# What is the current state in literature of the application of machine learning techniques to optimize EV charging stations?

**EV market**

Sales of electric vehicles (EVs) doubled in 2021 from the previous year to a new record of 6.6 million. (Energy Agency, 2022)

The global market value of electricity for EV charging is projected to grow over 20-fold in the APS, reaching approximately USD 190 billion by 2030, which is is equivalent to about one-tenth of today’s diesel and gasoline market value. (Energy Agency, 2022)

**Challenges of EV’s**

Still challenges with charging infrastructure and impact on grid integration. (Das et al., 2020)

As indicated in (Li et al., 2021a; Chen et al., 2020; Karmaker et al.; Ghasemi-­Marzbali, 2022; Ahmad et al., 2022b), the main challenges associatedwith integrating EV charging infrastructure into existing electrical power systems include voltage stability issues, peak load pressure, power efficiency, and transformer efficiency.(Yaghoubi et al., 2024)

The impact of EVs on the power grid is inevitable. The results indicate the peak demand increases by 3.4% when the deployment rate of EVs reaches 20% of the operating cars. (Alquthami et al., 2022)

The EPS is not designed to accommodate a sudden increase in EVs.

One of the main challenges associated with EV charging within the EPS is the occurrence of peak demand (Li et al., 2022). This increase in demand puts considerable pressure on the main grid. This pressure can result in power outages, reduced reliability, and increased costs for companies and consumers. The adoption of EVs has significant implications for the EPS, particularly in terms of managing peak demand and ensuring reliability. As shown in Fig. 11, there is a rising interest among researchers in understanding the implications of integrating EV charging into the main grid from 2016 to 2021. However, since 2022, there has been a gradual decline in this trend. (Yaghoubi et al., 2024)

**ML and EV’s overall**

In response to these challenges, scientists have started utilizing Machine Learning (ML) techniques to tackle problems related to charging infrastructure planning, including the placement of charging stations, predicting charging demand and scheduling charging (Deb). (Yaghoubi et al., 2024)

Data-driven ap­proaches, which utilize historical and real-time data to make predictions and decisions, offer superior real-world accuracy and adaptability in dynamic environments. (Yaghoubi et al., 2024)

The problems associated with EV charging can be resolved using scheduling, clustering, and forecasting methodologies (Shahriar et al., 2020; Al-et al., 2019; Zhu et al., 2016). These control algorithms consider both the demand for EV charging and the present condition of the EPS, increasing grid stability and efficiency while lowering operating costs and preventing peak loads. (Yaghoubi et al., 2024)

All three techniques - ML, DL, and ensemble learning - have the potential to revolutionize the EV industry by enabling data-driven insights and paving the way for a more sustainable future in transportation. These techniques can generate accurate forecasts that relieve pressure on the main grid and effectively reduce costs associated with constructing and maintaining EV charging infrastructure. As a result, a sustainable and environmentally friendly transportation system can be established. (Yaghoubi et al., 2024)

**ML and EV’s in detail**

In this paper, a short-term load forecasting method for EV charging stations combining NILA with CNN is established, where NI is used to improve the optimization performance of LA, and the hybrid technique NILA is introduced to determine the optimal parameters of CNN model, so as to obtain better prediction accuracy. Through analysis of load characteristics in the charging station, ten inﬂuential factors are selected as input, including seasonal category, maximum temperature, minimum temperature, weather condition, day type, and the loads at the same moment in previous ﬁve days. According to the case studies, CNN integrated with NILA outperforms other models in terms of prediction precision, indicating that NILA-CNN model is a promising technique for short-term load forecasting of EV charging station. (Li et al., 2018)

NILA = Lion algorithm improved by niche immunity

CNN = Convolutional neural network

The results indicate that a machine learning algorithm can learn to identify when to begin charging a PEV by distinguishing between low and high demand sections in the forecasted baseload. The results show that the algorithm can achieve a microaveraged F1 score, an indicator of a classifier’s overall accuracy, of 0.9284; hence, the algorithm can select the correct time to initiate charging 92.84% of the time. The analysis revealed that the algorithm valley-fills more effectively when more hours of the forecasted loads are provided as an input. In addition, its valley-filling capability increases when the length of forecasted baseload is given in smaller length intervals. It also was discovered that accuracy does not necessarily equate to valley-filling performance. Providing a lower-resolution view of the baseload increases classification accuracy, but results in a heavy generalization of the baseload that decreases the effectiveness.

More research should be conducted to investigate how other variations in the length of the forecasted baseload provided to the algorithm and its duration of time intervals affect the algorithm’s ability to select the correct charge initiation time. Only two variations in the length of the forecasted baseload provided to the algorithm and three variations of the duration of the time interval were considered; more should be evaluated. Furthermore, to decrease complexity, it was assumed that charging occurs using a constant rate and is delivered continuously until the vehicle reaches the desired charge level or unplugs. Further research should consider removing these constraints and expanding the problem space. Lastly, research should investigate how introducing input variables such as weather, holidays, and observed events can teach the algorithm how these entities affect the forecasted load. These inputs allow the algorithm to learn how historical baseloads can be modified to create more accurate forecasted baseload and improve valley-filling performance.. (Smith et al., 2021)