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

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 sales data & transaction data, product master data, cost data, historic prices, marketing data and business strategies. 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).

Internal Data

Product Attributes: This includes essential information such as cost, margin ceiling, base price, and MAP price. Product attributes (or product master data) is the digital representation of a retailer’s assortment and an important tool for dynamic price optimization. These data points often include product ID, master-variant assignment, current price, RRP, lower and upper price limit, seasonal identification, brand, color, size, stock level, expiration date or target sales date and much more. Grouping these attributes across categories is an important way of utilizing this type of data. It’s often difficult for the models to learn from data on single products alone, so it’s important to be able to utilize and learn from the data on a category level.

Inventory Levels: This is essential data regarding details about current inventory levels and overall supply. The existing supply is combined (via the inventory tracking) with the existing demand, which is a key determinant in how a dynamic pricing software calculates optimal prices in line with the market.

Transactional Data: this includes all transactions, units sold, price history, and conversions. This also includes buyer information, and manufacturing or sourcing costs. Any machine learning based dynamic pricing software will need a company’s sales and transaction data to calculate the demand for each product in your range. This forms the basis for every price decision of the AI. At the minimum, all sales information is needed, e.g. which items were sold at what price.

Additional transaction information improves the AI’s forecasting quality and enhances its results again. This can include items the customer has viewed, items they put in their shopping baskets, items they deleted or cancelled from their baskets, items they’ve saved or put on a wish list, and items they’ve searched for – as examples. viewed products, created shopping baskets, cancelled shopping baskets, saved watch lists or entered search terms, to name just a few examples.

External Data

Competitor Data

Competitor data can be far reaching but may include elements such as list price, ship price, buy-box price, FBA, out of stocks, geography, and product reviews and ratings. 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. Depending on a company’s business model, they will likely see sales go up or down depending on what day it is. Perhaps they’re more of a weekday business, or a weekend business.

A dynamic pricing strategy can take this data and set prices to increase or decrease over the weekend, based on demand for those specific days. Price optimization solutions that allow businesses to create custom timeframes for accurate implementation of one-time, ongoing, or limited-time price changes.

Holidays

Upcoming holidays will increase demand for certain items, for example wrapping paper in advance of Christmas, or flowers at Mother’s Day. By utilizing historic transaction data plotted against holiday seasons, retailers can pinpoint what items in their assortment show an increased demand and when. This data helps a dynamic pricing algorithm in forecasting demand and setting an optimal price for those respective items.

Regional Trends

E-commerce based retail has the advantage of being able to reach a much wider audience via online based platforms and marketing. However, localized factors and conditions may influence demand from different regional or geographic segments depending on what is occurring in their area. For instance, one region may be celebrating a festival or event which is driving up demand for certain products. Being able to use data to measure these regional variances can help in creating pricing strategies and distinctions down to the regional level, if desired.

Weather and Seasonal Data

Weather can affect the sales, both as a broader pattern, as well as of certain products. For example, good weather is bad for online retail, while if the weather outside is bad people will stay home and shop online. From a product perspective, when the temperature increases, consumers will start searching for standing fans and are more likely to buy them (e.g. higher probability of conversion). Another case in which weather data could be valuable is as winter approaches. When the temperature decreases, search volume for skis will increase. Temperature data and 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 analyzing 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.