

Predicting Electric Vehicle Demand for Charging Stations: Time Series and Machine Learning Approaches

Farnoosh Roozkhosh, Angela Yao

ABSTRACT: Although the global surge in electric vehicles (EVs) is expected to curb greenhouse gas emissions, it presents a significant challenge: the strategic allocation of charging infrastructure. Accurately forecasting EV demand for charging stations is critical to optimizing their placement, planning capacity, and ensuring a seamless charging experience. This paper presents a comprehensive study focused on predicting EV charging station demand, leveraging a robust dataset comprising temporal EV registration data, charging connector types, and geographic information on charging station locations.

Using time series forecasting models and machine learning algorithms, this research aims to enhance the precision and reliability of demand predictions. Specifically, Long Short-Term Memory (LSTM) and vector autoregressive (VAR) models are utilized to capture the temporal dynamics inherent in EV demand patterns. Additionally, the study harnesses the capabilities of machine learning algorithms, such as Random Forest and XGBoost, to uncover intricate relationships between features and address non-linear demand variations. To evaluate model performance, metrics like Mean Absolute Error and R Squared are employed to assess predictive accuracy.

KEYWORDS: electric vehicles; charging infrastructure; demand prediction; time series forecasting; machine learning algorithms

Research Questions

1. How do the registration patterns of electric vehicles (EVs) vary across various connector types (Tesla and Non-Tesla), seasons, and geographical regions?
2. In what ways do the distribution of charging stations and socioeconomic factors interplay to influence future EV registrations for different connector types in the next time epoch?
3. What models demonstrate superior performance in forecasting the demand for EV charging stations?

Introduction

Road transportation powered by fossil fuels is to blame for rising oil demand worldwide and air pollution, particularly in cities. Potential remedies for these problems include emerging vehicle technology like electric vehicles (EVs), which can run on alternate fuels (Shahraki et al., 2015). Several research has been undertaken to predict demand for EV charging stations. Wang et al., 2023, developed a Long Short-Term Memory (LSTM) neural network to predict the EV charging demand at the station level for the next few hours (e.g., 1–5 h), using a unique trajectory dataset containing over 76,000 private EVs in Beijing in January 2018. Yi et al., 2022, proposed a time-series forecasting of the monthly commercial EV charging demand using a deep learning approach-Sequence to Sequence (Seq2Seq). On the other hand, the impact of meteorological factors such as temperature, humidity, rainfall, and weather conditions (Arias and Bae, 2016; Yan et al., 2020; Zhang, Liu and Ge, 2022), socioeconomic factors (Li, Chen and Wang, 2017; Elkamel et al., 2020) in predicting the demand for EV charging stations were studied in several papers. Notably, despite these efforts, studies considering the influence of EV charging station accessibility on demand prediction remain scarce. Furthermore, this study uniquely categorizes EV charging connector types into Tesla and non-Tesla categories, (a distinction further explained in the Connector Types section), aiming to explore their role in predicting EV charging station demand. This study aims to centre on the seasonal forecasting of Electric Vehicle (EV) charging demand, targeting both Tesla and non-Tesla EVs. It plans to explore the predictive impact of two key categories: the accessibility of EV charging stations and various socioeconomic factors at the county level. These socioeconomic aspects encompass a wide range of metrics, including median income, the percentage of the population below the poverty line, home ownership rates, the proportion of the Black Population, overall population figures, demographic distribution (including percentages of the female population), employment rates, and the concentration of the young population. By integrating these factors into the analysis, the research seeks to provide a comprehensive understanding of how seasonal variations in EV charging demand for both Tesla and non-Tesla vehicles relate to accessibility to charging infrastructure and socioeconomic circumstances at the county level. The study's procedure involves: 1) Assessing accessibility to Tesla and non-Tesla charging stations across seasons. 2)Developing time series and machine learning models incorporating socioeconomic

factors and accessibility. 3)Analysing the performance of these models to forecast EV charging demand.

Method

The primary objective of this research is to forecast the future demand for Electric Vehicle (EV) charging stations across various connector types (Tesla and Non-Tesla). This prediction is based on EV registration data, charging station locations, and several key socioeconomic factors at the county level, encompassing median income, percentage of population below the poverty line, home ownership rates, percentage of Black Population, overall population, demographic distribution including percentages of female population, employment rates, and young population, and the accessibility to EV charging stations across different seasons.

To accomplish this objective, the study initially evaluates the accessibility of EV charging stations for both Tesla and Non-Tesla EVs during various seasons spanning from 2018 to 2023. Subsequently, leveraging pertinent socioeconomic indicators and charging station accessibility metrics, the study employs a suite of predictive models such as time series models (Long Short-Term Memory (LSTM), vector autoregressive (VAR) models), and machine learning algorithms (Random Forest and XGBoost). These models are used to anticipate EV registration data for forthcoming seasons, which serves as a proxy for estimating demand within this research. The diagram below illustrates the methodology employed in this paper's research process: (Figure 1).

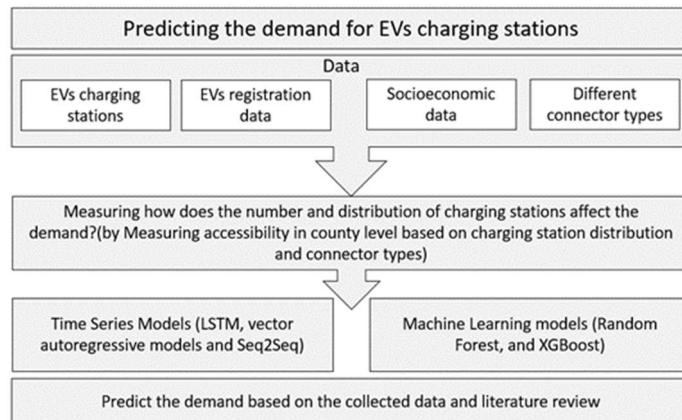


Figure 1: Research framework

Measuring Accessibility

In this research cumulative accessibility is used to measure accessibility of Tesla and non-Tesla EV charging stations at the county level (equation, 1).

(1)

$$A_i = \sum_{j=1}^J B_j O_j$$

where cumulative accessibility A_i means accessibility measured from a given point/zone i (in our article it is the centroids of each counties) to activities O_j (in our article it is the number of charging stations), where B_j takes the binary value of 1 if the place of residence is within a predefined time threshold (15 KM in our research, which is EVs accessible threshold) and 0 if it is beyond the time threshold. Figure 2 illustrates accessibility of Tesla and non-Tesla EV charging stations in county level in 2023.

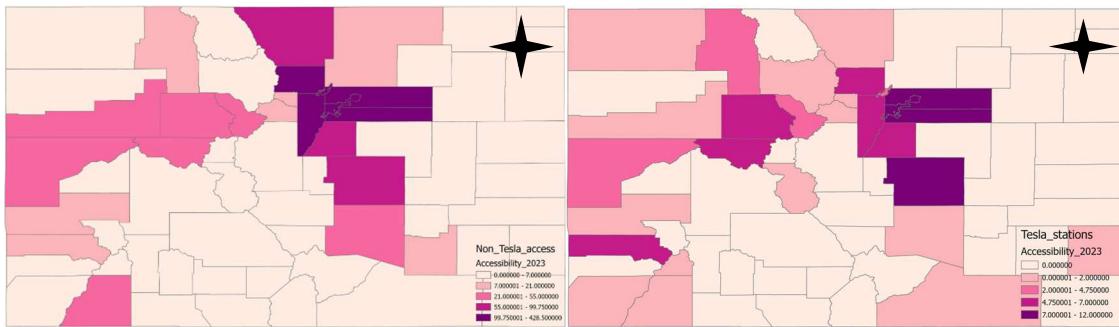


Figure 2: Accessibility of Tesla and non-Tesla EV charging stations in county level in 2023

Discussion and result

Random forest and XGBoost models

Here we have the visualization results of random forest and XGBoost models, which compares predicted results verses actual results for both Tesla and Non-Tesla EV demand predictions. Figure 3 shows that both Random Forest and XGBoost models perform well, predicting demand considering socioeconomic factors and accessibility to EV's charging stations.

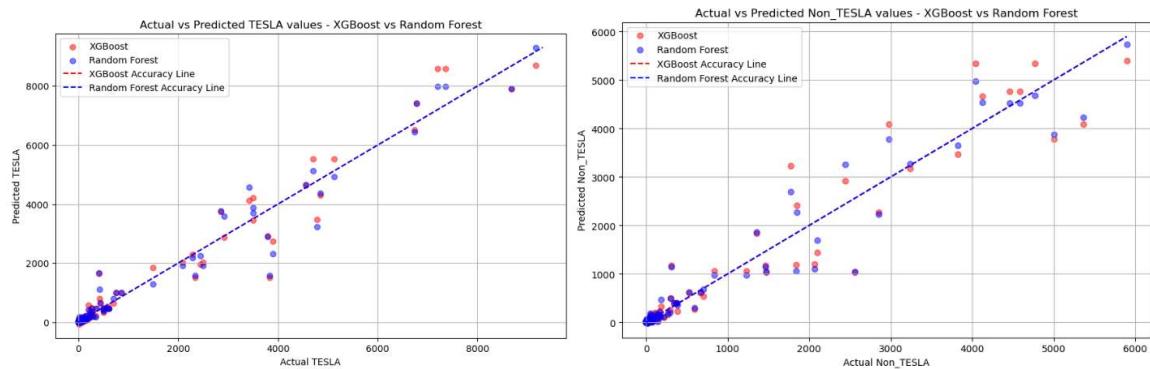


Figure 3: Random Forest and XGBoost models prediction verses actual for both Tesla and Non-Tesla EVs.

Time series models

LSTM: Figure 4 displays the comparison between the actual and predicted outcomes generated by LSTM for training data for both Tesla and non-Tesla EV charging station demands.

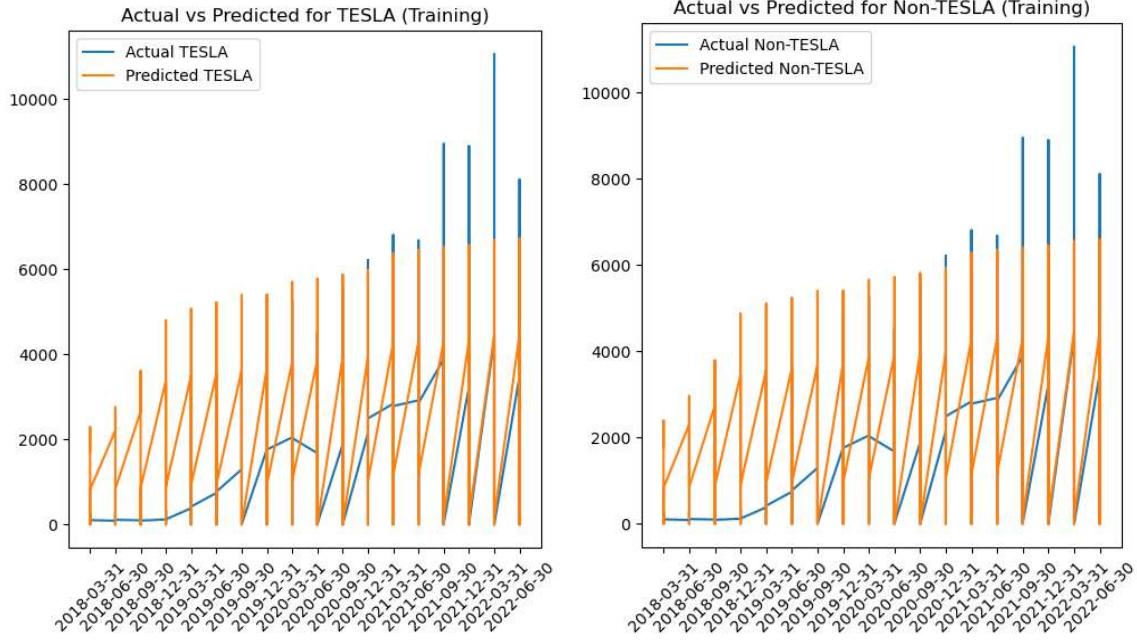


Figure 4: LSTM model predicted verses actual data for both Tesla and non-Tesla EV charging stations demand.

VAR: The VAR model was employed to generate lag features for both Tesla and non-Tesla variables at different time lags (1, 4, and 8 quarters). Figure 5 illustrates the comparison between the actual and predicted outcomes generated by VAR for training data for both Tesla and non-Tesla EV charging station demands.

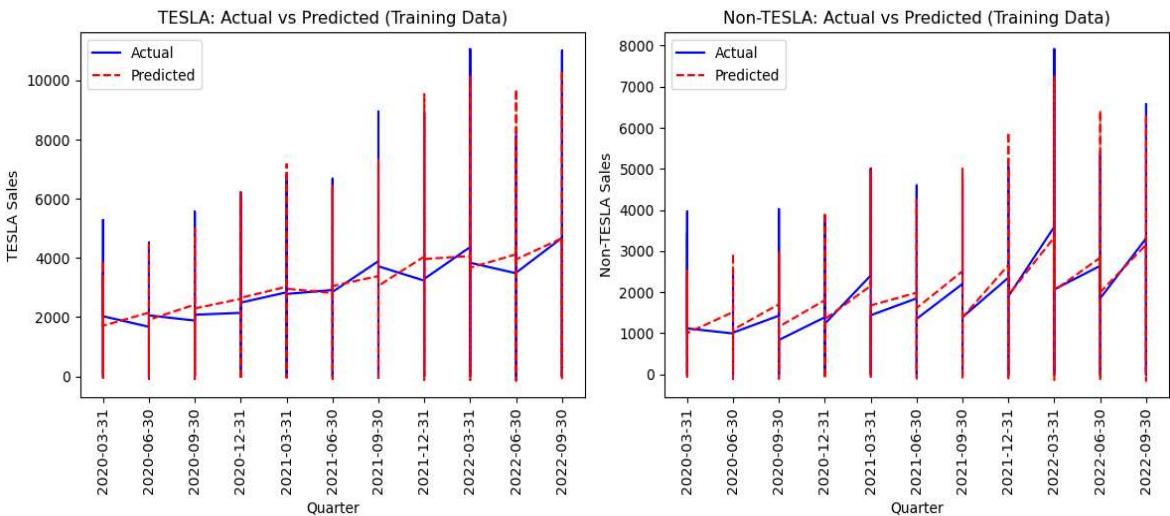


Figure 5: The VAR model predicted verses actual data for both Tesla and non-Tesla EV charging stations demand.

Table 1 shows a summary of different model's accuracy evaluation.

Table, 1. Summary of model's accuracy evaluation

<i>Model</i>	<i>Tesla R-squared</i>	<i>Tesla MSE</i>	<i>Non-Tesla R-squared</i>	<i>Non-Tesla MSE</i>
Random Forest	0.99	26440.37	0.98	14889.60
XGBoost	0.99	13811.80	0.99	7290.65
LSTM	0.65	847254.24	0.64	870450.90
VAR	0.98	82001.27	0.97	46402.04

Conclusion

Upon comparing the results across various models used for predicting demand in both Tesla and non-Tesla EV charging stations, it becomes evident that the XGBoost model performed notably better than other models in this context. The XGBoost model consistently exhibited higher R-squared values and lower Mean Squared Error (MSE) across both Tesla and non-Tesla stations compared to the Random Forest, Long Short-Term Memory (LSTM), and Vector Autoregression (VAR) models. For Tesla stations, both Random Forest and XGBoost models demonstrated high accuracy, yet the XGBoost model consistently outperformed the Random Forest model with substantially lower MSE and slightly higher R-squared values. Similarly, for non-Tesla stations, the XGBoost model showcased superior accuracy by achieving higher R-squared values and significantly lower MSE compared to the Random Forest model. In summary, based on the evaluation metrics observed, the XGBoost model emerges as the more effective and accurate model for forecasting demand in both Tesla and non-Tesla EV charging stations, showcasing superior predictive capabilities compared to the other models considered in this study.

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Farnoosh Roozkhosh, PhD student, Department of Geography, University of Georgia, Athens, GA 30602

Angela X Yao, Professor, Department of Geography, University of Georgia, Athens, GA 30602