Short-Term Forecasting of Electric Vehicle Load

Subjects: Others

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Electric vehicles (EVs) are inducing revolutionary developments to the transportation and power sectors. Their innumerable benefits are forcing nations to adopt this sustainable mode of transport. Governments are framing and implementing various green energy policies. Nonetheless, there exist several critical challenges and concerns to be resolved in order to reap the complete benefits of E-mobility. The impacts of unplanned EV charging are a major concern.

electric vehicles forecasting ARF SVR LSTM

1. Introduction

Global warming has been a pressing concern across the world over the last few decades. The main contributions toward global warming come from the transportation sector. Khurana et al. [1] found that China emits almost 25.9% of greenhouse gases (GHGs), followed by the USA with 13.87%, and India with 7.45%. The Paris Agreement of 2015 demands that all countries reduce their vehicle emissions with a view to protect the environment [2]. Around the globe, governments are aggressively implementing measures to reduce greenhouse gases and encourage green energy systems [3][4][5][6]. De-carbonizing the transportation industry can significantly reduce greenhouse emissions and help in attaining the green energy goal.

EVs are revolutionizing the transportation sector. The benefits offered to society by EVs are tremendous. Along with significant reductions in carbon emissions, the low cost of operation, energy efficiency, and easy integration with renewable sources of energy are the major benefits [7][8][9][10][11]. The introduction of smart grid systems and their widespread acceptance has given new directions to EVs. Some EVs can also provide various ancillary services, collectively called vehicle-to-everything, consisting of vehicle-to-grid, vehicle-to-device, vehicle-to-home, etc. Such EVs, known as gridable electric vehicles (GEVs) also create many research opportunities and developments in the energy and power sectors [12][13][14].

The success and implementation of the above developments in the transportation and power sectors require proper planning and management. Like any other technology, even with all the benefits, there are concerns and challenges regarding the implementation and adoption of EVs in society. Charge scheduling problems, charging infrastructure requirements, range anxiety, cost of ownership, sophisticated communication requirements, and consumer ignorance are the critical factors delaying the adoption of EVs [15][16][17][18]. Among the above concerns, the charge scheduling of EVs is the prime focus. Studies show that EV sales increased considerably in 2020. By 2030, globally, EVs will account for almost 50% of all cars on the road [19]. A large increase in the number of EVs will adversely affect the utility grid by causing frequency and voltage fluctuations, unexpected peaks, and an overall rise in energy demand. Also, the uncoordinated charging of a large number of EVs simultaneously can even cause power shutdowns.

2. Short-Term Forecasting of Electric Vehicle Load Using Time Series, Machine Learning, and Deep Learning Techniques

The impacts of EV charging on various aspects in the distribution grid are discussed in [20][21][22][23][24][25][26]. The adverse effects of EV penetration can be remedied through proper scheduling, clustering, and forecasting measures [27]. Scheduling helps decrease the burden on the grid by moving EV charging to light-load hours. Clustering is a technique to discover the most common, similar, and repeating events. The clustering strategy, applied to EV charging data, helps identify groups of similar charging objects. By clustering the data for a period (e.g., a week, a month, or a year), patterns for different charging behaviours can be understood. Accurate and efficient EV load forecasting is critical for grid development decisions. It also helps in the prevention of faults and network stability.

Sharma et al. [28] discussed the impact of plug-in electric vehicles (PEVs) in unbalanced residential distribution systems. Their work showed that the uncontrolled charging of EVs can lead to an increase in feeder current and peak demand and result in low voltage at nodes. The authors also proposed a smart distribution power flow (SDPF) model for calculating the schedules for smart charging. Various schemes for uncontrolled and controlled charging are also compared in the work. The literature by Masoum et al. [29] is directed toward the loading and stress on distribution transformers due to PEV penetrations. The authors studied the various loading scenarios of the transformers, and a coordination scheme to evaluate the stress on the distribution transformers in residential networks was designed. By controling the rate of EV charging, high penetration levels can be accommodated in the existing systems [30]. The charging rate for each EV was decided using the linear programming method, with an objective to maximize the overall energy given to the EVs. Clement-Nyns et al. [31] agree upon the impacts on the grid due to uncoordinated charging and emphasize the need for coordinated charging. A coordinated strategy to minimize voltage fluctuation and power loss is proposed. Quadratic and dynamic programming techniques are employed, among which the best results are obtained using quadratic programming.

With regard to the above concerns, forecasting the EV/PEV charging load is imperative. Several studies are currently being conducted on forecasting the charging demand of individuals and fleets of EVs. Demand forecasting can be broadly divided into three groups: short-term load forecasting (STLF), medium-term load forecasting (MTLF), and long-term load forecasting (LTLF). STLF refers to the forecasting of charging demand for a short period, which can be from a few hours up to one week. This is very crucial for the next-day operation knowledge. MTLF is the load prediction from a week to a year and helps in system planning, system maintenance planning, etc. LTLF refers to the forecasting of EV charging load for several years in advance. Management decisions related to infrastructure investments and additional power generation facilities depend on LTLF. Considering the stochasticity in the EV charging process, LTLF has more challenges; hence, researchers have seen less accuracy for LTLF, compared to STLF [27][32].

Load forecasting techniques for EVs are of multiple types: mathematical modeling techniques, statistical methods, and AI methods [33].

Mathematical Modeling Techniques:

In [34], the authors propose a model using fluid dynamic traffic model and M/M/s queuing theory. Here, the first ‘M’ indicates the Poisson distribution of vehicle arrival at the charging station. The second ‘M’ indicates the time taken to charge each EV. Thirdly, ‘s’ indicates the number of charging pumps in a station. The traffic model is used to predict the entry of EVs to a charging station. The queuing theory predicts the charge requirement. This model very well captures the EV charging dynamics. In [35], a Monte Carlo model is employed for EV load forecasting in China. The charging period is determined based on the probability distribution. Charging time is calculated depending on the state of charge (SoC), charging methods, and the needs of various types of vehicles. The initial charging point is decided using the Monte Carlo method. Shao et al. [36] propose another probability modeling-based forecasting technique. This consists of an origin–destination analysis, followed by the Monte Carlo method for estimating the EV charging characteristics for a day. A Baskett-Chandy-Muntz-Palacios (BCMP) queuing model is proposed in [37] to evaluate the demands from multiple stations. The model is validated using real vehicle traffic statistics. All the mathematical models have uncertainties in some or the other factors, which makes the results unreliable.

Statistical Methods:

Several statistical methods, including regression, exponential smoothing method, etc., are discussed in the literature. An autoregressive integrated moving average (ARIMA) model is proposed in [38]. EV demand and electrical load demand are simultaneously forecasted. The model inputs distances and daily driving patterns and determines the charging load profiles. Louie [39] proposes a time series seasonal ARIMA model for forecasting aggregated demand at EV stations, using two years of data from over 2400 charging stations.

AI Methods:

AI-based methods are extensively used in forecasting applications. The suitability of AI techniques in various forecasting applications is explained in [40][41][42]. The superior performance of an artificial neural network (ANN) for forecasting applications, compared to conventional methods, is discussed in [43]. Arias and Bae [44] present a model of the hourly traffic and weather information in South Korea. The proposal includes cluster analysis, relational analysis, and classification. Cluster analysis identifies patterns in the traffic; relational analysis assesses the various influencing components; and finally, the decision tree model is used for classification. The validation of the model conducted on real-world scenarios is also presented in their work. Another short-term load forecasting model is discussed in [45]. This work uses a time series reconstruction technique followed by support vector regression

(SVR) using EV data from Jiang Su, China. The method shows good prediction results compared to the conventional SVR method.

Majidpour [46] proposes two forecasting methods: modified pattern sequence forecasting (MPSF) and time weighted dot product nearest neighbor (TWDP NN). Data collected from the UCLA campus, parking lots, and PV panels were used. On account of the speed of prediction, TWDP NN performed better, by decreasing the processing time by one-third. Majidpour et al. [47] employ three algorithms, k-Nearest Neighbor (kNN), ARIMA, and pattern sequence sorecasting (PSF), for modeling and forecasting EV charging demand using the UCLA campus data. Using error metric, symmetric mean absolute percentage error (SMAPE), kNN with k = 1, performs better than the other two methods. PSF is found to have the worst performance. Therefore, MPSF is designed to combine NN and PSF, for which a better performance is obtained. Three supervised ML-based forecasting models are compared in [48]. Random forest, XGBoost, and support vector machine are the models used. Public charging data from Nebraska, USA, collected over seven years are used. Results show that XGBoost is superior to other techniques in EV load demand prediction.

Kumar et al. [49] use ANN to forecast the charging demand of a building. The model uses initial and final SoC and earlier charging behaviours for demand prediction. Further EV scheduling is also demonstrated using the charging profiles and the predicted demand.

EV load forecasting using LSTM has attracted many research possibilities. Various LSTM models, univariate and multivariate, have shown superior performance compared to ML models. Among LSTM models, multivariate LSTM models, considering features like wind speed, temperature, and humidity, show better performance than univariate ones [50][51]. Elahe et al. [52] study in detail the various possible factors impacting the charging load, like weather, calendar, and seasons, and use five DL models for forecasting. LSTM, Bi-LSTM, CNN-LSTM, ConvLSTM, and GRU are the models studied and performance evaluated.

A unique DL approach using a transformer, which is an attention-based model using an encoding-decoding structure, is mentioned in [53]. Model performance is compared against the methods, ARIMA, SARIMA, recurrent neural network (RNN), and LSTM. Test results demonstrate excellent prediction capabilities for the transformer model, with low training error and faster convergence. A 2D dilated causal convolution neural network is discussed in [33]. The model performance is contrasted with a ConvLSTM model, and the improved accuracy is evident in the test results.

Various hybrid forecasting techniques are also discussed in the literature. Li et al. [54] propose a model employing a convolutional neural network (CNN) and lion algorithm. A variety of features are employed for forecasting the demand, including the type of day, weather, season, and temperature. Load that occurred at the same time for the last five days is also considered. The model has improved stability and accuracy for STLF. Also, test results highlight the model performance in terms of prediction precision.

Wavelet neural network (WNN), a combination of wavelet theory and NN, is used in many fields, including forecasting [55][56][57]. Several exogenous factors influencing the power consumption of electric buses (EBs) are analyzed using gray relational analysis (GRA), and a forecasting model using WNN is developed [57]. The model is validated on real electricity consumption data of EBs in Baoding. Lei et al. [58] propose another wavelet-based technique for the short-period forecasting of EB charging stations' demand.

A multiple decomposition model for EV fleet charging is discussed in [59]. The technique uses swarm decomposition (SWD) and complete ensemble empirical mode decomposition adaptive noise (CEEMDAN) method. The forecasting models used are multi-layer perceptron (MLP), LSTM, and bidirectional LSTM (Bi-LSTM). The method demonstrated good performance with a coefficient of determination (R2R2) value of 0.9766.

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