Eon Data Challenge

E-Mobility Location Prediction

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***Abstract*— This paper aims to look into how machine learning models can be used to select new locations for placement of EV Fast Chargers. This project was carried in corporation with E.ON and the data provided by them on the utilization of their existing chargers. The model is also supported by some external datasets. Machine learning models including Gradient Boosting Regressor, Random Forest Regressor, and Multilayer Perceptron were trained and tested to achieve best performance for predicting the utility level of a fast charger at a certain location. Then we deployed a strategy of selecting new fast charger locations based on the locations of existing gas stations among Germany highways. The potential utility level of a fast charger at these gas station locations were predicted and those with highest utility levels were selected as potential new locations for EV Fast Charger placement.**

I. Introduction

. E-mobility is on the rise and the German government predicts to have over 10 million e-vehicles on the road by 2030 [1]. Germany is already leading the race of change in Europe, and is the fastest growing market on the continent, globally, it comes second, only to China. This makes us question the infrastructure to support this growing segment. The current infrastructure needs massive investment to support the expected growth. Germany needs a proper network to provide power to these e-vehicles. However, forming a network of charging stations needs to be planned in a proper way to optimize output. This is where our project comes to implementation, it aims to provide a data-backed solution to the question "Where do we place a charging station?"

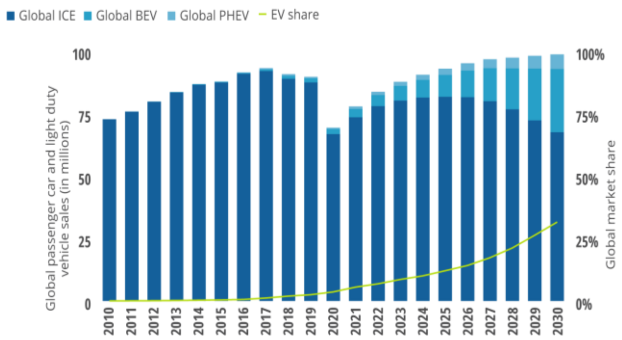

Fig1: Outlook of Passenger Vehicles in the Future [1]

We use data provided by our partners "E.ON" and externally scraped data to predict the next best 1000 locations to set up a rapid charging station in Germany.

In the following report, we take you through a detailed plan of implementation using the CRISP-DM model, that our team used to get a data-backed, feasible solution to predict the best locations to set up rapid charging stations in Germany. We start with a discussion of the business understanding, and what we believe is an implementable strategy, we did not want to provide our partners E.ON with arbitrary locations in the middle of nowhere which would be impossible to set up a charging station due to non-availability of a power grid or a proper road network. After understanding the basics of charging, the market trends, and situations, we move on to data understanding and preparation, where we look at the data we received and the data we collected. How we cleaned and prepared this to be used to form a model to be implemented. This model helps us evaluate the locations and predict the ideal possible locations for the charging stations. Our project helped us predict over a thousand locations from which we provide geo-locations of the thousand best locations to set up rapid charging stations is Germany.

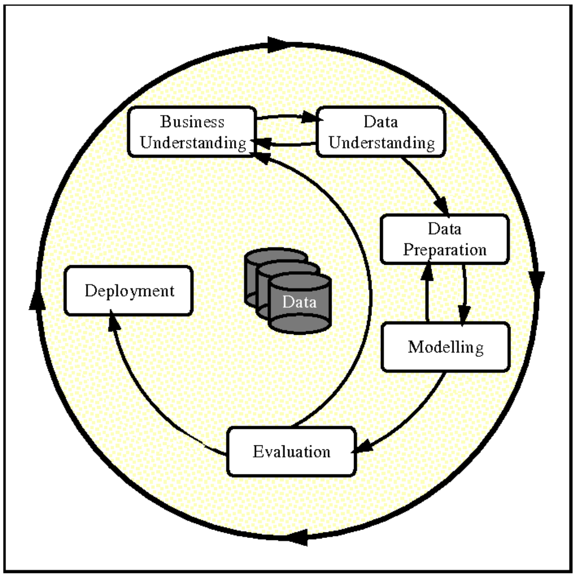

Fig2: CRISP-DM Model [2]

II. BUSINESS UNDERSTANDING

We start by analyzing the problem from the perspective of our end user, the drivers and passengers of the e-vehicle. As an owner of an e-mobility vehicle, the biggest hurdle currently is traveling long distances on a single charge. Even on a full charge, most EV's will give you a range of around 330 KMs [3].This is not enough if you plan to travel between two major cities in Germany, hence the skepticism to buy an EV, or not to use it to drive long distances. The alternative, the gasoline car, can make a small stopover for 5-10 minutes and get a complete refuel, so you can continue your journey, however EV's require time to charge, and the even bigger problem, there is not enough infrastructure or charging stations currently available to charge them.

Most EV owners have the option to charge their vehicles at home, and use overnight charging to provide them power to use their car within the cities during the day. There are also multiple charging stations available at parking and public places, where they might leave their cars. Hence commuting within the cities is often not as big an issue, but charging while traveling long distances is a huge hurdle to navigate for most consumers. This leads us to further understand EV charging and the options currently available for the customers.

A. EV Charging

There are two ways a car can receive power for charging, these can be through AC (Alternating Current) charging or through DC (Direct Current) charging. However the car battery requires Direct Current for the battery to be charged. Hence, the Ev's have an internal converter, for converting power from AC sources to Direct Current, so it can be used for the battery to be charged. [4]

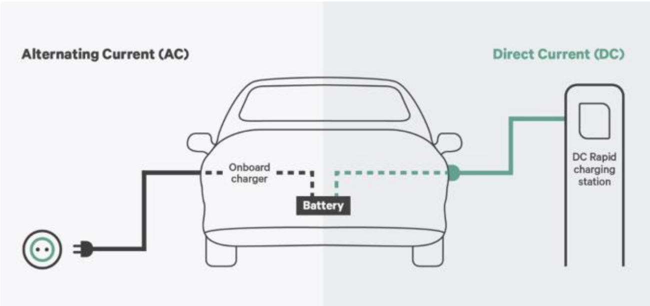

Fig3: AC vs DC Charging [5]

Alternating current sources have much slower charging times, as they use on board converters of cars, and usually have much lesser power available. AC charging is further divided into two sub categories, slow charging, that uses up to 7kW power to charge the car, and fast AC charging which uses up to 22kW power to charge the car. This would mean charging a car from no power to full power takes anywhere between 4 hours to over 24 hours, depending on the size of the battery and the power of the source being used to charge the vehicle. AC charging is used while charging cars at home, and often in parking lots and public spaces within the city. Setting them up is not extremely expensive, as you already have AC power sources available everywhere. However, imagine having to spend 8 hours mid journey, to recharge your car for the next 330 KM. It clearly isn't a feasible solution for long distance journeys. [4]

Direct Current charging is much faster, as the charger supplies DC power to the battery directly. These chargers, often referred to as "Rapid Chargers", and usually have a power of over 50kW. They can charge EV's from no power to full power, between 30 minutes to 90 minutes, depending on the size of the battery and power of the outlet. This makes DC chargers a much more viable solution for passengers driving on German highways between major cities. [6]

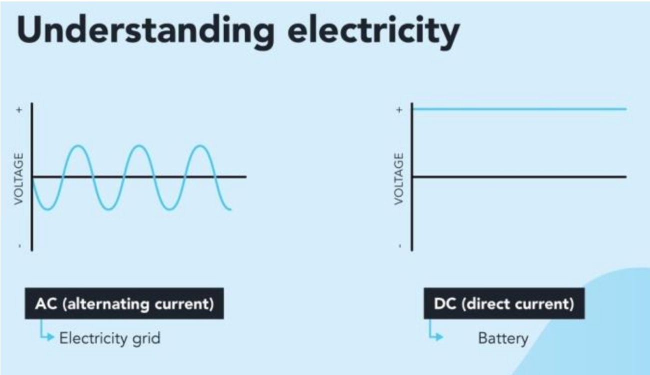

Fig4: Alternating Current and DC Current [7]

Some other facts that were considered while planning a strategy include the fact that there is standardization of charging ports used within the European Union, hence we do not need to set up facilities with specific charging ports that might cater to some, but not all EV's. Another number that leads us to believe that DC charging is the way to go for German highways is the average full charge running being 332 KM for EV's, and distances between major cities is much higher. The current number of DC chargers in Germany is less than 20% [8].

Since we now understand the basis of charging and the problem we face, let us now look towards some market research and trends.

B. *Market Research & Trends*

The number of EV's in Germany increased 207% during the pandemic hit year between 2019 and 2020. This is the highest growth across all of the major economies of the world, and confirms our case to build a solid network of charging stations as a profitable business model. Over 194,000 EV's were sold in Germany in the year 2020. Given the goal of the government, to have over 10 million EVs on the road by 2030, and the exponential growth rates, charging stations will see a lot of investment and hopefully technological advancements to decrease charging times further.

The growth of the segment is already accompanied by the infrastructure to support it. Germany already has over 3000 registered rapid charging stations (2021), and 50,000 charging stations overall (2021). The numbers will see a massive growth, since the government plans to have over a million charging stations by 2030. [8] This is also in line with the strategy for E.ON to invest and deliver 1000 Rapid charging stations each year.

If we look at history and take inspiration, we realize how the boost in gasoline vehicles led to a growth in gasoline stations. We can also learn from how these stations were placed, and which ones were more successful. Hence, we learnt from the data that Germany has 14,459 gas stations, which have been constantly decreasing since 1970, when the gas station numbers were over 46,000 [9]. This points us in the direction to have an optimum strategy, unlike the gas stations, which suffered. The gas station networks were expanded to protect big oil companies, and their business models were created around that. Hence, what we see now, are the most optimal locations, that have survived over the years, and these locations can be used as part of our data set, to help us predict better locations. This will also help us in making better choices, as a gas station will already have a location, which is connected on the grid, and hence will have power lines available to draw from. It will also give us enough space that is visible on the highways, to better place charging stations. Ideally a successful gas station was categorized by being on a strong motorway and by being visible. Similar concepts can be used to place them close to strong motorways, however, given the use of GPS systems and maps, placing them can be easier, as technology will make them more visible.

As part of a business strategy, it also makes sense to make use of the service station model, and provide a proper area for passengers to spend up to 60 minutes, while their vehicles recharge. This creates additional revenue streams, and will make E- on charging stations much more desirable than the other charging stations.

Looking further at what other companies are doing, our team spoke to startups in the field, and what problems they are trying to solve. Our first interaction was with "charge.xyz" who are trying to create decentralized charging stations, which are not owned by any particular companies, but by individuals on the blockchain, who can own a share of the charging station, and earn profits on that. This solves the customer problem of having their data collected by companies, while their cars are being charged. Another interesting field in which multiple start ups are working is in the field of load management. We interacted with "ChargeX" who are working on solutions to solve the problem of load management, which will be a major problem, as more EV owners enter the market. Imagine having all cars connected to the grid, for charging, this will lead to a failure in the grid, hence load management is an important problem to solve, given the bright EV future. The trends and research helped us get a direction for our strategy, as you will learn by the end of our report.

C. *Other Considerations*

Getting our direction from research on business and the trends was insightful, however there are always uncertainties, and scenarios, that will help us optimize the final solution. Our ultimate goal, to provide the lowest charging time for EVs and to get them at par with the current gasoline vehicles.

Our first expectation to achieve the above will be technological developments. Given the changes in the sector in the last 5 years, we do expect charging times to go down further, based on improvement in battery technology and on the increase in power delivered by the power outlets. These numbers have been constantly improving, and will surely improve, as EVs are adopted further.

Another interesting fact to be considered is that charging times are dependent on several factors, besides power and battery capacities. These include weather and external environmental conditions, but more interestingly, the percentage charge while charging a battery. The charging time of a battery is much higher when it is over 80% charged, compared to when it is almost drained out due to the negatively charged ions. This leads us to the question, would you rather have more chargers, and charge EV batteries at certain intervals, rather than charging them fully and then draining them completely [10].

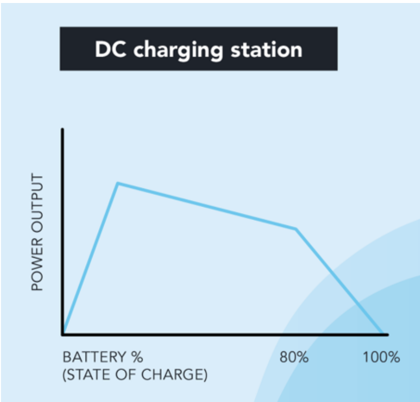

Fig5: DC Charging Cycle [11]

III. DATA UNDERSTANDING AND PREPARATION

After acquainting ourselves with the basics of e-mobility charging and having understood the problem at hand, we moved on to analyzing the available data and ideating on possible external data sets to be used. We brainstormed and tried coming up with a strategy that would yield the 1000 next feasible locations for E.ON to put their chargers in order to have maximum utilization.

A. *Internal Dataset*

We were provided two datasets from E.ON, a training set and a holdout set. Our model is based on the training dataset. The training data set had 141427 observations on the daily information of E.ON UFC(Ultra-Fast Charging) station in Germany from 2018-01-01 until 2022-05-19. Each row in the data describes the daily usage of a given electric vehicle supply equipment (corresponds to evse_id) on a given day (corresponds to evse_charge_day) with regards to the mean number of sessions (evse_mean_sessions), the mean duration of a session (evse_mean_duration), and the mean energy consumption (evse_mean_energy_wh,) together with a set of features on the used charger and location. In order to anonymize the data while still giving the students a chance to work on a real-life project, E.ON ran a basic machine learning model and The usage variables evse_mean_sessions, evse_mean_duration, evse_mean_energy_wh contained only the residual values. This meant that the respective means of these columns were close to zero and also had some negative values. This made the analysis more challenging because it was difficult to assess the utilization of a particular charger. In order to solve this problem, we were provided with another dataset from E.ON which had the duration and energy attributes aggregated over a month.

We divided the provided data into three broad categories: Utilization Attributes(energy, duration), Charger Attributes(Vendor, Connector type), and Location Attributes (GPS coordinates, postal code, city). The data quality of the provided dataset was really good but we still had to clean certain attributes, especially with the Charger and Location attributes.

After performing the initial cleaning in Excel itself, the data was visualized in Tableau and here we discuss some of the initial observations and findings. Looking at the Charger Attributes, we identified 4 vendors with EFCAEC being the most popular. In fact, almost 60% of chargers were from EFACEC, and the most commonly used model was Efapower-EV QC with a share of 54%. Looking at plug type, DC chargers use either CCS or Chademo.

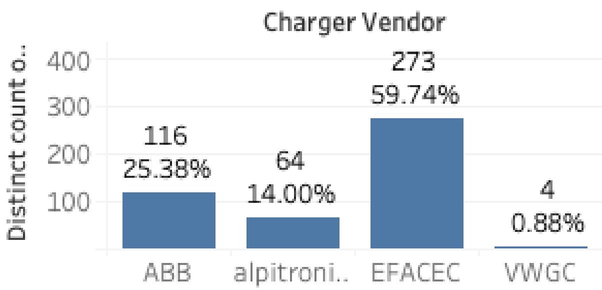

Fig6: Charger Vendor Types

Looking at the Location Attributes, we found that there are 258 unique locations with 456 E.ON Chargers, about 60% of them being DC chargers. Here you can see an overview of the data segmented according to the charger's latest known status: in-maintenance, in-service and out-of-service. Plotting the location data on the map, we realized that Western Germany has a higher proportion of electrical chargers with the maximum density in the NRW region.

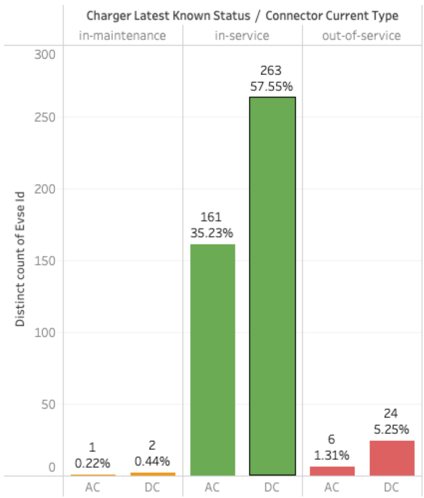

Fig7: Charger Last Known Status

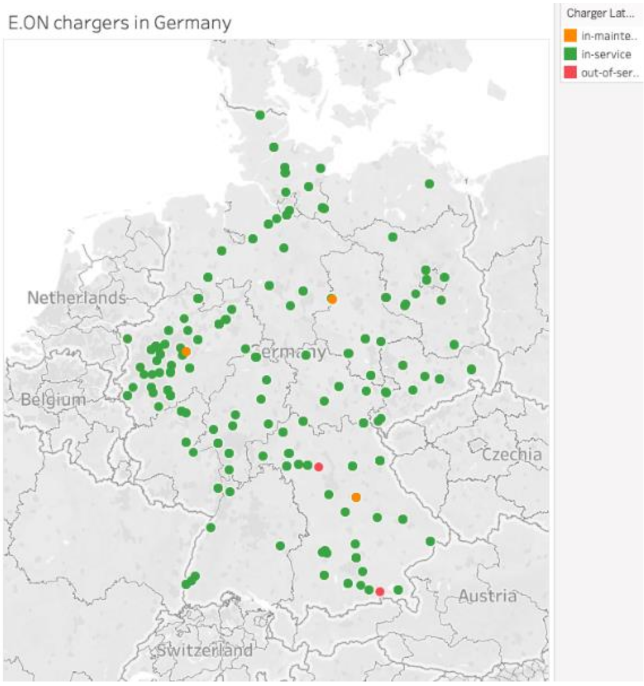

Fig8: Charger Mapping

Looking at the Utilization Attributes, we analyzed all available usage information, and using both business and data acumen, we decided that evse_sum_energy_wh is the attribute that captures the essence of the utilization of a particular charger. We narrowed down on sum_energy after checking for correlations with other attributes and researching on how the pricing of EV chargers works in real life. We then used this attribute and mapped down the utilization of the existing E.ON fast chargers.

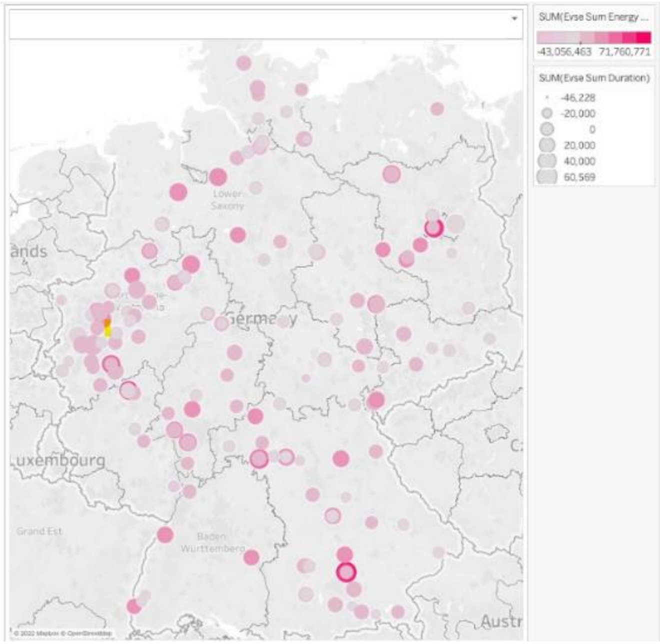

Fig9: Utilization of E.ON Chargers

B. External Dataset

Analyzing the dataset provided by E.ON, we understood that the given attributes are not enough to make a good model for predicting the utilization of a charger at a particular location. We brainstormed and looked for external data sets to add to our analysis. In this section, we discuss some of the external datasets that we looked into and how we utilized them in our final analysis. We looked into multiple external data sources but finally narrowed it down to two datasets that we used for our model.

Starting with the demographics, we looked into the population density and found a dataset that maps the population density per postal code [12]. We tried appending the data to the existing dataset and although on a first examination we did see some correlation in population densities and utilization of current E.ON chargers but soon realized that most of the population density is focused within the cities and doesn't align with the fact that the focus of this project was to find optimum locations for ultra-fast chargers that are usually placed on the highways outside the city centers. So we decided against using this dataset for our model building.

The second dataset that we looked into was the vehicle density data from Kraftfahrt-Bundesamt [13]. We found a dataset that had information on all the electric vehicles registered within Germany mapped according to postal codes. This dataset again was laced with the same problem as the population density dataset. Most of the vehicles are actually registered within the cities and there are not a lot of registration offices on highways. So using this dataset also didn't make much sense but it still gave us an idea of which states andregions have higher adoption of electric vehicles within the country.

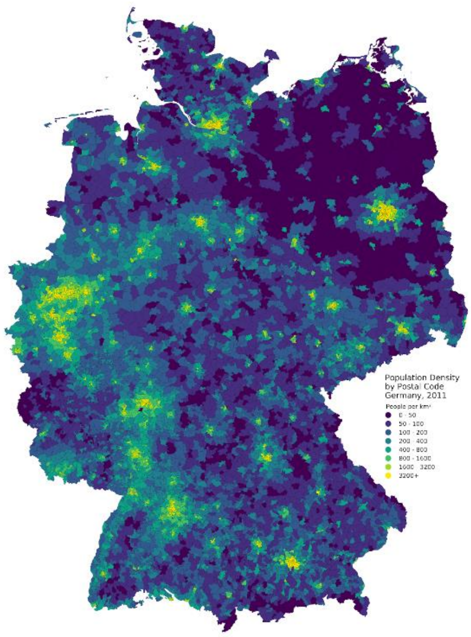

Fig10: Population Density Map [12]

The third dataset that we looked into was traffic flow. Our thesis was to place the next set of chargers next to points of high vehicle traffic density. We found an appropriate dataset from Bundesanstalt für Straßenwesen [14] and it worked well for our Highway thesis but the problem with this dataset was that the data available was from 2020. If not for the pandemic we would have expected similar trends for 2022 but our research showed that a lot has changed over the pandemic in terms of electric vehicle mobility and adoption rates. So we decided against using this outdated dataset because it did not make sense to append it to a dataset(E.ON) that has updated values until May 2022.

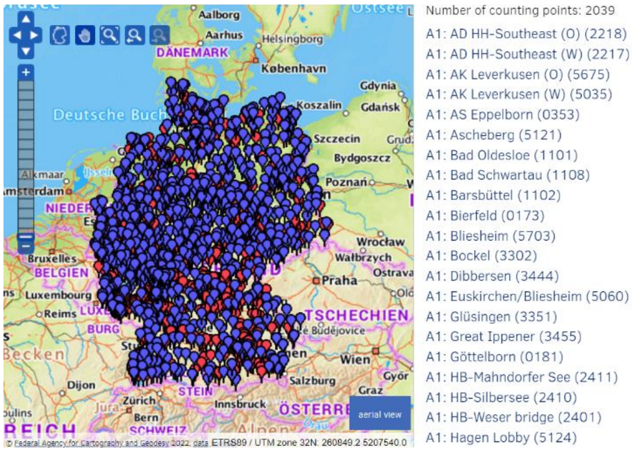

Fig11: Traffic Density [14]

The fourth dataset that we looked into was the national registry of all EV chargers in the country [15]. We could not get the data on the utilization of these chargers but we could still get information on connector type, Charger power, and the GPS coordinates of these chargers. The thesis behind exploring this dataset was that the utilization of a charger in a particular charger depends on how many other chargers are there in the vicinity. Here again, we only focused on DC fast chargers and tried calculating the distance of each existing E.ON charger from the nearest other chargers. Manhattan distance was selected as an approximation for driving distance to make the analysis less complex.

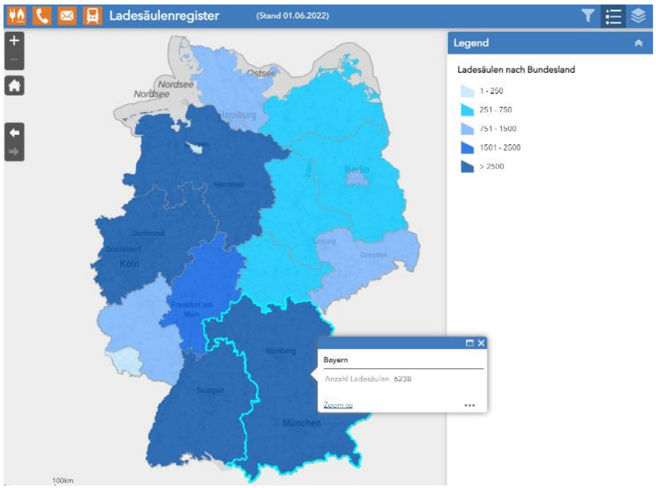

Fig 12: EV Charger Registry Map [15]

The fifth dataset that we looked into was information on rest stops, parking stops, and gas stations along the major German highways. The motive behind looking into this information was not to add another feature to the model but to have an input set for locations to pass into the model once the model is built. We figured that it wouldn't be feasible to pass all possible GPS coordinates in Germany into the model because that might lead to the selection of an optimum location in the middle of the forest. So we instead found a website that compared gas prices at different gas stations along all the highways [16]. Using a third-party web scrapping tool we collected the addresses of all these gas stations and then later used a geo-mapping encoder to get the exact longitude and latitude of these stations.

C. *Business Strategy*

Having familiarized ourselves with the internal data set from E.ON and having explored external data sets, we now tried to narrow down our thesis and make an actual business case out of the available data. The aim was to predict the utilization of a fast charger at a particular location and use this utilization as a factor to select the next 1000 locations for E.ON to put their chargers. The GPS coordinates of the existing E.ON chargers and their Manhattan distance from the nearest other chargers (E.ON or non-E.ON) were the two features used to build our model. We then used the GPS coordinates of the gas stations to predict the utilization if a charger were to be put there.

Our strategy was inspired by how McDonalds and Burger King expanded their network in the past . In order to find new locations, McDonalds does the entire process of evaluating all possible locations and ranking them based on certain attributes, Burger King then swoops in and places an outlet just next to the McDonalds. In our case, the existing gas stations are like McDonalds who already put in a lot of thought and effort and placed their stations in strategic locations and now E.ON can swoop in like Burger King and place their next set of chargers right by the existing gas stations. The existing gas stations not only provide us with an already analyzed location but also provides an entire ecosystem of infrastructure for a customer to charge their vehicles and in the meantime also use the facilities or convenience stores usually built within these gas stations.

IV. DATA USED FOR MODELLING

As analysed before, two datasets were selected to train and test the model and one dataset was fed into the model to derive new charging locations.

First dataset for modelling is "2018_2022_dc_charging_output_month.csv" provided by E.ON. Location related attributes were cleaned in Excel. Second dataset for modelling includes Manhattan distance from every existing E.ON DC charger to the nearest other DC chargers. The dataset used to derive new charging locations includes the longitudes and latitudes of gas stations along major German highways. In this dataset, 4 outliers are found and excluded as their latitudes and longitudes are not in the territory of Germany.

V. MODELLING

Machine learning methods can be divided into three types, including supervised learning, unsupervised learning, and reinforcement learning. https://towardsdatascience.com/all-machine-learning-models-explained-in-6-minutes-9fe30ff6776a

Our purpose of modelling is to derive a model that could predict the utility of a DC charging station at a specific location precisely. We selected "evse_sum_energy_wh" as the indicator of utility, as this attribute is the monthly sum of the energy consumption of all sessions of a specific charging station within this month in watt-hours. Since the given data can be assigned to this output variable, the model to be used belongs to supervised learning. And with this utility value being continuous, the model to be used is a regression model.

The input variables include 6 variables: "location_latitude","location_longitude", "location_postal_code", "Pincode" (the first three digits of postal code), "Latitude_nearest_charger", "Longitude_nearest_charger", "Distance_nearest_charger".These attributes are selected as they are related to the utility value and would be available when trying to open a new charging station. And the output variable for utility is "evse_sum_energy_wh". Besides that, we also conducted predictions for other utility variables to verify our model performance.

After data points including NaN values and 40 outliers containing rare extreme values are dropped, there are 5736 data points left. We conducted a 0.8:0.2 train-test-split for these data points.

Different machine learning regression models were applied to address the prediction problem. The models include Gradient Boosting Regressor, Random Forest Regressor, and Multilayer Perceptron. Linear Regression model is also used as the baseline of prediction errors.

Gradient Boosting Regressor: In Gradient Boosting Regression, Boosting means coming up with a composite model from different simple models. This algorithm uses gradient descent to minimize the loss function. Simple models are called weak learners. As we combine more and more simple models, we come up with a strong predictor. Decision trees are used as the weak learners in gradient boosting. Decision Tree solves the problem of machine learning by transforming the data into tree representation. In the decision tree the internal node of the tree represents an attribute and each leaf represents a class label. Then squared error is calculated which is the loss function. The loss function needs to be differentiable. Gradient boosting Regressor calculates the difference between the current prediction and the known correct target value. This difference is called residual. After that Gradient boosting Regression trains a weak model that maps features to that residual. This residual predicted by a weak model is added to the existing model input and thus this process gives the correct target [17].

Random Forest Regressor: Random forest regressor uses ensemble learning method. In Ensembling learning, it combines predictions from various machine learning algorithms to give the final prediction which is way more accurate if we use single model instead. This method constructs several decision trees while training and give an output of the mean of all the classes as the prediction of all the trees. This model is more powerful and accurate. In order to assess the model performance we uses R^2 score. This value tells how well our model is fitted with the data. It compares the given data distribution with the average line of the dependent variable. If the score is close to 1 means the model is performing really well while if it is close to 0 means the model performance is not good [18].

Multilayer Perceptron: Multilayer perceptron trains on the given input-output pair and finds the correlation between those input-output values. In order to minimize the error while training, it adjusts the parameters and uses backpropagation to make the parameters adjustment relative to the error. The error is measured in terms of root mean square error. Multilayer perceptrons involve two motions: back and forth. In forward motion, the signal flow moves from the input layer through hidden layers to the output layers and the decision of the output layer is measured. While in the back direction, the chain rule of the partial derivative of the error function with respect to the parameters is backpropagated. This process converges finally by lowering the error [19].

VI. Evaluation

There are three main metrics for regression model evaluation, R Square, Mean Square Error(MSE), and Mean Absolute Error(MAE) [20]. In our research, MAE is the criteria for the selection of the final model as it is less sensitive to extreme values.

	Model	MAE	MSE
2	RandomForestRegressor	0.103407	0.030307
1	GBRegressor	0.106661	0.030192
3	MLPRegressor	0.108584	0.03142
0	LinearRegression	0.121029	0.036353

Fig13: Models' ranking according to their MAEs

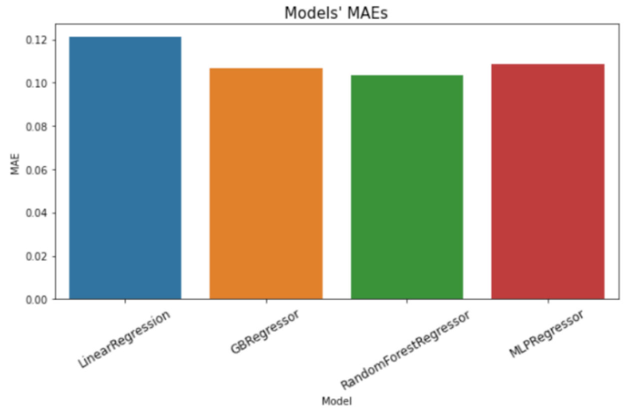

Fig14: Models' MAEs

As demonstrated by the chart, all machine learning models have smaller errors than the linear regression model, which is the baseline.

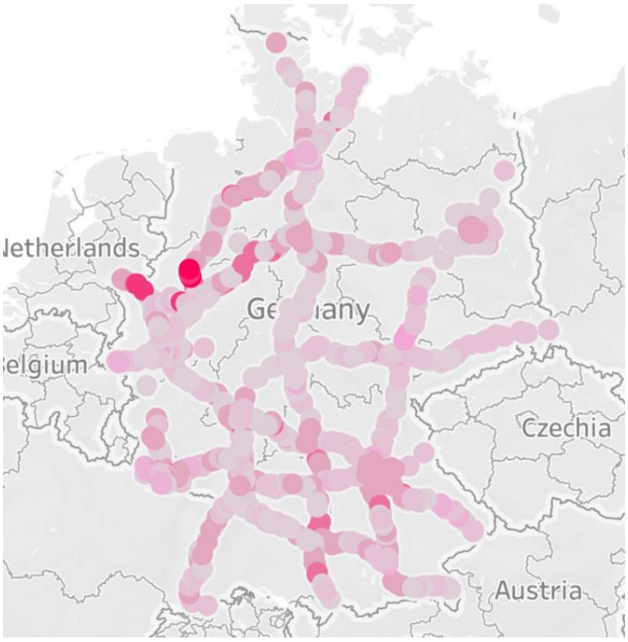

Fig 15: Predicted utilization at all the Input Locations

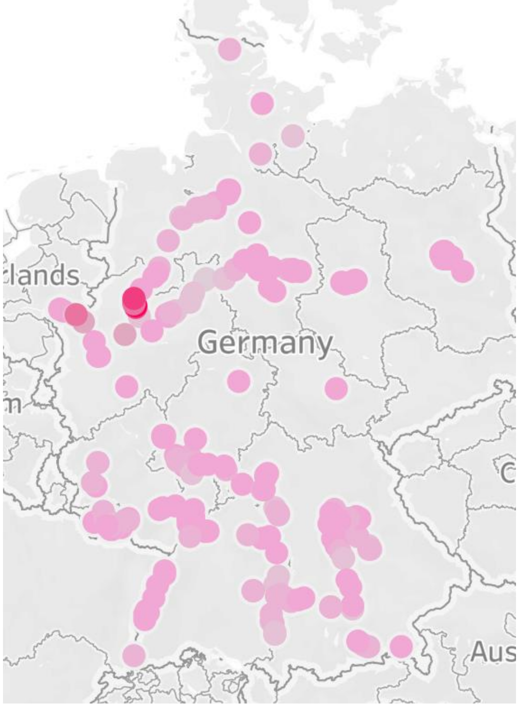

Fig 16: Top 1000 Locations with the highest utility predicted by the final model

With the least mean absolute error, Random Forest is the final model we used for selecting new locations. Possible reasons why Random Forest has the best performance in our research include that it uses ensemble learning, its default hyperparameters return great results and the system is great at avoiding overfitting. Moreover, it is a pretty good indicator of the importance it assigns to the features.

VII. Deployment

This machine learning model could be used in different roles in the company.

A data analysis team should be maintaining and iterating the model with updated data. As the opening of new charging stations and the closing of existing ones will affect the utility of a charging station, the data used for the model needs to be updated on a regular and frequent basis. Taking costs into consideration, once a month is a reasonable frequency.

The accuracy of the model proves itself to be a solid tool in terms of predicting utility. Based on this, the managers could justify their strategic decisions of opening new charging locations at specific locations.

Normally, prices from using charging stations include a combination of per kWh, per unit time, and per session costs [21]. This flexibility allows freedom in pricing plans and E.ON could leverage the knowledge of utility to its pricing plans to achieve higher profit and revenues.

Further steps of this work include three major directions. First, more input locations could be taken into consideration to achieve a more comprehensive strategy instead of focusing on existing gas station locations. Second, in-depth tuning of the models and also other new models could be conducted to achieve better accuracy. Except for the model, the data being used could also be improved by more effective data cleaning and applying NaN value imputation. Also, if an up-to-date traffic flow dataset is available it could also be used as input as discussed in this paper. Last but not least, it is important to verify the feasibility by checking the potential economic and technical issues at the selected new locations for opening charging stations.

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