSTM-EMD	8.93	–
[34]	IEEE Transactions on Intelligent Transportation Systems	ACN	seq-seq attention LSTM	19.70	10.33
–	–	ACN	**DeepBoost**	**2.61**	**1.81**

The proposed model achieved a RMSE and MAE of 60.53 and 46.83, respectively. To improve the forecasting output of the deep learning network, the authors in [34,51] presented hybrid methodologies by combining LSTM with attention mechanisms and decomposition strategies, respectively. The attention mechanism in [34] enables the network to focus on the most relevant information in the long sequence of events, improving the performance of LSTM. The authors in [51] employed data preprocessing strategies using EMD and K-mean clustering for the data decomposition and removal of the outlier. The LSTM model, when trained with the preprocessed data, reported better performance. In [28], the authors implemented Bayesian theory for initializing weights and biases of the LSTM network. The proposed methods initialized with Bayesian theory recorded RMSE and MAE of 4.367 and 2.782, respectively. Compared to these reported techniques, the proposed DeepBoost reported superior performance. Integrating parametric and non-parametric techniques enables DeepBoost to learn data patterns effectively. For the ACN dataset, the DeepBoost recorded RMSE and MAE of 2.61 and 1.81, respectively, outperforming the existing techniques.

6. Discussion

The study findings reveal that the proposed DeepBoost algorithm outperforms different state-of-the-art DNNs and the models reported in the literature for day-ahead EVs charging station load forecasting. The proposed DeepBoost approach leverages the advantages of DNN, ensemble approaches and LR model. Integrating different approaches enables the DeepBoost algorithm to learn the hidden temporal patterns of the dataset more effectively. The holistic DeepBoost approach combines the parametric and non-parametric techniques, overcomes the individual models' shortcomings, processes the nuanced relationship among the data points effectively, and provides accurate fitting of the day-ahead EV charging station load curve. However, the DeepBoost approach poses computational challenges due to the integration of different techniques in its architecture. A parallel processing technique can be used to ensure the scalability of DeepBoost. With parallel processing, extensive datasets can be handled efficiently. Moreover, the proposed approach can also integrate with distributed computing frameworks like "Apache Spark". These frameworks process the big data with reduced computational burdens.

The proposed DeepBoost demonstrates superior performance compared to state-of-the-art methodologies. However, it is important to acknowledge the real-time implementation challenges and limitations of this study. The real-time application of DeepBoost poses challenges related to latency and data pipelines for the continuous input of the data. The DNNs have more computational burden than the GBDT algorithms. The integration of the LSTM network in the DeepBoost technique can introduce delays. Models pruning and quantization are needed to optimize the inference time. This helps overcome the latency of generating forecasts. For real-time applications, efficient data pipelines are also required for the continuous inflow of data and its processing. Tools like "Apache Kafka, and Apache Flink" can be used for this purpose. Moreover, updating the model's parameters in a dynamic environment is critical. The open machine learning tools with data pipelines enable the model to adapt to changes regarding data pattern variations.

This study focuses on univariate forecasting with the exclusion of external factors. However, external factors like weather conditions and market regulations may affect EVs charging load pattern. In the future, we aim to extend the study by incorporating the external factors and scheduling the EVs charging activities based on the forecasted load. This extension provides an advancement in developing sustainable EVs charging infrastructure.

7. Conclusions

This study presented a novel DeepBoost approach for the more accurate forecasting of day-ahead EVs charging station load. The proposed holistic method is the combination of classical models, LR, DNN and GBDT algorithms. The proposed DeepBoost consists of CatBoost, XgBoost, LSTM as level 1 learner and LR model as level 2 learner. The DeepBoost approach leverages the advantages of different techniques in learning the data pattern. This holistic combination of the models overcomes the shortcomings of the individual networks in processing the temporal dependencies of the data. For the generalizability and robustness, the study is conducted for three different datasets. The extensive comparative analysis proves the superiority of DeepBoost technique over the individual models of CatBoost, XgBoost, LSTM and Informers and different hybrid methodologies of deep learning networks. Findings report that the MAE of the DeepBoost is improved by 9.4%, 32.7% and 88% as compared to CatBoost, XgBoost and LSTM networks, respectively, for the ACN dataset. In the case of Palo Alto dataset, the MAE of the proposed method improves by 27.6%, 29.7% and 88.6% as compared to CatBoost, XgBoost and LSTM models. Furthermore, the robustness of the DeepBoost approach for day-ahead EV charging station load forecasting is also highlighted through the literature comparison where DeepBoost outperforms the techniques which are reported in the literature.

For real-world applications, the proposed DeepBoost helps in optimizing energy scheduling. The accurate load projection helps in grid operations in terms of unit scheduling which leads to grid stability and reduces operational costs.

CRediT authorship contribution statement

Joveria Siddiqui: Writing – original draft, Methodology, Visualization, Software, Investigation, Formal analysis, Data curation, Conceptualization. **Ubaid Ahmed:** Writing – original draft, Methodology, Visualization, Software, Investigation, Formal analysis, Data curation, Conceptualization. **Adil Amin:** Writing – review & editing, Supervision, Resources, Investigation, Formal analysis, Conceptualization. **Talal Alharbi:** Writing – review & editing, Validation, Resources, Funding acquisition, Data curation. **Abdulelah Alharbi:** Writing – review & editing, Validation, Resources, Funding acquisition, Data curation. **Imran Aziz:** Writing – review & editing, Validation, Software, Resources, Data curation. **Ahsan Raza Khan:** Writing – review & editing, Software, Project administration, Investigation, Formal analysis, Conceptualization. **Anzar Mahmood:** Writing – review & editing, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The datasets and code files are available at the github repository: https://github.com/Ubaid014/DeepBoost-for-EVs-charging-station-load-forecasting.

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