Evaluating the Fulfilment Rate of Charging Demand for Electric Vehicles Using Open-Source Data

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Abstract: With the shift towards electric vehicles accelerating; we are working with open-source data to estimate to which degree existing charging infrastructure is fulfilling the demand created by electric vehicles. This paper is explaining how to create such a calculation by extracting data from large public areas in the city of Lindau (Bodensee), Germany as a showcase. With this data we aim to evaluate whether charging stations located in the premises of public and commercial buildings cover the demand of electric vehicles reaching the said buildings. This research is conducted as a first step of methodologies development that aims on the long term to create a tool that supports in the optimal placement of new charging stations. The methodology chosen is inspired by two main concepts: the first is the attractiveness factor concept used for the creation of travel models, while the second is the classification of charging stations based on location to determine their rate of occupancy. They are both used to cluster buildings and charging stations respectively to be able to determine the number of users in the area of study (AOS) compared to the overall number of electric vehicles reaching the destination in a given day. This paper takes the island in the centre of the city of Lindau (Bodensee) as its area under investigation and uses open-source data along with the appropriate assumptions as a base for its calculations.

1 INTRODUCTION

In recent years, the distribution of Electric Vehicles (EVs) has significantly increased. More and more people switch from Combustion Vehicles (CVs) replace them especially with Battery-Driven Electric Vehicles (BEVs). Together with the increasing availability of green energy, this development leads to a positive effect for the greenhouse gas balance of our economies. On the other side of the coin, Charging Infrastructure (CI) is being increasingly requested and utilised. Following the initial spread of publicly available Charging Stations (CSs) across the countries in order to decrease the hurdles for the shift to more sustainable transportation, now the question arises, at which locations the CI should be strengthened in order to satisfy the needs of the EV users (Klinkhardt et al., 2021).

In recent years, there has been several research approaches and studies to evaluate the energy demand and market development of electric vehicles including extrapolations into the nearer future either for particular cities (Schlote et al., 2021) or for whole countries (Zhou et al., 2015). Other studies answered the question about the current utilisation of CI (Hecht et al., 2020). In order to estimate arrivals at certain locations it has been proposed to analyse the popularity index (as known, e. g., from Google maps), showing the occupation of certain locations by time. From this studies, we know in rather general terms how CI needs to be developed in the upcoming years.

However, an open challenge is to precisely estimate the demand for CI around a particular location or set of locations. With this information, more targeted investments into CI would be possible taking the actual demands of EV drivers into its focus. On the one hand it needs to be answered, if visitors of a certain place find sufficient charging possibilities for their EVs within walking distance. On the other hand, it needs to be considered, if it makes sense for EV users to charge their vehicle at a given location, which basically is related to the time, that people typically stay at a given location, State of Charge (SOC) of the EV and the user preferences. The approaches, which analyse traffic situations at particular locations in or-

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der to estimate arrivals do not take into consideration typical stay times.

Our research objective has been to develop an approach to estimate the demand for charging in walking distance to particular locations or buildings using publicly available sources of data. In order to estimate how many CSs should be available in walking distance of a particular building, we propose a methodology to determine the purpose of the building, which gives an indication for typical stay times and the opening hours of a building. Additionally, we consider the characteristics of the building such as the size of the building, which gives, together with the building / location purpose, an estimation on the number of people that arrive to the building based on statistical data and building regulations. For the analysis, we limit ourselves to publicly available OpenStreetMap (OSM) data to ensure that the approach is transferable to arbitrary regions and we also consider if buildings have multiple purposes, for instance, if an apartment buildings has a shop floor. The methodology we present is based on a re-classification and standardization of OSM data. We feel that our approach can be well used as an extension to already existing approaches, which take traffic data and car arrivals at particular locations into their consideration.

From a scientific point of view, our work contributes to the development of methodologies aimed at estimating the demand and capacity of CIs. In extension to the existing work, we particularly emphasize the use of open data, and how types of real world data (building data, location, charging station, location attractiveness data, and statistical information) is merged into a single automated workflow.

2 RELATED WORK

Among the various approaches for estimating the charging demand for EVs, some focus on the charging stations while some approaches focus on the tracks the cars travel in. For both approaches two general directions can be found: empirical investigations and simulations.

Empirical investigations: van den Akker (J.M. van den Akker, 2020) used a preprocessed data set of 4.9M charging processes provided externally, containing: arrival time, connection time, distance (between adjacent chargers in a straight line), time between sessions, category of a charging session (13 different types differentiating charging time, same or different charging location, duration of the session - same, medium, long-, time between charging events, and type of a distribution – narrow, wide, broad-). Additionally, drivers are modelled by their behaviour described through the probability over the 13 types of charging session the users perform. For each individual EV the distances are computed through the energy consumption between charging processes.

An important empirical approach has been provided by Hecht et al. (Hecht et al., 2020), who analysed the occupancy rate of charging stations all over Germany. For this, the authors classified charging stations by their power and their location (urban, suburban, industrial, uninhabited). The work provides average statistical data on when charging stations are used and how utilised they are being.

Another empirical approach is given by Draz and Albayrak (Draz and Albayrak, 2019), who estimate the energy demand of a vehicle through stochastically defining the SOC when the vehicle arrives and the battery size. Based on this it is estimated whether a car uses a high power CS (with low SOC) or a normal charging power. Based on the arrival times of EVs and the number of charging points at a location, the number of charging services is defined. Given a charging profile for a EV, it is now possible to calculate the energy demand.

simulative investigation: A simulative approach has been described by Schlote et al. (Schlote et al., 2021), where the energy consumption of EV is modeled on the basis of the Markovian net, taking some parameters such as slope of the road segment, average speed, acceleration, and potential of regenerative breaking into account. Technically, the SUMO traffic simulator is utilised for evaluation of the model. The motion trajectories of cars are based again on the Markov model where the probabilities that a car is driving along certain road segments are derived; the segments being defined by the road intersections. The destinations of cars (which could give an indication where cars recharge), are determined by a random process estimating how many cars are travelling from which origin to which destination. Different general strategies for route selection are taken such as a ”minimum popularity routing”, or ”minimum energy routing”. As a vehicle model, a single standard vehicle has been used by the authors to be modeled via a small set of parameters.

Another simulative approach uses the SUMO traffic simulator and extends it with a physics-based model for the energy consumption of different classes of vehicles (Koch et al., 2021). Different power-trains can be simulated with this extension. In a large-scale study, the authors investigated the energy consumption of the German city of Paderborn in various scenarios describing the total share of EV of corresponding car segments. For this purpose, the authors used three potential scenarios for the development of the local traffic including the share and type of EVs in Paderborn based on recent developments with an outlook towards 2030. For the first scenario, the current set of car segments is used, for the second scenario a dominance of small vehicles is assumed. In scenario 3, the increasing trend of SUVs of 13% per year with 1% decrease for the next 10 years is assumed, making SUVs the most dominant car by 2030. For technical information about cars, statistical data for the development of the EV market has been used.

A third simulative approach is the demand estimation of the EVs using Multi-Agent-System (MAS)-based open source traffic simulation software called MATSim (Jahn et al., 2020). Four car classes with different average consumption per km are used for the car simulation. In the MAS, the agents follow their daily schedule composed by the activities of working, shopping, and other leisure activities, which have been derived from census data. Each agent is applied with transportation modes such as car, bike, public transport, etc. Distances, transport modes, etc. are backed with open source and census data.

Also Hernández-Moreno et al. provided a simulative approach for estimating the energy consumption of a single EV using the MATLAB/SIMULINK package ADVISOR, which is capable of estimating the energy consumption of arbitrary power-trains (Hernández-Moreno et al., 2022). The cars are modelled through parameters describing the chassis, the e-motor, the battery set, and a storage block for regenerative breaking. The authors used the Tesla Model 3 as their base model due to the public availability of the required data. Dynamic traffic parameters have been modelled with a Markov M/D/n queuing model, the parameters of which have been captured from a real-world traffic observation based on video tracking. From the computation of the queuing model the parameters for a SUMO MAS simulation have been derived. From that simulation, driving parameters for individual cars have been gathered, which, in turn, have been used for analysing the energy consumption of these cars.

3 DATA

Continuing on the carried-on research, our aim is to come up and apply a methodology to create a model that depends solely on open-data, and hence could further on be applied to different contextual locations to calculate more precisely the required expansions in the local CS infrastructures for cities and the optimal locations of new stations. The methodology to be explained in this section and demonstrated in Fig 1 is inspired by the overlapping of the work of Klinkerhardt et.al. (Klinkhardt et al., 2021) and that of Hecht et.al. (Hecht et al., 2020). Using classified OSM information on buildings and Points of Interests (POIs) data organized by tags representing particular features of locations, we can can provide an estimation of the maximum number of people visiting a certain building during a chosen time interval. This data is then overlapped with open-data on CS which can be categorized based on the study from Hecht et al. (Hecht et al., 2020) and therefore have an average percentage of occupancy rate during these chosen time intervals.

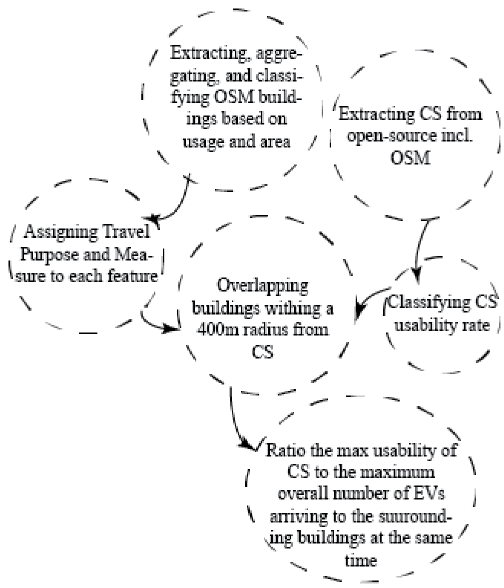

Figure 1: Methodology Logic.

3.1 Working with Geographical Data

POIs and Building uses construct the basis of our Trip Purpose tables. We use the following “Trip Purpose” definition extracted from different research on travel model: “the categorized list of destinations based on the function” (Klinkhardt et al., 2021). To ensure the adaptability of the methodology to different scenarios, this research paper uses OSM as a main source for geographical data. This decision ensures availability of data for most locations, the ability to enhance the data thanks to the open-source characteristic of the platform, and the ability to calculate the accuracy of data in comparison to other areas. The use of OSM as a source has also allowed for the acquisition of what is considered “raw data”; meaning that no pre-processing has been carried out on it and therefore the data can be filtered and clustered to fit into our travel model.

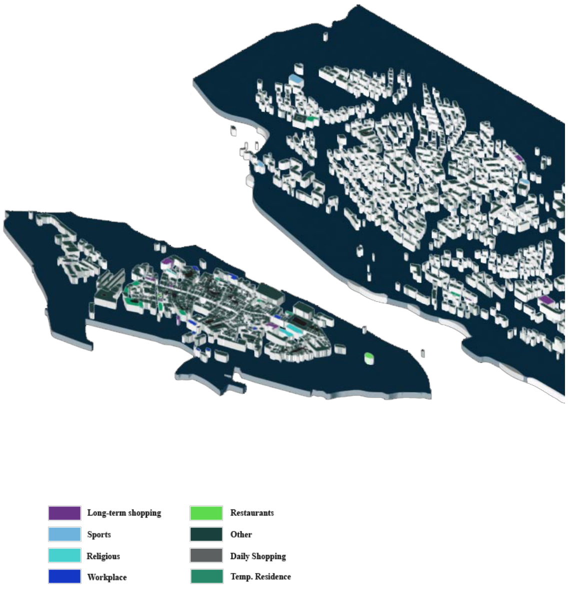

Figure 2: Classified buildings.

To ensure our travel model includes all types of trips; we extracted all buildings from OSM and then proceeded to assign different uses to buildings based on the tags assigned to them. This way we ensure all tags are considered. We therefore extracted the list of attributes related to our downloaded buildings and created a prioritization list based on the data filled in. We were then, able through comparison of different attributes and their rate of usability, and using PyQGIS script for the automation of the process; to create a new “fclass” local feature attribute to contain the identified use of the building. During the prioritization, some keys’ values were eliminated; those were values that didn’t provide an indication of a place that could host people but rather indicated either a quick stop or an attachment to a place (as with the key value ”attached” often found). The first “quick stop” elimination is to adapt the data to our need, which is the allocation of new Charging Stations. Quick stops are not in themselves destinations and don’t provide a time long enough for charging an E-vehicle. The second elimination of “attachments” was to avoid duplication of data by eliminating ”attached buildings” whereas the main building was found to be sufficient for the calculations. A third type of elimination also took place. This was to eliminate polygons features that were mistakenly mapped as buildings when they maintain the function of a plot of land.

For the POIs, a different type of features - “Points”- was studied. What created the challenge, with handling the POIs, is their inaccurate allocation where they sometimes overlapped with buildings with different uses. Nevertheless, POIs add a layer of accuracy as they include uses and places of attractions that may not be added to the buildings’ attributes. To calculate the factor of attractiveness in this research, however, area calculations are necessary. For Lindau, we could then merge POIs with their nearest buildings- which is usually the case in reality- and proceed to treat the resulting building as a multipurpose. This sequence of processes resulted in the map shown in Fig 2, where an overall use of each building in the city of Lindau (Bodensee) can be seen.

3.2 Building Areas / Points of Interest Areas

Having performed a first clustering of buildings based on usage, a second layer of clustering is carried out based on trip purposes and the type of visitors. According to Klinkerhart et al., a specified list of purposes can be created to identify the reason a person would want to reach a destination as well as the type of person (i.e., student – customer – worker – etc.). This table can be matched with open databases on attractiveness factor. An attractiveness factor describes the rate by which this destination is likely to be chosen for a trip. Our next step to identify an exact number of visitors is therefore to multiply this factor by the number of visitors in the area of the building; assuming the capacity of 1 person per square metre (pers/sqm).

3.3 Open Data on Charging Stations

In this research we focus on two types of information concerning the charging stations in Lindau: geographical and statistical. Being that geographical information refers to the location of charging stations; the statistical information refers to the statistical data on the usage rate of charging stations. The later is based on the study by Hecht et al.(Hecht et al., 2020), classifying the CS based on location and assigning usage rates to each class.

From OSM and other public sources we acquire locations and some of the other parameters of the charging stations currently available in the area of study such as charging power, accessibility, opening hours. However, this data does not contain information of their typical utilisation which can be described mainly by the typical number of charging events per day. As a starting point we use the classification as proposed by Hecht et al., who classify charging stations according to the location and the nominal charging power. Location classes are “industrial”, “urban”, “suburban”, “uninhabited”, while classes for the charging power are “$P <= 4kW$”, “$4kW < P <= 12kW$”, “$12kW < P <= 25kW$”, “$25kW < P <=$

$100kW$" "$P < 100kW$"). The authors provide utilisation profiles for each of these classes by weekday. For our analysis and considering our area of study, we will focus on the data for urban-class CSs with 22 kW (class: "$12kW < P <= 25kW$") and use a correcting factor according to the building classification and the typical stay time.

3.4 Data on Electric Vehicles Stock Shares

For the estimation of the number of e-vehicles (BEV and PHEV) in Lindau we take general statistical values for Germany into consideration. Official statistics indicate a market share of 2.6% of BEV (1.3%) and PHEV (1.3%) of the total number of vehicles in 2022 (Kraftfahrt-Bundesamt, 2022). For the development of the market share until 2030 several studies have been conducted, most of them aiming at a total market share of BEV and PHEV between one-fourth (Detlef Borscheid and Kraftfahrt-Bundesamt, 2020) and one-third (Center of automotive management, 2022). For 2025, Borscheid (Detlef Borscheid and Kraftfahrt-Bundesamt, 2020) assumes a stock share of about 11%.

Thus, for our study, we assume a stock share of BEV and PHEV vehicles of 11% for 2025. For 2030, we assume 30% stock share.

4 METHODOLOGY

The aim of the applied methodology is to prepare a model that could further on be used for different contextual locations and for more precise calculations on the required CS infrastructure for cities and their optimal locations. The methodology is inspired by the overlapping of the work of Klinkerhardt et.al. (Klinkhardt et al., 2021) and that of Hecht et.al. (Hecht et al., 2020). Using classified OSM buildings and POIs data, we can provide an estimation of the maximum number of people visiting a certain building during a chosen time interval. This data is then overlapped with open-data on CS which can be categorized based on the study from Hecht et al. (Hecht et al., 2020) and therefore have an average percentage of occupancy rate during these same time intervals.

4.1 Methodology Logic

Having gathered and aggregated the building data from OSM, we used the calculation of the building capacity based on the usage regulations to identify

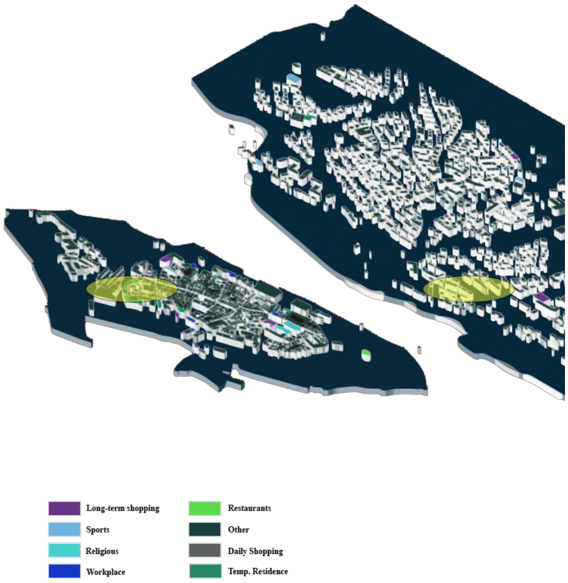

Figure 3: Buffer of OSM available CS.

the buildings with the highest capacity. The assumption taken at this point is that during rush hours these buildings will be at full capacity. In the work of Klinkhardt et al, attractiveness factor databases were used as a solution against this assumption and to calculate a concrete number of visitors. This attractiveness factor can differ based on the use of the space but also based on more case-specific factors such as the brand name for commercial buildings for example. Sources for attractiveness factors were found to be proprietary, as opposed to common architectural recommendations for sqm/pers. For the purpose of this research, which is to investigate the reliability of open-data in conducting such a study; the attractiveness factor has been substituted by the building capacity. These recommendation tables and tools such as found in the Neufert's book (Neufert et al., 2012) can help determine the standard sqm/pers based on which a maximum floor building capacity could be calculated. The assumption then made is that the floor area is at full capacity during the simulation interval. The next layers to be overlapped are the number of EVs arriving to each destination and the CS data layer. Assuming all visitors arrive with personal vehicles to the destination, and taking the EVs stock shares mentioned in subsection 3.6 into consideration, we can use the following equation to estimate the maximum number of EVs (n_{ev}). Number of vehicles being n_v, number of EVs is n_{ev} , and building capacity is b, if we assume the building is at full capacity we would have $(n_v) = (b)$ and since in 2022 the share of EV in Germany was 2.6 $n_{ev} = 2.6/100 * (n_v)$ then $n_{ev} = 2.6/100 * b$.

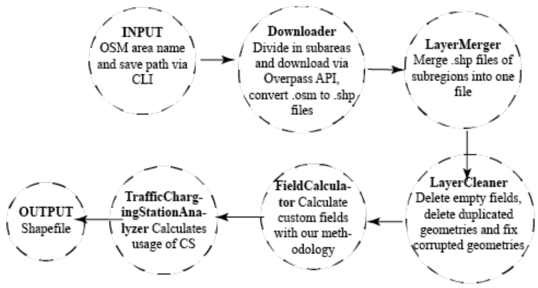

Figure 4: Automation Framework.

Some more sophisticated models such that created by the ”Ver-Bau” tool work on the same basis but include however more case specific factors such as the time of day, etc. The Ver-Bau tool was used, for example, to determine the needed number of parking slots attributed to the commercial building Lindaupark (Engstler et al., 2021).To expand the model by specifying when building are visited based on open data, in the case of Germany or Austria, standard load profiles of buildings can be used. These provide information on the distribution of electricity demand generated by the economic activity. A classification of POIs with regard of this demand profile, can help to identify the moments in which the POI is going to be more visited.

Allocating the buildings with the highest number of EVs reaching them, we can investigate the surrounding CSs which are, in our case study, categorized as urban CS.From the literature review and more specifically based on the work of Hecht et al. (Hecht et al., 2020), we can conclude that on average an urban CS is occupied and used 20% of the working time. Time is therefore our point of intersection between the number of EVs in a destination and the CS demand. For a building (A) in the time interval of 5 hours between 12 to 17h, the number n_{ev} is stationed in front of the building each hour. We know from charging behaviour studies, that an EV stationed in front of a building for a certain duration, will occupy the CS for the same duration; regardless of the time needed to complete a charging profile. Looking at the time of the study, it is possible then to assume that a CS is occupied by the same vehicle. In the 400m recommended buffer, an Urban Charging Station (UCS) is stationed, which is occupied 20% of the time; approximately 1h of the 5-hour study time. Since the number n_{ev} is taken as a constant for each hour, UCS is then fulfilling 20% of the demand in the span of these 5 hours.

4.2 Methodology Application

Taking the characteristics of the city of Lindau (Bodensee) as inputs, we started the process of applying our logic and visualizing the results on the map using QGIS. Because the whole process of downloading and analyzing the OSM data manually is time consuming and difficult to replicate, we started to automate the process via PyQGIS. PyQGIS is the python interface for QGIS which allows us to build a modular standalone data processing pipeline, with the workflow as explained in Fig.4. The only dependency is a valid, platform independent, QGIS (in our case QGIS LTR 3.22.x). The CLI interface expects two input parameters: the name of the are to be processed, and a directory path to save the output data. To begin, the “Downloader”-Module tries to find the corresponding OSM-ID of the given area name. It sends a POST-Request to the Overpass Interpreter Endpoint with the following query:

```
[out:json][timeout:900];
relation["boundary"="administrative"]
["name"="{0}"]["type"="boundary"];
(._;>;);
out body;
```

This query searches for all administrative boundaries with the given name. The result of that query contains information about the administrative level of the boundary area, which can then be split up by searching for boundaries with a higher OSM administrative level (smaller real-world area) to avoid maxing out the run-time of the API. Because each OSM building is referenced to be within a boundary, we can query for all buildings in the resulting boundaries. After downloading all buildings in .osm formats, we continue to merge them back together into one file. At first, we convert each downloaded “.osm” file into two shapefiles: a polygon and a point, by using the “ogr2ogr” CLI tool. Using the “native:mergevectorlayers” algorithm, the “LayerMerger”-module merges all polygon files and all point files into corresponding joint files. Moving forward, the “LayerCleaner”-Module first deletes duplicated geometries by using a custom algorithm, that iterates over each feature, saves its ID into a list; if an ID is already included in the list, the feature gets discarded. Otherwise, the feature gets copied into a new in-memory layer. Simultaneously every attribute column is checked to find completely empty attributes across the whole data set. These attributes get then deleted by the ”layer.dataProvider().deleteAttributes()” function. The “LayerCleaner”-Module finishes by saving the newly created in memory layer as a shapefile on disk.

Table 1: Percentage of fulfilment of CS of the overall charging demand in the AOS.

	Current rate of contribution	Rate by 2025	Rate by 2030
Existing CS	20 %	4.7 %	1.7%

The last and biggest processing step is handled by the "FieldCalculator"-module. Its purpose is to apply the above-described in the methodology logic and in Section 3 to calculate the measure and travel purpose for each building. Based on our current dataset we could attribute attractiveness factors to certain types of buildings. For that, we begin with creating new attribute fields ("fclass_t", "measure", "trip_purp", "attr_rate", "buil_cap" and "area") on the polygon layer by using the "layer_provider.addAttributes()" function. After that the module iterates over each polygon feature. We begin be determining the "fclass" by comparing the "leisure", "office", "tourism", "shop" and "building" fields. Going forward the polygon area in square meters is calculated and saved in the "area" field by using the "QGSDistanceArea().measureArea()" function. After that the "measure", "trip_purpose" and "attr_rate" are determined by looking up the corresponding value in relation to the "fclass" in a predefined "fclass_traffic_matrix. An extract of that matrix looks like this:

```
FCLASS_TRAFFIC_MATRIX = {
'office': {
    'measure': 'Workplaces',
    'trip_purpose': 'Business',
    'attraction_rate': 0.1
}, ... }
```

We defined for each possible fclass a measure, trip purpose and attraction rate. The module finishes by selecting all features in the layer and saving them to the user-defined output directory as a copy with the "native:saveselectedfeatures" algorithm. The "TrafficChargingStationAnalyzer"-module proceeds then to iterate over OSM mapped charging stations (downloaded again by the "Downloader"-Module, but querying this time for "charging_stations"), calculates a 150-meter buffer (native "geometry().buffer()" function) around it as shown in Fih 3 and sums up the previously determined building capacity of all buildings inside the buffer. Based on the stock shares concluded for EVs (2,6% for 2022, 11% for 2025 and 30% for 2030), the total number of EVs and the charging station usage is calculated for each year and results in the percentages demonstrated in Table 1.

As a result, there are two layers, one shapefile with every building and one shapefile with all charging stations and their corresponding calculated values. The pipeline finishes by validating if the output file exists and then deleting all temporal files. In case something goes wrong, the pipeline can pick up at a user controllable step so not everything needs to be run again. Having automated these calculations can demonstrate the variation in which existing charging stations will answer to the increased demand.

5 CONCLUSIONS AND FUTURE WORK

The final goal of our research is the development of a method for gaining insight into the sufficiency of CI for EVs, particularly BEV. In this article, we reported about the first results in our pursue for the overall goal: a method for determining to which degree available CI is fulfilling the demands created by EV.

The motivation behind this work stems from the support of both, the movement towards the traffic electrification, which subsequently results into a rise in the use of EVs, the movement towards enhancing and providing more open-source data that can be used for social and civil improvements. The presented methodology therefore provides groundwork for how planning CS infrastructure could be carried on using open-source data but also provides an overview of the challenges that researchers would face in that attempt. As open-source data would fall short in accuracy, the results acquired through this work don't represent, therefore, a real-life estimation but rather showcases the falling-short of CS infrastructure. In the current step of our research we are also able to analyse different scenarios with larger shares of EVs and/or more CSs in the region.

In our planned future work, this methodology is enhanced through the acquisition and integration of more case-specific data such as CS profiles, demographic data for drivers behaviors and used cars, more specific data on building uses and, vehicles' energy usage and charging behaviour. It is, hence, important to keep track of the rate of accuracy of the results and to provide more validation methodologies in the future.

More specifically, our planned next steps will particularly include detailed information about traffic and vehicles. To go about that, first, additional data sources needs to be processed and included. Most importantly, Floating Car Data (FCD) and traffic census data will be used to get insights into the local traffic situation by capturing the traffic in the region under investigation. This particularly includes the number of cars in the region and the origin-destination relations they typically exhibit. With this, we are able to estimate how probable or important a recharging of a car is, when it arrives (short distance drivers are less probable to recharge then long-distance drivers). We expect a more detailed estimation of the CS occupation. Furthermore, FCD would allow us also to capture hourly distributions of EV arrivals in order to estimate the CS occupation by our of day, this also includes the extension of our building usage model by opening or typical usage times.

In a next step, also the car types, which are typical in the region will be included. This information is used together with the typical travel distances, typical stay times, energy consumption data for charging processes, and a vehicle energy consumption simulation to finally calculate the actual energy demand for EVs in the investigated region. This is particularly important for estimating the potentials for reinforcement of CI. Particularly, when information about the power distribution grid are taken into account.

Another envisioned step is the improvement of the attractiveness factor by adding a metric describing the reach of a particular building. Based on the building use, the reach metric describes from which distance cars typically arrive as this could essentially differ, for instance, at a supermarket from a public authority building with supra-regional significance.

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