Machine Learning Methods to Predicting Electric Vehicle Charging Behavior

## Introduction

The automotive industry is undergoing a profound transformation, driven by the rapid growth of electric vehicles (EVs). In 2021, global EV sales reached a new peak, doubling from the previous year to a record 6.6 million units. This surge in EV demand has been accompanied by a swift expansion of the necessary charging infrastructure, with the number of chargers installed worldwide reaching 1.8 million by the end of 2021, including a 37% increase in public charging stations[1]. Electric vehicles have emerged as a promising solution to the environmental challenges posed by the transportation sector, since EVs have the potential to reduce carbon emissions by up to 45% compared to conventional internal combustion engine (ICE) vehicles[2].

Despite the promising advancements, several challenges remain. Most EVs require lengthy charging times, causing significant inconvenience, and many EV owners lack the ability to charge their vehicles at home, relying on public charging stations[3], [4], [5]. The high-power demands of EVs, when integrated on a large scale, will place substantial constraints on the power distribution grid, potentially leading to further degradation and instability. The power limitations make it virtually impossible to increase charging station capacity to meet the growing demand. In contrast to conventional gas stations, where refueling takes minutes, EVs often require hours to recharge. Deploying more charging stations is not a feasible solution, as this is limited by both power requirements and physical space constraints. Therefore, the optimal approach lies in better managing the scheduling of existing charging infrastructure to ensure the efficient and reliable operation of the distribution grid.

Advancements in battery capacity and fast charging enhance EV convenience, but also strain electricity grids. To address the challenges posed by the large-scale integration of EVs, researchers have turned to data-driven approaches, leveraging the power of big data analytics and machine learning (ML) techniques. By analyzing historical data on charging load and user behavior, ML algorithms can be trained to identify patterns and trends, enabling accurate predictions of future charging behavior[6], [7], [8]. These predictions can then be utilized to enhance EV charging scheduling strategies, optimizing the utilization of the existing infrastructure, and mitigating the strain on the power grid.

Traditional methods, such as qualitative studies and modeling simulations, have limitations in integrating their findings into practical applications[9]. In contrast, ML-based models can incorporate a wider range of variables, including weather conditions and traffic patterns, to provide more accurate forecasts of charging behavior. These data-driven approaches have the potential to revolutionize the management of EV charging, ensuring efficient and sustainable integration of electric vehicles into the transportation ecosystem.

This review aims to explore the various machine learning techniques that have been employed to address the challenges surrounding EV charging behavior. By delving into the current state of the art, the review will provide valuable insights into the potential of ML-based solutions to optimize the integration of electric vehicles and support the transition towards a more sustainable transportation future.

## Machine Learning Approaches

Traditional machine learning methods, particularly supervised learning methods, have been extensively utilized in predicting charging behaviors. In supervised learning, labeled training datasets are employed to train ML models. Predicting session duration and energy consumption are two tasks that have been extensively researched. Xiong et al. [10] utilized linear regression (LR) to predict the start time, end time, and energy consumption of charging sessions. In [11], the authors employed Gaussian mixture models (GMM) to predict session duration and energy consumption, achieving symmetric mean absolute percentage errors (SMAPEs) of 14.4% and 15.9%, respectively. [12] also studied the problem using support vector regression (SVR), random forest (RF), and diffusion-based kernel density estimator (DKDE) combined to form an ensemble model, yielding better results with SMAPEs of 10.4% and 7.54%, respectively. Majidpour et al. [13] used k-nearest neighbor (KNN) to predict energy consumption at a charging outlet. The model achieved its best performance with a SMAPE of 15.27% when k equals 1. The algorithm pattern sequence-based forecasting (PSF) was applied with KNN in [14], optimizing the results to a SMAPE of 7.85%. Other charging behaviors have also been studied. To predict EV charging departure time, Frendo et al. [15] and Xu [16] utilized XGBoost [17] and support vector machine (SVM), respectively.

Another traditional machine learning method is unsupervised learning, which trains models without labels in the datasets. Since data labeling is time-consuming and costly in many practical applications, unsupervised learning is an effective approach to address the problem. Most studies use unsupervised learning methods to cluster charging behaviors. Helmus et al. [18] identified 13 distinct clusters of charging behavior using GMM, revealing that daytime and overnight charging were the most significant distinctions among all types of charging sessions. GMM was also used in [19], where it created EV profiles that captured charging behavior from existing data. Several studies have employed the K-means algorithm. Xiong et al. [20] categorized user charging behavior into four groups using K-means clustering with the Euclidean distance cost function, then used artificial neural network (ANN) to classify user behavior. The authors of [21] applied a similar approach but used KNN for user behavior classification, achieving 97.9% accuracy and an area under the ROC curve (AUC) value of 0.994. The work [22] also used k-means clustering with the squared Euclidean distance cost function to obtain six clusters, then used KNN to predict the future instance category, achieving a precision of 0.5 and a recall of 0.47.

Deep learning (DL) models are becoming increasingly popular and are widely used to solve problems in various areas, yielding excellent results. The ANN used by Xiong et al. [20] achieved an accuracy of 78% in predicting charging behavior. The work [23] predicted the hourly charging load using multiple recurrent neural networks (RNN)-based models, including RNN, long short-term memory (LSTM), and gated recurrent units (GRU), with the best model achieving a normalized Root mean square error (RMSE) of 2.89%. Yi et al. [24] used the Sequence to Sequence (Seq2Seq) model to forecast monthly commercial EV charging demand. Their study demonstrates that the Seq2Seq model outperforms traditional time-series and machine learning models, particularly for multi-step ahead predictions, achieving a Mean Absolute Error (MAE) of 10.6 and an RMSE of 14.73. [25] also addressed the challenge of accurately predicting electric vehicle (EV) charging station loads. The authors propose a Bayesian deep learning approach that employs an LSTM network combined with Bayesian probability theory to capture the uncertainty inherent in EV charging behavior. Their method outperforms traditional forecasting techniques, including support vector regression and quantile regression, in terms of accuracy and reliability.

## Conclusion

In conclusion, machine learning techniques have demonstrated significant potential in addressing the challenges associated with electric vehicle (EV) charging behavior. The review has highlighted the effectiveness of traditional machine learning methods, such as supervised and unsupervised learning, especially the increasing popularity and widespread adoption of deep learning approaches in recent years. Their ability to capture complex patterns and handle large datasets makes them well-suited for this task. These advanced algorithms have shown remarkable accuracy in predicting various aspects of EV charging behavior, ultimately contributing to the optimization of charging scheduling and the alleviation of strain on the power grid. As the EV market continues to expand, the integration of these data-driven solutions will be essential in ensuring efficient and sustainable management of charging infrastructure, supporting the transition towards a more environmentally friendly transportation future.

## Reference

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