

A Review On Machine Learning Models For Estimating EV Charging Demand

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Abstract- Machine Learning and Data Analytics are extensively used for optimizing the performance of electric vehicles. As electric vehicles (EVs) become more prevalent globally, the need for efficient infrastructure planning and energy management grows. One critical aspect of this transition is accurately estimating EV charging demand, which is vital for grid stability, charging station placement, and energy cost optimization. Traditional forecasting methods often fall short due to the complex and dynamic nature of EV usage patterns. Machine learning (ML) offers a promising solution by leveraging historical and real-time data to make accurate and adaptive demand predictions. This paper presents a comprehensive review on multiple machine learning models which are extensively used for Estimating EV Charging Demand. The analysis of the benchmark models would allow researchers in developing an optimized data driven model with the objective of attaining high accuracy.

Keywords- Machine Learning, Electric Vehicles, EV Charging Demand, Demand Forecasting, Regression Analysis.

I. INTRODUCTION

Many countries are implementing stringent emission regulations and providing subsidies, tax benefits, and other incentives to both consumers and manufacturers, encouraging the shift from internal combustion engine vehicles to electric alternatives. Besides, advancements in battery technology are significantly enhancing the range, performance, and affordability of EVs. Innovations such as solid-state batteries and improvements in lithium-ion batteries are reducing costs and increasing energy density, making EVs more appealing to consumers [1].

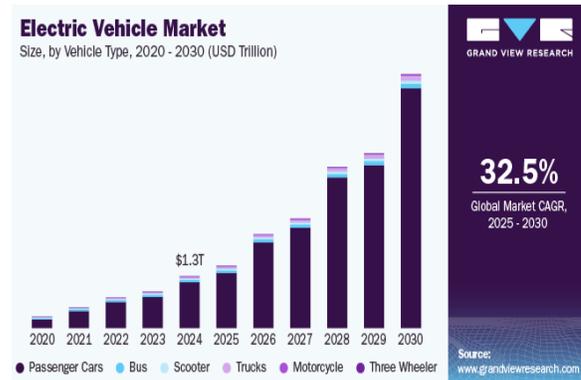


Fig.1 Forecasts and CAGR of EV Market

(Source: <https://www.grandviewresearch.com/industry-analysis/electric-vehicles-ev-market>)

Figure 1 depicts global EV market with estimated CAGR. The expansion of the transportation and logistics sectors significantly drives the rising demand for EVs. As global trade and e-commerce continue to surge, there is an increased need for efficient and sustainable transportation solutions. Electric vehicles offer a promising alternative to traditional internal combustion engines, as they produce lower emissions and reduce operational costs [2]. This shift is particularly evident in urban areas where delivery services are increasing, and the need to mitigate air pollution is critical. Consequently, logistics companies are increasingly integrating electric vans and trucks into their fleets, driven by both regulatory pressures and the economic benefits of lower fuel and maintenance expenses [3].

Technological advancements and infrastructure development are propelling the adoption of EVs in transportation and logistics. According to the U.S. Department of Energy, more than 10,000 EV charging stations were installed across the U.S. The installation of the EV charging station has bolstered the sales of battery and plug-in electric vehicles [4]. Besides, governments worldwide are also investing in EV charging infrastructure and providing incentives for EV adoption, which further supports this transition. As consumer awareness of environmental issues grows, there is an increase in demand for eco-friendly delivery options, prompting companies to prioritize EVs in their operations. This combination of economic, regulatory, and societal factors is accelerating the shift towards electric

vehicles, highlighting their crucial role in the future of transportation and logistics [5].

Advancements in battery technology, alongside affordable pricing, and enhanced performance, are propelling the rapid expansion of electric vehicles in the market. Innovations in battery chemistry, like lithium-ion and solid-state batteries, have boosted energy density and decreased charging durations, rendering EVs more feasible and enticing to consumers. Furthermore, the diminishing costs of batteries, attributable to economies of scale and refined manufacturing techniques, have bolstered the affordability and competitiveness of EVs against traditional internal combustion engine vehicles. Augmented performance capabilities, such as extended driving ranges, swifter acceleration, and smoother rides, further increase the adoption of EVs [6]. These dynamics, combined with sustainability concerns and supportive governmental measures, are accelerating the uptake of electric vehicles, marking a transformative upheaval in the automotive sector.

Moreover, replacing conventional fuel school buses and public transportation buses with electric counterparts offers significant environmental and economic benefits [7]. Electric buses produce zero tailpipe emissions, reducing air pollution and greenhouse gas emissions, which are major contributors to climate change and urban air quality issues. Although the initial investment in electric buses and charging infrastructure can be high, the total cost of ownership over the lifespan is often lower. Further, electric buses have fewer moving parts, leading to reduced maintenance costs and increased reliability [8].

EV charging demand is influenced by multiple factors, including user behavior, travel patterns, weather conditions, battery capacities, and charging station availability. These variables interact in nonlinear and time-dependent ways, making them difficult to model with conventional statistical techniques. Machine learning models can capture these complex relationships by learning from data without explicit programming, making them highly effective in understanding and forecasting demand across different urban and rural contexts [9].

Global Electric Vehicle (E.V.) Charging Infrastructure Market

Size, by Charger, 2022-2032 (USD Billion)

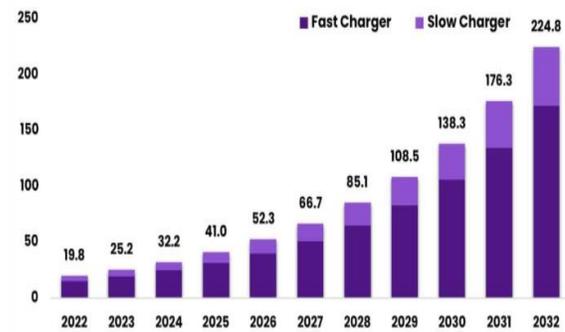


Fig.2EV Charging Market Statistics

(Source:<https://market.us/report/electric-vehicle-charging-infrastructure-market/>)

Figure 2 depicts the EV charging market which shows an estimated CAGR of 27.5%.

II. EXISTING MODELS

This section presents the existing models employed extensively for forecasting EV charging demand. Several ML algorithms are being employed to estimate EV charging demand. Time series models such as Long Short-Term Memory (LSTM) networks and ARIMA are used to capture temporal dependencies in charging data. Regression models like Random Forest, Gradient Boosting, and Support Vector Regression help in forecasting demand based on spatial and demographic variables [10]. Clustering techniques like K-Means are also useful for identifying usage patterns across different charging locations and times. These models provide dynamic, location-specific, and user-oriented demand forecasts.

Support Vector Machine (SVM):

Before the advent of deep learning, traditional machine learning models such as Support Vector Machines (SVM), Decision Trees, Random Forests, and K-Nearest Neighbors (KNN) were widely used for satellite object detection. These models typically relied on handcrafted features, such as texture, edges, and spectral indices, to distinguish between different objects [11].

The SVM classifies based on the hyperplane.

The selection of the hyperplane H is done on the basis of the maximum value or separation in the Euclidean distance d given by:

$$d = \sqrt{x_1^2 + \dots \dots \dots x_n^2} \tag{2}$$

Here,
 x represents the separation of a sample space variables or features of the data vector,
 n is the total number of such variables
 d is the Euclidean distance

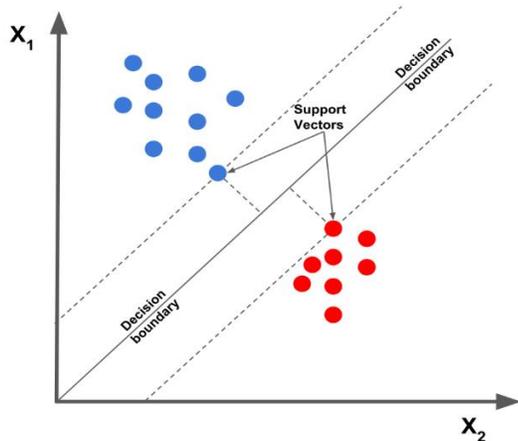


Fig.3 The SVM Model

Figure 3 depicts the SVM Model.

The (n-1) dimensional hyperplane classifies the data into categories based on the maximum separation. For a classification into one of ‘m’ categories, the hyperplane lies at the maximum separation of the data vector ‘X’. The categorization of a new sample ‘z’ is done based on the inequality [13]:

$$d_x^z = \text{Min}(d_{C1}^z, d_{C2}^z \dots d_{C2=m}^z) \tag{3}$$

Here,
 d_x^z is the minimum separation of a new data sample from ‘m’ separate categories
 $d_{C1}^z, d_{C2}^z \dots d_{C2=m}^z$ are the Euclidean distances of the new data sample ‘z’ from m separate data categories [14].

For instance, SVMs are effective for binary classification tasks, such as distinguishing between urban and rural areas, while Random Forests are used for multi-class classification problems, such as land cover mapping. However, these models struggle with complex patterns in high-resolution imagery and require extensive feature engineering, which limits their scalability and accuracy [15]

ARIMA:

In an autoregressive integrated moving average model commonly known as the ARIMA model assumes that the future value of a variable can be linearly modelled as a function previous samples of the variables and errors of prediction [16].

$$y_t = \theta_0 + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \varphi_p y_{t-p} + \dots \dots \dots \theta_q \varepsilon_{t-q} \tag{4}$$

Here,
 y_t is the value of the output variable at time ‘t’
 ε is the prediction error
 θ and φ are called the model parameters
 p and q are called the orders of the model

One of ARIMA's key strengths lies in its ability to handle both stationary and non-stationary data. While the ARIMA model assumes the input time series is stationary (i.e., its statistical properties like mean and variance remain constant over time), it incorporates differencing techniques to convert non-stationary data into a stationary format. This makes it highly adaptable for real-world datasets that often exhibit trends or seasonality [17].

Neural Networks:

Owing to the need of non-linearity in the separation of data classes, one of the most powerful classifiers which have become popular is the artificial neural network (ANN) [18]. The neural networks are capable to implement non-linear classification along with steep learning rates. The neural network tries to emulate the human brain’s functioning based on the fact that it can process parallel data streams and can learn and adapt as the data changes. This is done through the updates in the weights and activation functions [19].

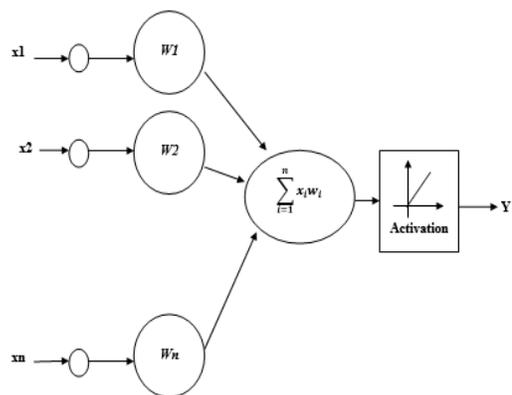


Fig.4 The ANN Model

Figure 4 depicts the ANN model.
The input-output relation of a CNN is given by:

$$y = f(\sum_{i=1}^n x_i w_i + b) \tag{5}$$

Here,
x denote the parallel inputs
y represents the output
w represents the bias
f represents the activation function

The neural network is a connection of such artificial neurons which are connected or stacked with each other as layers. The neural networks can be used for both regression and classification problems based on the type of data that is fed to them. Typically the neural networks have 3 major conceptual layers which are the input layer, hidden layer and output layer. The parallel inputs are fed to the input layer whose output is fed to the hidden layer. The hidden layer is responsible for analysing the data, and the output of the hidden layer goes to the output layer [20]. The number of hidden layers depends on the nature of the dataset and problem under consideration. If the neural network has multiple hidden layers, then such a neural network is termed as a deep neural network. The training algorithm for such a deep neural network is often termed as deep learning which is a subset of machine learning. Typically, the multiple hidden layers are responsible for computation of different levels of features of the data [22].

Long Short Term Memory (LSTM):

The LSTM networks are a specialized type of recurrent neural network (RNN) designed to process and predict data sequences by learning long-term dependencies. Unlike traditional RNNs, which suffer from vanishing or exploding gradient problems during training, LSTMs incorporate a unique architecture with gates and memory cells that help retain important information over long periods [23].

The LSTM primarily has 3 gates:

- 1) Input gate: This gate collects the presents inputs and also considers the past outputs as the inputs.
- 2) Output gate: This gate combines all cell states and produces the output.
- 3) Forget gate: This is an extremely important feature of the LSTM which received a cell state value governing the amount of data to be remembered and forgotten.

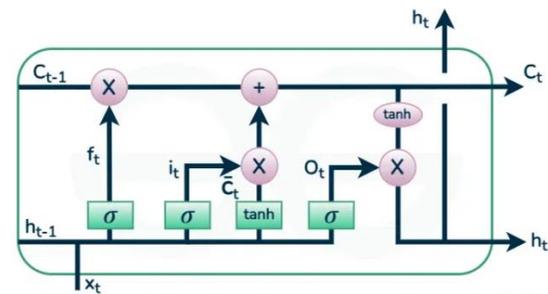


Fig.5 The LSTM Model

Figure 5 depicts the LSTM model.

The relation to forget by the forget gate is given by [24]

$$f = \sigma(W_f[h_{t-1}, x_t] + b_i) \tag{6}$$

Here,
 f denotes forget gate activation
 w_f are forget gate weights.
 h_{t-1} Denotes Hidden state from the previous time step
 x_t is present input.
 b_i is the bias

The advantages of LSM are:

- Capturing Long-Term Dependencies: LSTMs maintain long-term memory using the cell state, unlike traditional RNNs.
- Mitigating Vanishing/Exploding Gradients: Gates help regulate gradient flow, enabling stable training over long sequences.
- Versatility: Useful for several time series prediction problems.

However, the major challenge happens to be the problem of overfitting.

Convolutional Neural Networks (CNNs): The family of CNNs are the backbone of modern satellite object detection. CNNs automatically learn hierarchical features from raw images, eliminating the need for manual feature extraction. The Convolutional Neural Networks (CNNs) can automatically extract hierarchical characteristics from images, they have become the mainstay for image classification applications. These neural networks perform exceptionally well in applications like picture identification because they are specifically made for processing organised grid data [25].

Convolutional, pooling, and fully linked layers are among the layers that make up a CNN's architecture. Convolutional layers identify patterns in the input image by

applying filters, hence identifying local features. By reducing spatial dimensions, pooling layers preserve significant information. High-level features are integrated for categorization in fully connected layers.

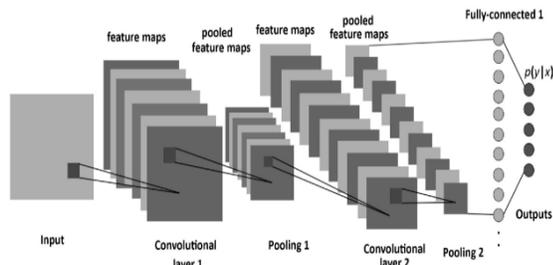


Fig.6 The CNN Model

Figure 6 depicts the CNN model.

The convolution operation is given by [26]:

$$x(t) * h(t) = \int_{-\infty}^{\infty} x(\tau)h(t - \tau)d\tau \quad (7)$$

Here,

$x(t)$ is the input

$h(t)$ is the system under consideration.

y is the output

*is the convolution operation in continuous domain

For a discrete or digital counterpart of the data sequence, the convolution is computed using:

$$y(n) = \sum_{-\infty}^{\infty} x(k)h(n - k) \quad (8)$$

Here

$x(n)$ is the input

$h(n)$ is the system under consideration.

y is the output

*is the convolution operation in discrete domain

In this approach, the back propagation based neural network model has been used. A backpropagation neural network for traffic speed forecasting typically consists of an input layer, one or more hidden layers, and an output layer. The number of nodes in the input layer corresponds to the features used for prediction, The hidden layers contain nodes that learn and capture the intricate patterns within the data, while the output layer provides the predicted traffic speed. The training of a backpropagation neural network involves the iterative application of the backpropagation algorithm. During the training process, historical data is used to feed the network, and the algorithm calculates the error between the predicted and actual energy demands. This error is then propagated backward through the network, adjusting the

weights and biases of the connections to minimize the prediction error. This iterative process continues until the network converges to a state where the error is minimized. Successful backpropagation neural network models for traffic speed forecasting can be integrated into energy management systems [27].

III. PREVIOUS WORK

The section presents the important contribution in the domain of research.

Orzechowski et al. [28] proposed that the swift integration of electric vehicles (EVs) will create unparalleled challenges in the management of electricity supply and charging infrastructure.. In this study to utilize machine learning for predicting medium-term public electric vehicle charging demand, leveraging weather and additional variables at public charging stations, and forecasting demand over numerous stations and the complete network. It is shown that the approach surpasses the benchmark time series method, achieving a symmetric mean absolute percentage error (SMAPE) of 5.9% and a mean absolute error (MAE) of 124.7 kWh, which constitutes less than twelve percent of the average daily demand.

Shahriar et al. [29] presented a comprehensive review on the EV charging infrastructure and associated challenges. It was shown that EVs are regarded as a fundamental component of intelligent transportation systems. This article aims to deliver a thorough study of supervised and unsupervised machine learning, together with deep neural networks, for the analysis and prediction of charging behavior. Recommendations and prospective research avenues are also addressed.

Wang et al. [30]proposed a Long Short-Term Memory (LSTM) neural network to forecast electric vehicle (EV) charging demand at the station level for the subsequent hours (e.g., 1–5 hours), employing a distinctive trajectory dataset comprising over 76,000 private EVs in Beijing from January 2018. To evaluate the efficacy of the LSTM model, we established four scenarios: 1) contrasting LSTM with two conventional time series forecasting models, namely the Auto-Regressive Integrated Moving Average model (ARIMA) and the Multi-Layer Perceptron model (MLP), and 2) examining the impact of varying input data configurations, sample sizes, and temporal spans and intervals on model accuracy. performance.

Shariar et al. [31]proposed that a significant concern, is the pressure on power grid infrastructure resulting from extensive electric vehicle deployment.. In this research, authors suggest

utilizing previous charging data with weather, traffic, and event data to forecast EV session duration and energy consumption through established machine learning methods, including random forest, SVM, XGBoost, and deep neural networks. An ensemble learning model demonstrates superior predictive performance, attaining SMAPE scores of 9.9% for session duration and 11.6% for energy usage, hence surpassing previous studies in the literature. Both forecasts exhibit a substantial enhancement relative to prior research on the identical dataset, underscoring the significance of traffic and weather data in forecasting charging behavior.

Hafees et al. [32] proposed that global organizations are undertaking significant initiatives to mitigate CO2 emissions. Studies indicate that by 2030, electric vehicles can decrease CO2 emissions by 28%. Two significant barriers hinder the extensive adoption of electric vehicles: the elevated cost of EVs and the insufficient availability of charging stations. This research introduces a thorough data-driven methodology for demand-side control of a solar-powered electric vehicle charging station integrated with a microgrid. The proposed method employs a solar-powered electric vehicle charging station to offset energy demands during peak periods, therefore diminishing reliance on conventional energy sources and alleviating the scarcity of electric vehicle charging stations in the present context.

Typically, training algorithms try to attain low error rate metrics, which are defined next [33]:

The mean square error or mse given by:

$$mse = \frac{\sum_{i=1}^n e_i^2}{n} \quad (8)$$

The final computation of the performance metric is the mean absolute percentage error given by:

$$MAPE = \frac{100}{M} \sum_{i=1}^N \frac{E-E_i}{i} \quad (9)$$

The accuracy of prediction is computed as:

$$Ac = 100 - \frac{100}{M} \sum_{i=1}^N \frac{E-E_i}{i} \% \quad (10)$$

Here,

n is the number of errors

i is the iteration number

E is the actual value

E_i is the predicted value

V. CONCLUSION

It can be concluded that, machine learning models offer a transformative approach to estimating EV charging demand. By leveraging diverse datasets and adaptive algorithms, they enable smarter infrastructure planning, grid management, and user services. While challenges in data privacy, model reliability, and system integration remain, ongoing research and technological advancements are steadily overcoming these barriers. As the EV ecosystem expands, ML will be an essential tool in supporting sustainable and efficient electric mobility. Implementing ML models in EV infrastructure planning brings multiple benefits. Accurate demand forecasting enables utility providers and city planners to optimize energy distribution, reduce peak load stress on the grid, and prevent blackouts. It also helps in identifying optimal locations for new charging stations based on predicted usage, thereby improving accessibility and user satisfaction. Moreover, these models can be updated with new data to continuously improve predictions and adapt to changing mobility trends. This paper presents a comprehensive review of existing machine learning approaches for estimating EV charging demand.

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