Conclusion

Dynamic pricing for EV charging is of increasing interest, since it can help to solve issues related to grid integration of EVs and to the profitable operation of public EV charging stations. There are a growing number of publications, proposing different approaches to dynamic pricing for EV charging, which address different flexibilities of users.

How do EV drivers respond to dynamic prices in reality and how external factors influence the user preferences? Such factors can be, for example, the time of day or the location of the charging facility. Furthermore, it is not clear if a dynamic pricing scheme would be accepted by the users at all.

Although it is highly expected that Dynamic Pricing will resist the increase of Monopoly of one particular company in the market as there will be a competition factor on deciding the dynamic pricing.

Unfortunately, there is a lack of user studies, which fully answer these questions. However, there exists literature, providing helpful starting points.

Implementation steps:

**The types of data used for dynamic pricing optimization**

machine-learning based dynamic pricing requires massive amount of data and external factors that need to be considered for price determination: sales data, inventory levels, competitor data, promo data, transaction data, seasonal trends, weather data – and more

**Structured data:** this type of data includes names, addresses, transactions history, loyalty programs, and mostly any other data that involves an “amount” type of measurement.

**Unstructured data:** this type of data includes product reviews, images, social likes and mentions, and any other social media data.

In addition to ‘structured’ and ‘unstructured’ types of data mentioned above, it’s important to utilize both micro and macro level data when developing machine learning-based price optimization. This includes:

**Micro level data:** internal data including current price per unit, charging stations maintenance cost, load on that charging stations (number of EVs currently charging) etc.

**Inventory level:** This is essential data regarding details among current availability if the ports (existing supplies combine with existing demand), which is a key determinant in how a dynamic pricing will be calculated.

**Electricity cost:** Electricity cost per unit is a deciding factor.

**Maintenance charges:** This includes all the cost which must be spent as human resources, rent for the lands of charging stations, and also maintenance charges for the software or cloud service charges.

**Macro level data:** this is external market data and influential factors that include competitor data, time-oriented data (e.g. day of the week; the season), and location specific data (e.g. regional data; weather data), review of the charging stations, etc.

**Competitor Data:**

Competitor data can be far reaching. This data can be gathered by crawling (also called ‘scraping’) software which gathers the information from publicly available sources. Businesses are becoming increasingly sophisticated with regards to trying to limit the ability of their competitors to gather this data.

**Days of the Week:**

Days of the week have an influence on consumer demand, such as on office days, the demand for charging may increase in evening (it is expected that consumer will charge their EVs at the evening as charging takes up to 30 to 40 mins.), Or at the first half of office hours (as they may charge in parking lots.)

The dynamic pricing strategy will take this data and set prices to increase or decrease based on demand for specific hours.

**Holidays:**

The demand of charging may vary. On certain charging stations demand may increase (charging stations that nearer to attractions, movies halls, shopping malls, etc.). And decrease on some charging stations (charging stations in parking slot of offices.)

**Weather and Seasonal Data:**

Weather can affect the demand, both as a broader pattern. For example, good weather is good for demand, while if the weather outside is bad people will stay home. Weather forecast data can therefore help in predicting demand and optimizing prices accordingly.

**Data** **collection**

When it comes to building a tailored, machine learning based dynamic pricing solution, the targeted internal data will be gathered from traffic modelling simulation on a time slice basis. The simulation will prepare the data on their end, that will be extracted and making sure all of the proper variables are contained. There will be an automated programs that help to manage this data.

When it comes to external data, this is gathered on the basis of business strategy and needs. open APIs are utilized to gather this information as per our requirement.

Competitor data will gather in different ways, usually by a web crawling service or software that gathers the requested data points from open sources. This is increasingly difficult to do as companies are becoming more protective of their data.

**Data processing**

Managing large and complex datasets can be challenging.

After data is collected, it must be cleaned of errors and prepared for further processing. This step is challenging because data of different formats from different sources must be merged.

The task is to ensure that the data is correctly and completely transformed into an algorithm.

Once the data has been gathered and gone through an initial cleaning process, further prepare the data to feed into the algorithm.

**Data inputting**

From the prepared data, we will then create features and deciding factors – input variables for the machine learning models – that are tailored to specific charging stations and take account of their unique strategic needs. Depending on the particular needs of a charging station different features may be more or less suitable for explaining an outcome. The type of machine learning model and which parameters are used can also differ very much from case to case.

**Data and dynamic pricing algorithms**

By analysing their massive quantities of available data, in combination with current market events and other external data sources, retailers can optimize their prices for the customers with the help of algorithms. We can differentiate between two types of algorithms that are being used in pricing:

**Traditional**, **rule-based algorithms:** the logic of these algorithms has been explicitly programmed. They often consist of a range of “if/then” rules that determine prices based on a range of influencing factors.

**Machine learning based algorithms:** these algorithms learn on a set of training data to make predictions on the price effect on sales, revenue and profit. Based on that forecast, one can run optimizations to reach business targets. This algorithm and its logic of prediction is not explicitly programmed. The algorithm continuously learns from new data.

A limitation of traditional algorithms is that they can only consider a limited amount of influencing factors, often less than three. Managing and monitoring this rule-based approach also takes a fair amount of time and effort.

In contrast, by utilizing big data in conjunction with a machine learning based approach, retailers are now more equipped to define the most appropriate pricing strategy for their business.

A machine learning based approach can calculate considering a range of influencing factors, both internal (e.g. electricity consumption charges, charging station maintenance price etc.) as well as external (e.g. competitor data, time-based and weather factors).

By using machine learning based dynamic price optimization, these systems can identify narrow segments, determine what drives value for each one, and match that with historical transactional data. This allows charging stations to set optimal prices for clusters of customers and segments based on data.

Automation also makes it much easier to replicate and tweak analyses so it’s not necessary to start from scratch every time, as the pricing algorithm learns and adapts with data over time.