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REAL-WORLD DATA-DRIVEN DECISION SUPPORT SYSTEM FOR ELECTRIC VEHICLE CHARGING INFRASTRUCTURE DEVELOPMENT

DOCTORAL THESIS

Supervisor: Associate Professor Vedran Podobnik, PhD

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SUSTAV ZA POTPORU ODLUČIVANJU O RAZVITKU INFRASTRUKTURE PUNIONICA ZA ELEKTRIČNA VOZILA ZASNOVAN NA PODACIMA IZ STVARNOGA SVIJETA

DOKTORSKI RAD

Mentor: izv. prof. dr. sc. Vedran Podobnik, PhD

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About the Supervisor

Vedran Podobnik was born in Zagreb in 1982. He received M.Eng. (2006, Electrical Engineering) and Ph.D. (2010, Computer Science) degrees from the University of Zagreb, Faculty of Electrical Engineering and Computing (FER), Zagreb, Croatia, as well as M.Phil. (2013, Technology Policy) degree from the University of Cambridge, Judge Business School, Cambridge, UK.

From 2006, he works at the Department of Telecommunications at FER (from 2016 as the Associate Professor). He is the founder and Director of the "Social Networking and Computing Laboratory (socialLAB)" and co-founder of the "FER's student startup incubator SPOCK". He led several national and international scientific and industrial projects. Currently, he is a work package leader in the only national centre of research excellence (CoRE) in the field of technical sciences, the "CoRE for Data Science and Cooperative Systems", and the management board member at FER's "Center for Artificial Intelligence". His teaching and research activities are in transdisciplinary fields of network and data science, social computing, and technology policy. He co-authored over 100 scientific and professional papers, including publications in Information Sciences, Information Technology & People, International Journal of Energy Research and AI Magazine journals. From 2018, he advises the global technology company Hewlett Packard Enterprise (HPE) in the fields of data platforms, data analytics and artificial intelligence. He received scientific titles in two fields of engineering - electrical engineering and computer science.

Assoc. Prof. Podobnik is a member of IEEE, ACM, INFORMS, AIS and KES International associations, as well as the Cambridge Union Society. He has participated in the program and organizing committees of many scientific conferences and summer schools, and has served as a peer reviewer in various international journals. He coordinated an international team that received the "Success Story Award" for a particularly successful ERASMUS+ Strategic Partnerships project, the first such award in the higher education sector in Croatia (2018, awarded by the European Commission). He was a leader of an interdisciplinary team which was awarded the highest national award for notable achievements in the education activity (2015, awarded by the Croatian Parliament) as well as the annual national PMI Project of the Year Award (2016, awarded by the world's leading project management professionals association PMI). As a junior researcher, he received the Croatian Annual National Award for Science in the field of technical sciences (2011, awarded by the Croatian Parliament), as well as the Silver Medal "Josip Loncar" award for outstanding doctoral dissertation and particularly successful scientific research (2010, awarded by FER).

O mentoru

Vedran Podobnik rođen je u Zagrebu 1982. godine. Diplomirao je u polju elektrotehnike te doktorirao u polju računarstva na Sveučilištu u Zagrebu Fakultetu elektrotehnike i računarstva (FER), 2006. odnosno 2010. godine. Također je magistrirao u području upravljanja tehnologijom 2013. godine na Sveučilištu u Cambridgeu, Judge Business School (Ujedinjeno Kraljevstvo).

Od 2006. godine radi na Zavodu za telekomunikacije FER-a (od 2016. kao izvanredni profesor). Utemeljitelj je i voditelj "Laboratorija za društveno umrežavanje i društveno računarstvo (socialLAB)" te jedan od utemeljitelja "FER-ovog studentskog startup inkubatora SPOCK". Bio je voditelj većeg broja domaćih i međunarodnih znanstvenih projekata te projekata suradnje s gospodarstvom. Trenutno je voditelj radnog paketa u jedinom nacionalnom znanstvenom centru izvrsnosti (ZCI) u području tehničkih znanosti "ZCI za znanost o podatcima i kooperativne sustave" te član Upravljačkog vijeća FER-ovog "Centra za umjetnu inteligenciju". Provodi nastavne i istraživačke aktivnosti u transdisciplinarnim područjima znanosti o mrežama i podacima, društvenog računarstva i upravljanja tehnologijom. Objavio je više od 100 znanstvenih i stručnih radova, uključujući radove u časopisima Information Sciences, Information Technology & People, International Journal of Energy Research i AI Magazine. Od 2018. godine savjetuje globalnu tehnološku kompaniju Hewlett Packard Enterprise (HPE) u području podatkovnih platformi, analitike te umjetne inteligencije. Izabran je u znanstvena zvanja u dva polja tehničkih znanosti – elektrotehnici i računarstvu.

Izv. prof. Podobnik član je stručnih udruga IEEE, ACM, INFORMS, AIS i KES International te društva Cambridge Union Society. Sudjelovao je u programskim i organizacijskim odborima mnogih znanstvenih konferencija i ljetnih škola, te sudjeluje kao recenzent u većem broju inozemnih časopisa. Koordinirao je međunarodni tim koji je dobio priznanje "Success Story" za iznimno uspješno provedeni projekt u programu ERASMUS+ Strateška partnerstva, što je prva takva nagrada u sektoru visokog obrazovanja u Republici Hrvatskoj (2018., dodijelila Europska komisija). Bio je voditelj interdisciplinarnog tima koji je nagrađen najvišom hrvatskom državnom nagradom u području edukacije (2015., dodijelio Hrvatski sabor) te godišnjom nacionalnom nagradom PMI Projekt godine (2016., dodijelila vodeća svjetska profesionalna udruga projektnih menadžera PMI). Kao mladi istraživač primio je godišnju nacionalnu nagradu za znanost u području tehničkih znanosti (2011., dodijelio Hrvatski sabor), kao i srebrnu plaketu "Josip Lončar" za posebno istaknutu doktorsku disertaciju (2010., dodijelio FER).

Special thanks to my family and friends for their support over the years, and my girlfriend for motivating me and pushing me over the finish line.

Abstract

The dissertation presents the results of research in the field of decision support for the development of a charging infrastructure for electric vehicles. It is based on an interdisciplinary approach that includes data science, energy informatics and sustainable transport and takes into account different stakeholders, i.e. owners and potential owners of electric vehicles, charging operators and public administration. The Electric Vehicle Charging Infrastructure (EVCI) framework proposed in the paper includes macro and micro development models that differ in the availability of real world data. Namely, in situations characterised by a lack of transactional data on charging services, or due to an underdeveloped infrastructure or because they are not available, it is necessary to rely on general, publicly available data on the location of charging stations and the places and categories of places of interest to drivers (trade, entertainment, travel, socialising, business activities). This is in line with the macro development model. The micro model is intended for situations where transaction data collected by the charging point operator is available. This allows the planning and management of the infrastructure based on the prediction of the utilisation of existing and new charging stations. Two concepts closely related to the framework are discussed, the so-called range anxiety and the geospatial analysis of charging stations and places of interest. The functionality of the derived robust data-based decision support system is illustrated by case studies describing a macro development model for underdeveloped and developed infrastructure and micro development using transactional data from a charging point operator.

The first chapter contains a short description of the research motivation, research problems and related questions and introduces the content of the doctoral thesis.

The second chapter provides a literature review with a focus on data science and energy informatics. The work in this area is analysed under socio-economic and socio-technical aspects. The first concerns the relationship between the owner and the potential owner of the electric vehicle and the vehicle itself. Research on the acceptance of electric vehicles and the preferences of potential owners as well as studies on their future sales are discussed in detail. The second aspect describes the interaction between the electric vehicle and the network and between the owner and the network. Approaches to developing the infrastructure of charging stations were discussed, used algorithms, as well as the approaches to estimate the behaviour of owners of electric vehicles with respect to charging.

The key concepts discussed in the third chapter are the range anxiety and the geospatial analysis of charging stations and places of interest. The range anxiety, i.e. the fear of drivers that they will run out of electricity before reaching the charging station, is considered a serious psychological barrier to the acceptance of electric vehicles. Research is based on the methodology CRISP -DM (Crass-Industry Standard Process far Data Mining), and was conducted as an

online survey with the tool LimeSurvey. The survey consists of three parts: demographic questions, questions comparing charging station and petrol station infrastructures, and randomly generated scenarios collecting views on refuelling requirements. The responses were collected from 274 participants, and after rejecting responses with discrepancies, the remaining 213 (79 owners of electric vehicles and 134 who are not) were processed. The results of the analysis are presented in great detail, which indicates a different perception of the state of charge and remaining range by owners of electric vehicles and those who do not own electric vehicles. For both groups, the desired average distance between neighbouring charging stations is 7 km. The geospatial analysis of the existing charging station infrastructure is based on the data contained in the Open Charge Map. In addition, information on points of interest contained in the Open Street Map was used to model the context of the charging stations. The following indicators for the state of development of the charging station infrastructure were defined: the density of charging stations, which shows how the number of charging stations corresponds to the size of the area, and the lack of charging stations, which describes the distribution of charging stations by zones in the area.

The fourth chapter deals with the EVCI framework, the conceptual model of the decision support system for the management of the charging station infrastructure and its program implementation. The framework consists of a data component and parts for macro and micro development. The data component of the framework comprises the collection and processing of the following data: location of charging stations, location of competing charging stations, transactions at charging stations and location of places of interest and their categories. The development part of the macro model is based only on geospatial analysis and hierarchical grouping of charging stations based on distance, which leads to the definition of charging zones. These three objective functions are defined to support decision making: connecting major cities with charging stations, merging the two largest charging zones with charging stations, and connecting the two nearest zones with charging stations. The development of micro-models allows to include the calculation of charging station usage in zones based on transaction data and to predict usage when new charging stations are introduced. The functions of the target when deciding on a new charging station in a given zone are as follows: maximise the total utilisation of charging stations, place the charging station in an insufficiently covered area and a hybrid approach between the previous two. In addition to the real world data sets, an estimate of future electric vehicle sales is included as an additional option that can affect the accuracy of the utilisation prediction model. Two machine learning algorithms are used to predict the utilisation of charging stations; a multiple linear regression model to estimate the effect of each variable on utilisation, and the XGBoost algorithm for the prediction itself.

The fifth chapter presents three case studies, two of which present relevant decisions based on a geospatial analysis of the developed charging infrastructure in Germany and the underdeveloped infrastructure in Croatia (macro level), and the third deals with decisions based on charging transactions for infrastructure development in the Netherlands (micro level). The case studies covered all the objective functions proposed in the EVCI framework.

The final chapter summarizes the main objectives and contributions of the doctoral thesis and outlines the directions of future research.

Keywords: Electric Vehicles, Charging Station, Range Anxiety, Data Science

Sažetak

Doktorski rad prikazuje rezultate istraživanja u području e-mobilnosti, odnosno potpore odlučivanju o razvitku strukture punionica električnih automobila. Rad je zasnovan na interdisciplinarnom pristupu koji obuhvaća znanost o podatcima, energetsku informatiku i održivi prijevoz, a uzima u obzir različite dionike, odnosno vlasnike i potencijalne vlasnike električnih vozila, operatore punionica i državna tjela. Radni okvir infrastrukture punionica za električna vozila (EVCI - Electric Vehicle Charging Infrastructure) predložen u radu obuhvaća modele makro i mikro razvoja koji se razlikuju po raspoloživosti podataka iz stvarnog svijeta. Ako nema podataka o transakcijama punjenja ili ako punionice ne postoje, ili je njihov broj značajno mali, , neophodno je osloniti se na opće, javno dostupne podatke o lokacijama punionica te lokacijama i kategorijama mjesta od interesa za vozače. To je u radnom okviru predstavljeno kao makro upravljanje infrastrukturom punionica. Mikro model namijenjen je situacijama u kojima su transakcijski podaci koje prikuplja operator punionice raspoloživi. Time se omogućuje planiranje i upravljanje infrastrukture zasnovano na predviđanju iskorištenosti punionica. Obrađena su dva koncepta vezana za radni okvir, anksioznost dometa te geoprostorna analiza punionica i mjesta od interesa. Funkcionalnost izvedenog robusnog sustava za potporu odlucivanju zasnovanog na podatcima prikazana je na studijskim slučajevima koji opisuju model makro razvoja za nerazvijenu i razvijenu infrastrukturu te mikro razvoja uz korištenje transakcijskih podataka punjenja.

Prvo poglavlje donosi opis motivacije za istraživanje, detektiranih istraživanih problema te pitanja koja se na njih odnose, zajedno sa preloženim potencijalnim rješenjima.

Drugo poglavlje daje pregled literature usredotočen na znanost o podatcima i energetsku informatiku. Radovi su u ovom podrucju analizirani s društveno-ekonomske i socio-tehničke perspektive. Društveno ekonomska perspektiva prikazuje odnos vlasnika i potencijalnog vlasnika električnog vozila i samog vozila. Obrađena su istrazivanja o prihvaćanju elektricnih vozila i preferencijama potencijalnih vlasnika te studije koje se bave njihovom budućom prodajom. Druga perspektiva prikazuje međudjelovanje električnog vozila i mreže. Obrađeni su pristupi razvoju infrastrukture punionica i navike punjenja vlasnika električnih vozila.

Treće poglavlje obrađuje ključne EVCI koncepte, anksioznost dometa i geoprostornu analizu punionica i mjesta od interesa. Anksioznost dometa, tj, strah vozača da će ostati bez električne energije prije dolaska do dostupne punionice smatra se jednim od većih faktora koji utjece na prihvaćanje električnih vozila. Istraživanje se zasniva na metodologiji CRISP-DM (Crass-lndustry Standard Pracess far Data Mining), a izvedeno je kao anketa koja sadrži tri dijela: demagrafska pitanja, pitanja kojima se uspoređuje infrastruktura punionica i benzinskih postaja te proizvoljno generirani scenariji kojima se prikupljaju stavovi o zahtjevima za punjenje. Obrađeno je 213 odgovora (79 vlasnika electricnih vozila i 134 anih koji to nisu). Geoprostorna analiza postojeće infrastrukture punionica temelji se na podacima sadržanim u Open Charge Map. Uz to, informacije o mjestima od interesa sadržane u Open Street Map korištene su za modeliranje konteksta punionica. Definirani su sljedeci pokazatelji stanja razvoja infrastrukture punionica: gustoća punionica koja pokazuje kako broj punionica odgovara veličini područja i nedostatak punionica koji opisuje raspodjelu punionica po zonama u tom području.

Četvrto opisuje konceptualni model radnog okvira EVCI. Okvir se sastoji od komponente za dohvaćanje i obradu podataka te od komponente za mikro i makro upravljanje infrastrukturom punionica. Razvojni dio makro modela temeljen je samo na geoprostornoj analizi i hijerarhijskom grupiranju punionica na temelju udaljenosti. Razvoj mikro modela omogućuje uključivanje izračuna iskorištenosti na temelju transakcijskih podataka i predviđanje iskorištenosti pri uvođenju novih punionica. Dva algoritma strojnog učenja koriste se za predviđanje iskorištenosti punionica; model s višestrukom linearnom regresijom za procjenu utjecaja svake varijable na iskorištenost, a algoritam XGBoost za samo predviđanje.

Peto poglavlje predstavlja tri studije slučaja, od kojih dvije prikazuju relevantne odluke temeljene na geoprostornoj analizi razvijene infrastrukture za punjenje u Njemačkoj i nerazvijene u Hrvatskoj (makro razina), a treća se odnosi na donošenje odluka temeljenih na transakcijama vezanima uz punjenje za razvoj infrastrukture u Nizozemskoj (mikro razina). Studijama slučaja obuhvaćene su sve funkcije cilja predložene u okviru EVCI.

Zaključno poglavlje prikazuje glavne ciljeve doktorskog rada kao i smjerove budućeg istraživanja.

Ključne riječi: Električni Automobil, Punionica, Anksioznost Dometa, Znanost o Podacima

Glossaries

Alternative fuelled vehicle (AVF) - Vehicles that can be fuelled by electricity, hydrogen, biodiesel or solar power.

Electric vehicle (EV) - A subgroup of AFVs that are fuelled by electricity.

Internal Combustion Engine Vehicle (ICE) - Vehicles powered by traditional fossil fuels, diesel or benzine.

Charging station (CS) - A place where EV owner can charge their vehicle.

Charging point operator (CPO) - A company operating a pool of charging points.

Electromobility (service) provider (EMSP) - A company offering an EV charging service to EV drivers.

Range anxiety - Fear of running out of electricity before reaching another available charging station.

Place of interest (PoI) - A public location with certain characteristics important to an indefinite number of people.

Charging zone (CZ) - An area covered with charging stations in a predefined proximity.

Electric vehicle charging infrastructure extender (EVCI) - A framework implementing smart models for deploying new charging stations.

Energy Informatics - A research area focused on the information and information flows in the energy systems, especially on the use of computational algorithms in order to increase the efficiency of the energy systems.

Contents

Chapter 1

Introduction

Various environmental concerns, from climate-related changes and illnesses to rising seas, are considered to be among the most prominent challenges humans face [1, 2]. One of the prime factors behind numerous environmental problems is air pollution, of which the transportation domain is a major contributor to the CO_2 footprint. For example, more than 25% of the total greenhouse emissions in Europe are attributed to the transportation sector [3]. Reacting to the global increase of the number of personal vehicles [4], academia, industry, and governments are putting effort into tackling environmental concerns by inventing and supporting alternative transportation technologies, commonly known as *alternative fuel vehicles* (AFV). AFVs can be fueled by electricity, hydrogen, biodiesel or solar power [5, 6, 7]. In this thesis, the focus is on electric vehicles (EVs), a subgroup of AFVs that are fulled by electricity. Ketter et al. [8] argued that EVs can significantly lower the transportation sector's negative impact on greenhouse gas footprint, especially if renewable sources are significantly present in their production.

More than 1 million EVs were sold in 2017, representing a 50% growth when compared to 2016, and leading to more than 3 million electric vehicles on the roads globally [9]. This number is on the rise ever since, and by today there is more than 10 million EVs on the world roads. There are two main driving factors behind this accelerated adoption of EVs. First, academia and industry managed to find ways to produce batteries of greater capacities at lower prices, resulting in increased EV autonomy and longer driving ranges. Second, governments have been providing incentives for purchasing and operating EVs, such as lower registrations costs and free public charging [10], as well as subsides for purchasing an EV.

Nonetheless, EVs are still far away from mass adoption. For example, EVs correspond to more than 1% of the market share among private vehicles in only three countries globally, namely Norway, Sweden, and China [11]. The *range anxiety* phenomenon, i.e., an EV driver's fear of running out of electricity before reaching another available charging station [12], is one of the most important factors that influence new-vehicle buyers when deciding on whether to purchase a traditional internal combustion engine (ICE) vehicle as opposed to an EV [13].

Arguably, range anxiety can be lowered by either increasing EV autonomy or by enhancing the existing charging infrastructure to be more secured and in terms of availability and time spent on charging as a well known traditional gas station infrastructure.

1.1 Motivation

As stated before, the main negative influence factor in a decision not to purchase an EV is the phenomenon known as a range anxiety. There are two possible solutions for lowering the aforementioned range anxiety: to increase the capacity of EV batteries, i.e., extend the EV autonomy, and/or to populate the EV charging station network with new chargers in order to make the infrastructure more reliable in terms of accessibility. This thesis focus is on the latter approach since the first one is limited by the existing technology and physical characteristics of batteries. Therefore, the most promising way of increasing the EV autonomy is by increasing the number of charging stations enabling unobstructed inter- and intra-city traversal.

The motivation throughout this thesis research is to contribute to the charging station infrastructure development in order to overcome one of the major obstacles in a decision to purchase an EV. The main challenge is to achieve the aforementioned goal in a way to satisfy all involved stakeholders: potential EV owners, charging point operators, grid operators, and governments.

The above setting leads us to formulate the following question: *"Where should an EV charging infrastructure provider place a new charging station, or remove either reallocate an existing one?"*. The answer to this question could be different based on the perspective of different stakeholders. First, from the grid operator's point of view, it is important to place new charging stations in a way to minimise peak load and distribute the load evenly. Second, from the charging point operator's point of view, it is important to maximise the total utilisation of the charging network to maximise profit. Finally, from EV owners' and local governments' points of view, placing new charging stations in less populated areas could be more important in order to mitigate the range anxiety, as depicted in the Figure 1.1.

That being said, this research is interdisciplinary in nature, touching on the areas of green transportation, energy informatics, and data science. First, *green transportation* is a generic term for zero-emission vehicles (e.g., cars, trains, or buses). Second, energy informatics uses information and communication technology to analyse and improve energy systems [14]. Finally, *data science* is a relatively new engineering area that provides methods and tools not only for statistical analysis of (big) datasets, but also for highly accurate predictive modelling. In this thesis data science tools, aligned with the key goals behind energy informatics, will be used for analysing and improving a specific green transportation challenge, namely the deployment of EV charging infrastructure.

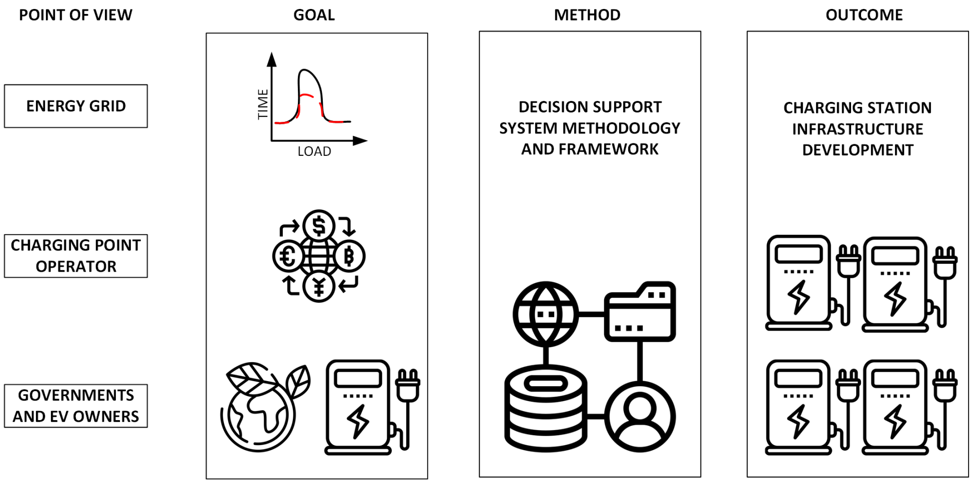


Figure 1.1: Thesis motivation from the three different perspectives

1.2 Problem statement

The main challenge introduced in the scope of this thesis is to lower the range anxiety by increasing the number of publicly available charging stations. This challenge must be tackled in a way to address needs of all parties involved: energy grid operators, charging point operators, as well as EV owners and governments. Besides ensuring the smart charging station deployment that will consider all parameters, it is equally important for the methodology to be generalised, i.e., to provide decision support for a new charging station placement regardless of the data variety. Hereby, EVCI framework is proposed as a solution for aforementioned challenge that can be summarised as: *how to design the decision support system for the development of the charging station infrastructure*.

Through the design of the methodology proposed in the Electric Vehicle Charging Infrastructure extender (EVCI) framework for the charging station infrastructure development, couple of research questions presented themselves. First one, that the whole methodology is based on, can be formulated as:

RQ1: *How to define and calculate the range anxiety?*

To answer this question, survey-based method is employed, with participants who are either owners or potential owners of the electric vehicle. This research, along with the outcomes, is in details described in Chapter 3.1. This calculation is crucial since every EVCI framework functionality depends on the range anxiety, i.e., the acceptable distance between two neighbouring charging stations.

The second research question that presented itself is associated with another especially significant input of the EVCI framework - *places of interest*.

RQ2.1: *How to define categories of places of interest (PoI) and relevant distance from the charging station?*
RQ2.2: *How to measure the influence of the certain PoI category on charging station placement?*

EVCI framework uses the information about the number of PoIs in a proximity to charging stations in order to draw a correlation between specific PoI category and the number of charging stations surrounding it. Aforementioned correlation can be used in the process of building the prediction model for assisting the decision making regarding the deployment of new charging stations. RQ 2.1, as well as RQ 2.2, is answered in the Chapter 3.2 of this thesis.

Finally, third research question is oriented towards the generalisation of the whole decision making process, which is especially important since the whole framework relies on the real-world data.

RQ3: *How to ensure the usability of the decision making model regardless of the available data?*

The answer to this research question is of utmost importance in order to tackle the challenge of underdeveloped charging infrastructure. The EVCI framework is intended to be used in both, places with developed infrastructure and structured transaction datasets, as well as in places with extremely underdeveloped charging infrastructure without any charging transactions data. Therefore, decision on a charging station placement must be possible with significant variation in the amount and variety of data available.

The main concept of the methodology implemented through the EVCI framework is to enable the decision support for a new charging station placement, regardless of the state of the existing charging infrastructure development. For example, if targeted area does not have developed charging infrastructure, and therefore no available charging transaction dataset, the macro development component of the EVCI framework can be used in order to deploy new charging stations, as explained in the Chapter 4. On the other hand, if the targeted area has well developed charging infrastructure, the micro development component of the EVCI framework can be used to prescribe the optimal location for a new charging station based on the charging station utilisation prediction model. The main difference between the micro and macro development of the charging infrastructure is in the deployment method. The micro deployment can be applied to a very specific area and depends on transaction data, while the macro deployment can be only applied on a wide area and does not depend on the contextual information, rather on geolocation and mathematical distribution of chargers. The concept of the EVCI framework is based on the decision which deployment method should be used in the decision making. As explained in Section 3 the key EV related concepts, i.e., the density of charging stations and the scatter attribute, can be used to decide weather the micro or macro development would be appropriate for a specific case study. The prediction model is built using the mandatory charging transaction data. Besides the mandatory data, the model can further be enriched with the information about the charging station belonging to other *charging point operators* (CPOs) or even the number of EVs using the targeted infrastructure (see Chapter 4).

Described behaviour of the EVCI framework points towards its general usage in multiple possible scenarios. Macro development of the charging infrastructure can always be used, since it is dependant on publicly available data about PoIs and locations of public charging stations. Micro development, on the other hand, is dependant on the proprietary data from the CPOs, however, the prediction model that is used in this mode can be *fine tuned* with numerous optional parameters.

1.3 Thesis outline

After the introductory Chapter 1, which stated the motivation for this research, together with the problem statement and the proposed solution, Chapter 2 provides detailed review of the *state-of-the-art* research regarding the *socio-economic* perspective of this interdisciplinary field, as well as the *socio-technical* perspective. At the end of the Chapter 2 discussion about the relevant reviewed studies is provided.

Before going into details about the EVCI framework, key concepts that the aforementioned framework is based upon have to be introduced. Chapter 3 serves as a introduction for those key concepts. First key concept that is presented is the phenomenon known as a *range anxiety*, more specifically, how the range anxiety is defined and calculated in the scope of this thesis. Second key concept introduced is the *geospatial analysis of charging stations and places of interest*, together with two important key performance indicators (KPIs) defined in this thesis: *charging infrastructure scatter factor*, and the *charging station density*.

Chapter 4 in details explains all major modules of the EVCI framework, with the examples of their functionality, while Chapter 5 elaborates upon application of the EVCI framework to the real-world scenarios.

Finally, Chapter 6 states final remarks and summary of this thesis, together with the ideas for the future work that would provide even more functionalities to the EVCI framework while in the same time improve existing functionalities, performances, as well as tackle identified limitations.

Chapter 2

State-of-the-art literature review

This Chapter presents a systematic review of *state-of-the-art* literature. The main focus is on the data science, i.e., multi-disciplinary field that uses various methods to extract knowledge from (un)structured data and energy informatics, i.e., analysing, designing, and implementing systems to increase the efficiency of energy demand and supply systems [15]. As depicted on the Figure 2.1 this Chapter is divided into two sections: (i) socio-economic field that describes interaction between potential EV owners, EV owners and EV, (ii) socio-technical field describing interactions between EV and the power grid, as well as the EV owner and the power grid.

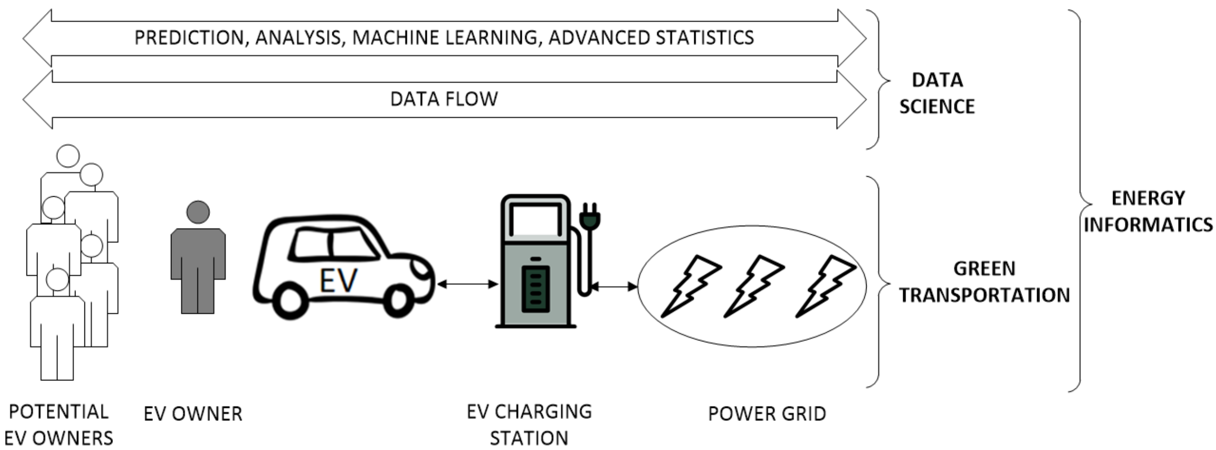


Figure 2.1: Interaction between entities in research area of interest

This review focuses on papers that were published between 2011 and 2018, since studies from earlier years are mainly focused on the electrical engineering aspect of the research area. The next filter is about the subject area: this review focuses only on *computer science* and *mathematics*, since primary focus is placed on data science in the area of EVs and those two broad areas are employing data science relevant methodologies. Lastly, only publications that are either *conference papers* or *articles* are considered. The three scientific databases that were used are: Scopus, the Elseviers' database of peer-reviewed literature [16], and IEEE Xplore Digital Library [17].

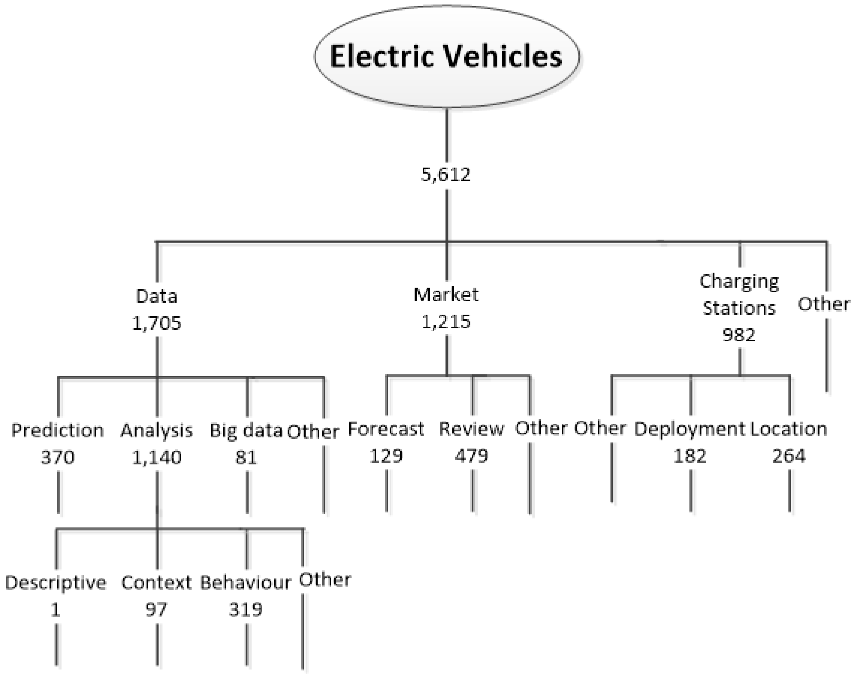


Figure 2.2: Hierarchy of keywords for related work search

The core search term was *"electric vehicles"*, search was further refined using three new keywords to cover the remaining three research areas: *charging station*, *data*, and *market* (see Figure 2.2). Note that the same paper can appear in multiple categories, since e.g., one paper can have keywords *data* and *charging station*.

The "data" science part is covered with keywords: *analysis* (1,140 results), *prediction* (370 results), and *big data* (81 results). Since keyword *analysis* returned 1,140 different results, that branch was further extended with keywords: *descriptive*, *context*, and *behaviour* for differentiation of studies which analyses the effect of surroundings (context analysis), and the effect of user behaviour on EVs. This group of papers is especially interesting, since this group can cover more topics, including the ones mentioned before (i.e., charging stations and market).

The "market" part covers the area of economics. That branch of related papers is further extended with keywords: *forecast* and *review* with 129 and 479 papers with those keywords. Papers in this area are mainly focused on market penetration, battery prices, and the forecast of previously mentioned.

Lastly, the "charging stations" keyword covers the area of energy informatics, after further extending the search for keywords: *deployment* and *location*, in this branch of related papers, there were 182 and 264 papers respectively.

The detailed taxonomy of keywords used for the related work is depicted in Figure 2.2. Each child node is derived from the search results of the parent node (e.g., the keyword *prediction* returns 370 papers that are all between 1,705 papers that were returned by search with the keyword *data*). After this step, relevant papers were hand-picked after reading their abstract and with regard to the number of citations and relevance for the area of interest.

All papers in this review that are published before 2011 are taken directly from the references of papers found with previously described method, because of their high relevance and value for the respective research field. The final number of papers that were processed in this review is 96.

2.1 Socio-economic perspective

The EV market is interesting field of research, because it does not only cover the sales number, but also innovations and current trends in the EV industry from the marketing perspective, (potential) EV owners motivations, constraints, and various forecasts (e.g., sales, battery capacity, etc.). Statistics about the number of EVs and prices are given through various reports on global and local scale.

The number of EVs is growing more and more each year, however the growth is not as steep as expected, as stated by Carty [18], United States, in 2009, invested over 2 billion dollars into development and subsidies for electric cars with goal to increase the number of EVs in US to at least 1 million until the end of 2015. Since at the end of 2016 the number of EVs in US was around 570,000 (Figure 2.3), one can conclude that the goal was not reached despite the forecasts. One of the main reasons behind that fact is range anxiety and the unfamiliarity of the potential EV owners with the electric vehicles, as described in Chapter 2.1.1.

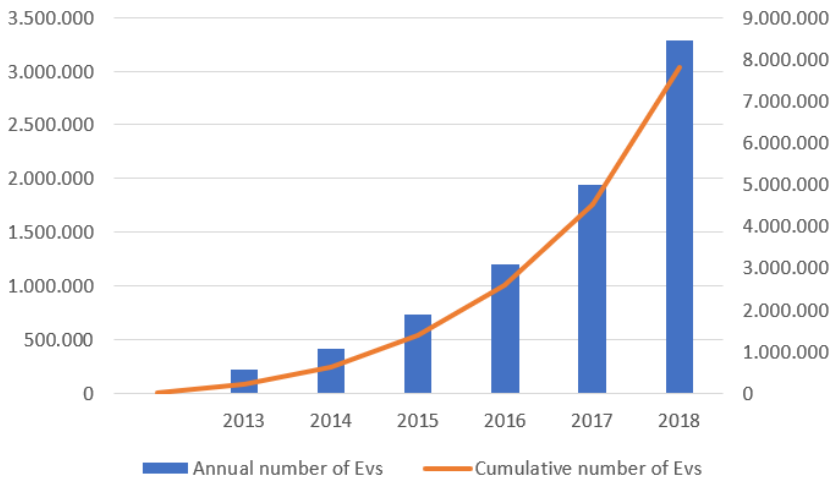
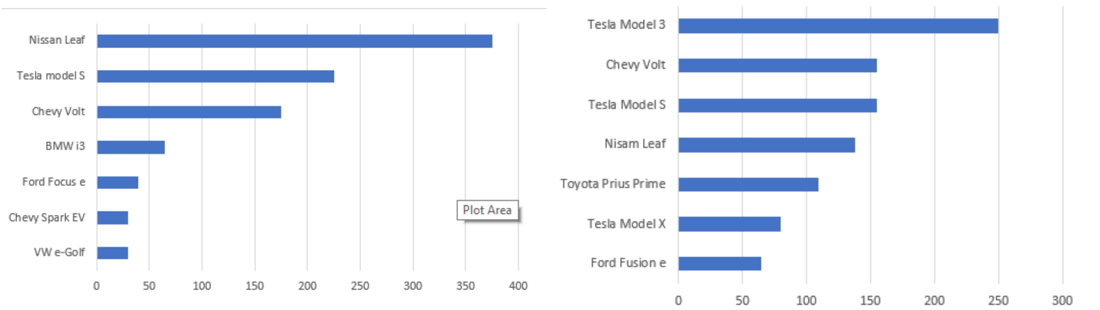


Figure 2.3: The number of EVs from 2010 to 2018 (annually and cumulative), derived from [19], [20], and [21]

In contrast to well established car manufacturers of ICVs (Internal Combustion Engine), EV-only manufacturers such as Tesla, become well known in the last decade due to increased interest in the EVs [22], and they are partially responsible for speeding up the transition to EVs (i.e., competition with other car manufacturers was one of the factors for traditional ICE car manufacturer switching to EVs [23]).

Another fact that supports the claim that EVs are the future of private and public transportation is the end of ICE vehicles (i.e., removing ICE vehicles from the market). Great Britain and France set the year 2040 as the year when ICE vehicles will be removed from the market, and every vehicle that is sold will have electric motor [24], [25]. Germany had similar initiative, plan was to ban ICE vehicles from the market by 2030, which was proven to be unrealistic and therefore declined [26]. Other countries that have the same initiatives to ban the ICE vehicles are either highly developed and environmentally friendly countries (e.g., Netherlands or Norway) or countries with great air pollution (e.g., India or China) [27].

Figure 2.4 depicts current state of EVs on global market by the end of 2016. As it can be seen, despite the Tesla advanced technology, due to the price of the competitors vehicle it is not the most common option. Instead Nissan Leaf takes the first spot with nearly 40% market share, although, Tesla plans to change that with introduction of their Model 3 with best price to range ratio [22], which they did, according to the new data.



(a) The market share of the most purchased EVs in 2016

(b) The market share of the most purchased EVs in 2019

Figure 2.4: The market share of the most purchased EVs in 2016 and 2019 [19] [21]

2.1.1 EV acceptance

To increase potential EV owners familiarity with electric vehicles, research based on the potential EV owners preferences (e.g., range, speed, and comfort) is crucial. Following paragraphs describes studies for parameters that have highest influence on a decision to buy or not to buy an EV in five regions with highest EV market penetration. Figure 2.5 depicts main findings of those studies. The focus is on the potential EV owners and each circle represents the factor that influences the potential EV owners (i.e., inner circle is positive, while outer is the most negative).

Ko and Hahn [28] (2013) stated the importance of knowing the potential EV owners preferences about electric vehicles. They further research their preference through the questionnaire

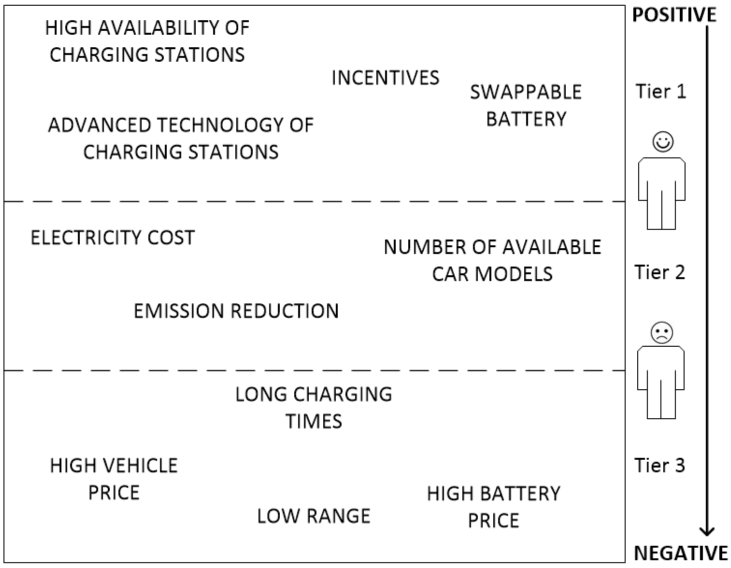


Figure 2.5: Factors that influence potential EV owners' decision to buy EV

among 250 households at the end of June 2009 in Korea. They used six key attributes to asses the willingness to pay for an EV: battery price, holding tax, subsidies type, subsidies level, battery swappability, and availability of recharging infrastructure. As expected, potential EV owners are willing to pay more if EV has swappable battery and if charging infrastructure is developed and easy to access, since that considerably lowers the range anxiety. Consumer also prefer lump-sum payment over the installment payment of subsidies. This research was of great importance for car manufacturers, governments, and the charging infrastructure providers, because it gives an insight into user preferences for adoption of EVs.

Wee et al. [29] (2018) looked into subsides and what effect they have on EV adoption rate. Authors used rich data set from 50 U.S. states about semi-annual new EV registrations from 2010 to 2015 to develop subsidies dependant models. Authors conclude that 1,000$ increase in the subsides for specific model in a specific state lead to around 10% increase in that model registrations number.

Zhang et al. [30] (2016) presented a framework used to estimate elasticity of the demand and supply of EVs. Authors took into the consideration the price of EVs, their technology, and incentives (i.e., bus lane access, toll waiver, and charging station density). To test their framework, the data from organization of actors in transport sector in Norway was used. The data consists of BEV sales from 2011 to 2013. Authors confirmed their hypothesis that the price is a negative factor, while innovative car technology is a very significant positive factor. Incentives are also positive factors, except access to bus lanes, which in case of personal consumers can be negative. There is also a significant difference between personal and business potential EV owners - business potential EV owners are less affected by price and technology. However, this work could be further improved by adding estimated influence of other incentives (e.g., taxes, subsidising purchase of EVs) or different data, since Norway has a very specific EV market (i.e., around 25% of vehicles on the road are electric [19]). Authors also stated that higher density of charging stations have high influence on potential EV owners, since 2013, battery technology has improved and range that EVs can cover has became nearly doubled, which means that charging station density should not be critical, but instead smart allocation of charging stations is highly important.

As the studies before, research from Hidrue et al. [31] (2011) is based on the data from more than 5 years ago, collected using on-line survey with purpose to asses the willingness to pay for electric vehicles. The data was collected in US for 2009. Attributes that were taken into consideration were: price, driving range, time to charge for 50 km driving range, acceleration, pollution, fuel cost of preferred gas vehicle. Attributes price and pollution are compared to preferred gas vehicle. With statistical methods, authors found that driving distance, charging time, performance, and pollution (in that order) have a high impact on potential EV owners. The most important factor is saving (i.e., compared to gas vehicles, since price of electricity is lower than the price of gas). Authors have explained that behavior with interest to save fuel, since long drives consume more fuel. Survey also suggest that younger, educated, and people with a *green lifestyle* are more likely to buy a EV.

Hoen and Koetse [32] (2014) conducted similar research as previous authors. In the Netherlands survey was conducted among 15,221 households with one or more cars (2011). Attributes considered were: car type, price, monthly cost, driving range, recharge/refueling type, additional detour time to reach a fuel or charging station, number of available models, and policy measure. Results show that potential EV owners prefer more conventional technologies (i.e., gas fueled cars), than alternative fueled vehicles. The main reasons behind that were limited driving range and long refueling time. Novelty of this work is segmentation of participants into second-hand and new buyer, second-hand buyers are more sensitive about price than new car buyers. This paper stated that low range and high refueling times are the main factors behind lower acceptance of EVs.

Tanaka et al. [33] (2014) explore differences between US and Japanese potential EV owners regarding alternative fueled vehicles. The dataset used was collected over an on-line survey, with around 4,000 participants from each state. Attributes used in this model were: purchase price, fuel cost (compared to gas fueled vehicles), driving range, emission reduction (compared to gas fueled vehicles), alternative fuel availability (share from all refueling stations), and home plug-in construction fee. Results show that US citizens are more sensitive about price reduction and availability of refueling stations than Japanese, while they are similarly influenced with driving range and emission reductions. This work also presents an interesting overview for 4 States in US: California, Texas, Michigan, and New York. California has around 50% higher willingness to pay for price reduction than other three states. The authors concluded, that in the future, due to technology advancement, share of the alternative fueled vehicles on the market would be doubled.

Smith et al. [34] (2017) conducted similar research as the studies before, but in the year 2017. Using a survey platform, 440 households in Australia were questioned about their preferences in a vehicle choice. As much as 48% answered that electric vehicle is their first choice of vehicle. The most influential negative factor on the potential EV owners is not the low range (i.e., small battery capacity), instead it is recharging infrastructure availability. As opposed to the previous studies that concentrate assumptions on the social-demographic factor, this research stated that far more important factors are attitude towards environment and the technology.

Between newer studies, the notable ones, beside the study by Smith et al. [34] is study by Wang et al. [35] (2017) and Anderson et al. [36] (2018). Wang et al. [35] in their paper presents the incentives for purchase of EVs that are currently active in China and develop a model for forecast of EV acceptance based on the linear regression. The data used in this research is sales number from 41 pilot cities and from the 37 cities with no purchase restriction. For each scenario (i.e., 41 cities and 37 cities), linear regression was performed for BEVs and PHEVs with independent socio-economic variables (e.g., population size, income per capita). The only common factor that was proven to be significant for all cases was the density of charging stations. Other notable factors that influence decision to purchase the EV in this research are education level and licence fee. Anderson et al. [36] applied survey methods to analyze EV owners preferences about the charging infrastructure. Authors concluded that more public chargers is needed and that slower chargers are acceptable on more visited locations, while fast chargers are needed on less frequently visited locations.

Previous studies are summarized in Table 2.1, with factors that were taken into the consideration, and the factors that have proven to be the most influential for the (potential) EV owners.

2.1.2 EV future sales

When it comes to exploring future sales of EVs, most of the studies in this field use either agent-based modelling or conjoint analysis methods, very few studies use other methods.

Agent-based modelling is a computational method that observes interaction and evolution of complex objects (i.e., agents) [39]. Agents enable reproduction of complex social interactions, which other methods (e.g., game theory or other equation based models) cannot as stated by Janssen [40]).

Agent-based modeling was used in by Yang et al. [41], Sullivan et al. [42], and Shafiei et al. [43]. All those studies define multiple agents: consumer population and car population. Studies [41] and [42] additionally define government and gas supplier agents, while in [41] charger and

Table 2.1: Comparison of important factors for purchasing electric vehicles

State	**Year**	**All factors**	**Most important factors**	**Paper**
Korea	2009	battery price, holding tax, subsidies type, subsidies level, battery swappability, and availability of recharging infrastructure	swappable battery and availability of recharging infrastructure	[28]
Norway	2011, 2012, 2013	price, technology, incentives (i.e., bus lane access, toll waiver, and charging station density)	technology	[30]
US	2018, 2012, 2009	price, driving range, time to charge, acceleration, pollution, fuel cost, alternative fuel availability, and home plug-in construction fee	price reduction	[31], [33], [29], [37]
Netherlands	2011	car type, price, monthly cost, driving range, recharge/refuelling type, additional detour time to reach a fuel or charging station, number of available models, and policy measure	low range, long refueling times	[32]
Japan	2012	price, fuel cost, driving range, emission reduction, alternative fuel availability, and home plug-in construction fee	availability of charging stations	[33]
Australia	2017	environmental concerns, technology, range, charging infrastructure	environmental concerns, technology	[34]
Croatia	2019	range, battery capacity, pricing of the charging service	pricing of the charging service	[37]
China	2017	environmental concerns, technology, education, charging infrastructure density, driving restriction	charging infrastructure density, licence fee	[38]
Germany	2018	environmental concerns, number of charging stations, charging station speed	availability of charging stations	[36]

grid operators are also defined.

Besides agent-based model, Yang et al. [41] define the system dynamics model that enables authors to analyze the impact of various parameters on the evolution of the defined EV ecosystem. On the case study of China, authors derived results for both models. Firstly according to the results of system dynamics model, with time, ownership of EVs will grow, while expectedly, ownership of conventional vehicles will drop. Agent-based modeling is used to simulate EV adoption in three types of regions: developed, middle-developed, and underdeveloped. According to the simulation, by 2030, market share of EVs in developed and middle-developed regions will be between 80% and 90%, while underdeveloped regions will have share of 30%.

Sullivan et al. [42] have used agent based simulation for forecast of PHEV adoption rates on United States market. Complex model, although again without social interactions, provides accurate results for near future prediction. Market penetration is predicted for 2015 and for 2020. For 2015 results show that sales of PHEVs could reach 2-3% while market penetration would be 1%, which is accurate for US market. The prediction for 2020 is that sales could reach 4-5% while fleet penetration would reach only 2%. This model also explores the role of subsidies, without them, the penetration on the market would be below 1%.

Similar study was conducted using the case study of Iceland by Shafiei et al. [43]. This model does not take into consideration complex dependencies between car manufacturers, energy grid, providers of charging infrastructure, or gas suppliers. Instead, this paper is more focused on interaction between (potential) EV owners and factors that influence them: marketing, word of mouth, and indirect word of mouth. Predictions developed with this model vary from market share of 70% all to 100% by 2040, dependant on the price of gasoline and the price of EVs.

Other group of studies is about conjoint analysis (i.e., survey based statistical technique) and choice based modelling. studies in this field dates all to late 90s (e.g., Segall [44]), those research results are not applicable today because of different level of knowledge about EVs. Despite that, those studies have greatly influenced some of the notable studies today.

Glerum et al. [45] have research what influences sales of Renault EV in Switzerland. Their research is based on survey conducted in 2011. Survey was structured in two phases: stated preferences (i.e., information about vehicles in the respondents households) and choice situation (i.e., three different cars similar to their own). To interpret survey results, author used statistical models: logit and latent variable model. The framework itself is not generated towards annual forecasting, but instead for forecasting market share when certain parameters are changed (e.g., price of EVs, monthly cost, subsidies, etc.). Similar work that does not focus on annual growth dates to 1981, and uses survey where participants ranked 16 cars. Beggs et al. [46] also used logistic model to interpret results.

Using the data from the same year as previous authors, Lebeau et al. [47] analysed adoption of BEVs and PHEVs in Belgium based on conjoint choice modelling. Novelty of this research is in the fact that authors modelled the future choice as the weighted function of car utilities (e.g., speed, acceleration, air bags, etc.). Forecast is that number of PHEVs will be higher than number of BEVs in near future (i.e., prediction was made up to 2030). Baseline is the penetration in the time research was conducted, which was around 4.85% for both PHEVs and BEVs. Prediction for 2020 is 13% while for 2030 it is 45%.

Another work that introduce novelty is study by Jensen et al. [48]. Authors of this paper created the survey with participants before and after driving the EV. Survey was conducted in Norway, Denmark, and Netherlands since they represent the most developed countries in Europe (EV wise). With basic model assumptions (i.e., assuming EV technology will only improve, which would lower the EV price) model resulted with prediction of 40% market share for 2020. The problem with this model is the assumption, new technologies do not mean necessarily lower prices. Also, prediction is consistent with the penetration today, which for Norway is around 30%.

Between notable studies are two papers from 2012, Higgins et al. [49] and Eggers [50]. First one was conducted based on the survey in Australia. It combines methods of choice modelling, multi-criteria analysis, and Bass diffusion model. Framework is used to analyse adoption patterns in consideration to factors that are important for the potential EV owners. Developed framework estimates penetration of 45% by 2030. This research also gives insight into adoption of EVs based on monthly income. Second research is based on the data from Germany, and same as first research uses combined method for prediction, choice and diffusion modelling. Predictions from that model are that penetration EVs and PHEVs will be around 55%, which is not the case. The model would have more reliable results if it included human interaction factor [51].

There are two distinguished studies that uses non of the methods used above. First one is paper by Becker et al. [53], author used simple Bass diffusion that is typically used to describe the process of how new products get adopted. The result is the most interested part of that research, research is dated to 2009, and forecast the number of EVs on the US market to approximately 600,000 by 2016, which is accurate according to the global EV outlook for the year 2016 [19]. Reason behind that accuracy is that authors did not only model potential EV owners behavior, but oil prices, internal combustion car cost, and other parameters. The article goes further in time, and predicts the 64% of sales and 24% of fleet (i.e., around 2.8 million) will be EVs by 2030. Other work is Zhang et al. [52]. This research uses multivariate and univariate time-series models for forecast based on the 60 month sales data in China, from January 2011, to December 2015. This work besides the forecast of EV market growth presents the comparison of the two before mentioned models (similar to Du and Witt [54] in domain of tourism demand). Since univariate model is used for short term forecast, in contrast to multivariate model (Chayama and

Table 2.2: Comparison of studies on forecasting future sales of EVs

State	Forecasting factors	Forecast year	Observation	Research method	Research
China	Dependency of decrease of the number of traditional cars on increase of EVs	2030	Developed regions 80% - 90% EV market penetration, underdeveloped regions 30% market penetration	agent-based modelling	[41]
	Data from sales (i.e., from 2011 to 2015)	2020	1 million EVs sold	univariate and multivariate time series modelling	[52]
USA	Subsidies	2020	EV sales 4% - 5%, EV fleet share 2%	agent-based modelling	[42]
	Gasoline prices, traditional car cost	2030	EV sales 64%, EV fleet share 24%	Bass diffusion	[53]
Iceland	Marketing and word of mouth	2040	70% - 100% EV adoption, based on the prices of gasoline and EVs	agent-based modelling	[43]
Switzerland	Choice between predefined cars	none	Changes in market influenced by EV cost, subsidies, and monthly cost of ownership	conjoint analysis	[45]
Belgium	Car utilities	2020	13% EV market share	conjoint analysis	[47]
Norway, Netherlands, and Denmark	Survey before and after driving a EV	2020	40% EV market share	conjoint analysis	[48]
Australia	Prices of electricity, income, and subsidies	2030	45% EV market share	conjoint analysis and Bass diffusion	[49]

Hirata [55]), that methodology is applied in this research too. For the short term forecast (i.e., end of 2017, around 350,000 EVs should be sold). For long term forecast (i.e., 2020) more than 1 million EVs should be sold. Besides from the economic point of view, research from Li et al. [56] are forecasting the number of EVs with the goal to balance the demand for electricity supply.

Majority of studies in this research area are from developed countries that are focusing their research and development on renewable energy sources. Since the EV industry is not yet fully developed, the market penetration forecast is mainly for the long future (i.e., 15+ years). More details about the main findings are summarized in the Table 2.2.

2.2 Socio-technical perspective

Previous Chapter dealt with challenges in EV market penetration and acceptance (see first three actors in Figure 2.1). This Chapter summarizes the studies with main focus on charging infrastructure and users driving patterns concerning charging and energy balancing.

2.2.1 Batteries

Batteries are the crucial part of electric vehicles and they are directly connected with EV acceptance rate, as described in previous paragraphs (e.g., range anxiety, charging infrastructure, price, etc.). There are many studies relevant to EV battery, although, not many in the field of data science. Most informations about battery capacities and prices are available through global reports and price lists. However there are some studies about second use potential of EV batteries like Nauber et al. [57] and [58]. Both works are motivated with restriction for market penetration growth due to battery cost. First work is oriented towards defining second-use for retired EV lithium-ion batteries which could partially recover the cost of battery. Authors concluded that using retired EV batteries as uninterruptible power supply, instead of lead-acid batteries, is more effective and would result in payback through 7 years. With various factors in mind (e.g., price of new battery or price of re-purposing), authors calculated that the price of re-purposed battery would range from 38-132 $/kWh. Second paper is earlier work of the same authors where they introduce their plan to research second-use of EV batteries.

Ahmadian et al. [59] reviewed the various studies on batteries degradation models and compared them with each other. Ahmadian et al. concluded that degradation of batteries is primarily caused by two factors: (i) time degradation and (ii) cycle degradation. Time degradation is dependant on temperature and the age of the battery, while cycle degradation is dependant on number of charging cycles and the depth of discharge. The main contribution in research by Ahmadian et al. is conceptual framework that enables use of batteries degradation models for smart grid studies.

As from the market perspective, best situation of current trends are given in the report [19]. Figure 2.6 depicts the prices of battery in from 2010 to 2015. As can be seen, the prices stagnates from 2013 to 2015, those prices are relevant even today. Prices stays the same because of physical restrictions (e.g., materials used and dimensions) and because of the lack of mass battery production. Tesla plans to change that with their Gigafactory that would mass produce the batteries [60]. To produce battery with higher capacity, one of the options is to build larger battery. The problem with large batteries is safety, the larger the battery is, the greater the chances are that it will broke. Ruiz et al. [61] extensively reviewed the standards for safety testing of batteries.

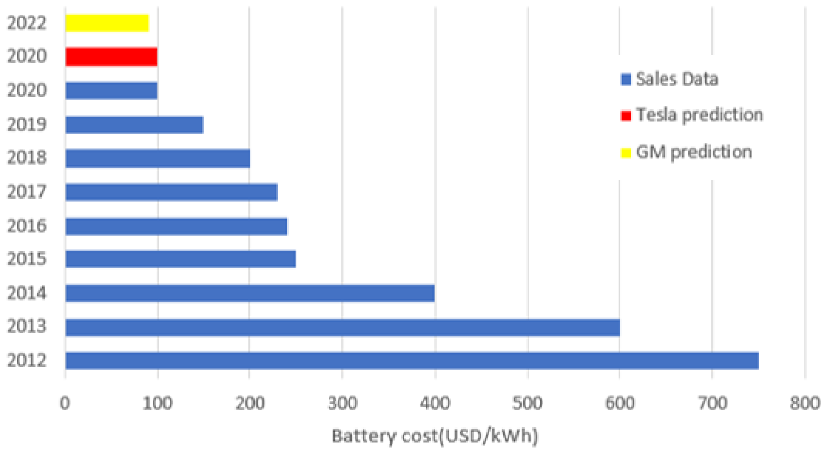


Figure 2.6: Battery prices, derived form [19] [21]

Rest of the studies that do not belong in the electrical engineering field are closely related to prediction of state of charge (SOC) and prediction of available range in the future based on various factors and past development.

2.2.2 Charging stations

Charging stations are in this state of development, underdeveloped [62] [63]. They are important factor in acceptance of EVs as a primary transport solution, since the problem of range anxiety is closely dependent on the number of charging stations [64]. Charging stations can be categorised based on: *the speed of charging* and *ownership*. Based on the charging speed chargers are divided into 4 types. *Level-1* charging is synonym for charging a car via household outlet of 120 volt. *Level-2* charging chargers at the 240 volt and provides 5 times faster charging than Level-1. *Level-3* and *Level-4* charging is also known as *fast-charging* since it provides energy for approximately 125 miles per hour, depending on a type of vehicle. Based on the ownership, the charging stations can be divided as: *private chargers* and *public chargers*. Private chargers are considered those that are installed in someone home or as a private ownership of someone (e.g., private firm parking). Public chargers are available to anyone, and they are the main focus of majority of researchers, since, data related to public charging stations is more accessible than for private chargers [65]. The future of charging stations is in the *wireless chargers* that can be placed under the road and ensure charging even while driving [66].

Charging stations deployment

Charging station deployment is one of the most challenging tasks, since it is not enough to simply place charging station somewhere, it is important to strategically place charging station on the right location. This sub chapter will provide survey of studies and their methods towards achieving that goal. Most of them can be divided into two categories, weather they use real-world data or simulation data, majority of studies in this field are either optimisation problems or simulation, as can be seen in Table 2.3.

Table 2.3: Categorisation of studies about CS deployment based on data and methodology

EV Data	Method	Algorithm	Research
Yes	Machine Learning	XGBoost, Clustering	[67]
		Clustering	[68], [69]
	Optimisation	Greedy, Genetic	[70]
		Mathematical programming	[71], [72], [73]
No	Optimisation	Genetic	[74], [75], [76]
		Mathematical programming	[77], [78], [79], [80]
	Simulation	Queuing theory	[81]
		Agent-based modelling	[82], [83]

He et al. [77] proposed mathematical framework for macroscopic deployment of charging stations taking into account the equilibrium between demand and supply of energy. Users desire to choose a destination was formulated based on: time, price, and availability of chargers. Supply side was formulated as a price of providing the electricity. This paper focuses on a large scale charging station (CS) deployment and this framework is able to answer only how many CSes should be deployed in certain region - specific location of CS cannot be determined.

Ip et al. [72] implements a two-step approach to decide optimal location for new CS. Although research methodology is similar to the one authors of previous paper used, this one provides more accurate location for CS. First step is to determine pieces of roads that are utilised the most and to divide them into x-y grid. Second step is to cluster those squares in the grid based on intensity of road utilisation and to apply optimisation algorithm to decide the most suitable cluster for CS deployment. This method uses the data generated by various sensors on the road (assuming there are sensors) and the limitation of this study is that collecting the data needed for calculations is impossible out of specifically developed areas. However, this work proposes the framework that itself is general and can be applied whenever there is a need for deciding the optimal location for something (e.g., train station or restaurant).

Frade et al. [78] on the case study of Lisbon, Portugal, implements optimisation model (i.e., maximise coverage) for CS deployment taking into account coverage of a single charging station between 400 and 600 meters walking distance and the demand for CS. To estimate the number of EVs, regression was used with parameters: size of household, building type, age, education, and employment. With those parameters, accurate model for the number of cars can be derived, but the number of EVs was further estimated with information about EV penetration. The demand for charging stations was calculated independently for day and night time, since those two time intervals have completely different patterns. This work however does not account for increasing EV penetration, and for factors that influence utilisation of charging stations (e.g., places of interest), therefore, charging stations could be underutilised.

Chen et al. [73] deals with the charging station deployment problem from the perspective of car parking. Firstly, based on the data from Washington state, parking space and duration was determined. Those information were used to build regression model for zone-level parking demands and trip-level parking demands. Last step is using mixed linear integer programming to chose optimal place for charging stations based on minimisation of price and distance between zones that have great parking demand. This model has proven to be fast and reliable, but it does not include data only on electric cars - for parking location and duration. Location of existing charging stations have great influence on EV owner parking behaviour. As opposed to previous studies, this one besides mathematical programming uses regression for forecasting demand for zone and trip level parking, which is valuable information for different fields of research.

Xi et al. [79] have developed a model for deploying charging stations in a way that maximises their use by private EV owners. The model does not use real-world data concerning charging stations, EVs, or driving patterns, instead, based on the number of population and households, authors have estimated the number of cars, and with the 1% EV penetration - number of EVs. The trip data was artificially generated by Mid-Ohio Regional Planning Commission. Using integer programming optimisation technique, authors calculated optimal number of charging stations in each traffic analysis zone. Another finding of this study is that combination of level 1 (i.e., 1.4 kWh) and 2 (i.e., 4 kWh) chargers is the most efficient, but with not enough funds, only level 1 chargers should be deployed.

Yan et al. [71] tested their optimisation method on the case study based on the 30-day taxi trace with 315 taxis and 4,638 landmarks in Rome. Optimisation methods goal is to maximise the flow of vehicles, with constraints to budget, charging availability, EV battery capacity, and energy consumption. With their algorithm, under different budget scenarios authors calculated optimal number of charging stations at each landmark. This work has simplified environment, authors assumed that the cost of deploying charging station is the same for all charging stations, and that cars and driver are homogeneous, which is not the case in reality. There are many social factors that influence the driving patterns, charging stations are only one of many.

Next studies, while also using optimisation method, are basing their optimisation techniques on genetic and greedy algorithms.

Research by Hess et al. [74] aims to decide the optimal location of charging station based on the genetic optimisation algorithm. The only data that is used in this research is the map of Vienna, parameters of electric cars, and the location of gas stations - this research as initial location of charging stations assumes the location of gas stations. The optimisation function used is to minimise the whole trip time of electric vehicle owner. This research extended the well known traffic simulation tool SUMO with electric vehicle behaviour. This work could be further improved with taking into account positions of current charging stations instead of gas stations.

Mehar and Senouci [75] are proposing genetic algorithm that takes into consideration area traffic density, land cost, infrastructure cost, investment cost, transportation cost toward the CS, charging station capacity and, energy grid capability. To optimise the placement of charging stations, authors propose to minimise two objective functions: *minimise the objective cost* and *minimise the transportation cost*. Algorithm was tested on simulation that describes the traffic in Cologne (Germany) from 6 AM to 8 AM, since that time window is considered to be peak hour. Algorithm is fast but lacks some context information. It does not take into consideration proximity of charging stations to public transport, or shops. Even if traffic is dense in certain area, population of car in that area dose not have to be comprised of EVs (i.e., authors assumed EV rate).

As opposed to previous studies, research by Sadeghi et al. [76] has a goal to optimally place *fast chargers* in the urban area. Fast chargers have capability to fully charge EV battery in 20 - 30 minutes [84]. The approach is based on genetic optimisation algorithm, with no EV related dataset. Authors have defined six test scenarios: *minimise all cost*, *ignore land cost*, *ignore the cost for EV owners*, *ignore the electric grid loss*, *no electricity charge to CS owners*, *private sector invest in CSes*. Authors decided to set the minimal distance between charging stations to 3 km, and considering previous scenarios they proposed optimal positioning of fast charging stations. This work is greatly significant considering amount of research about deploying fast charging stations. Xie et al. [80] are also dealing with the challenge of fast charger deployment. They tackled the challenge in three phases: (i) 2015-2019, (ii) 2020-2024, and (iii) 2025-2029. Authors developed optimisation based model that serves as a decision support system for policy makers for where, when, and how many fast chargers should be deployed.

Study by Vaziveh et al. [70] is using real-world data collected through the cell phone data over the Boston area, and with that, whole trip of a user was known. Goal of that research was to minimise the aggregate distance all drivers have to drive, from the end of their intended trip to the nearest charging station. Methods used to achieve previously described goal were: *greedy* and *genetic algorithm*. With those heuristic algorithms, near-optimal locations of charging stations can be found. Although, algorithm used in this paper include parameter *charging station coverage*, that limits the number of charging stations, it does not include the cost of new charging station, or contextual information if user really need to charge on the end of the trip, which makes this model currently not reliable. While this work uses genetic algorithm with the same goal as previous two studies, this one builds the model with real-world data.

Next three studies are based on machine learning techniques. First two uses only clustering, enhancing it with mathematics. Second research uses out-of-the-box machine learning algorithms to forecast utilisation of charging stations and decide where another one could be deployed. Naturally, both studies use real-world data.

Andrenacci et al. [68], used the demand side approach to decide the best placement for new CSes. Data used in this work is real traffic flow (i.e., GPS data) from 6% of privately owned cars in Rome. Assumption is that all of those are electric (i.e., switch to electric transportation). All destinations that ended in Rome urban area are further clustered in sub-areas where charging infrastructure is associated with the centre of a cluster. Next step is to mathematically calculate the demand for energy, sum of all energy spent to arrive at the goal, and that is the number of CSes needed in that area. This method has high quality data, and valuable division of Rome urban area into sub-areas. However, the number of CSes is not reliable, since the assumption is that all vehicles are electric (i.e., full conversion to electric transportation) and that all vehicles can satisfy their energy needs without queuing. This work does not provide exact location where CS should be deployed, rather the number of CSes in specific sub-area.

Momtazpour et al. [69] are using synthetic dataset because of the lack of real world data. Authors take into consideration duration of charging and decided to place chargers in locations that people visit for extended period of time. The region of Portland was divided into three clusters: high electricity load - low charging need - low stay duration, low electricity load - high charging need - high stay duration, and low electricity load - low charging need - low stay duration. Based on the cluster description, second cluster is ideal for deployment of charging stations: it can handle electricity load since it is low, there is need for more chargers, and people stay there for extended period of time. This work included places of interest in their research and the energy load making it significant and highly valuable.

Pevec et al. [67] have developed a real-world data driven, generic framework for extending EV charging infrastructure. The data used in that framework is from ELaadNL, one of the biggest charging infrastructure provider in Netherlands. The data consist from all transactions for four consecutive years (i.e., 2013 - 2016). First part of the framework clusters existing charging stations in clusters based on the distance between them with hierarchical clustering method. After charging stations have been clustered into zones, in each zone utilisation of charging stations was calculated and used as dependant variable in machine learning algorithm. The framework uses machine learning algorithm *XGBoost* to predict utilisation when certain parameters are changed. Parameters taken into consideration were: places of interest, EV penetration, time of day, number of charging stations in the defined zone, number of competitors charging stations, and is it weekend or weekday, since it has drastic effect on charging pattern. Third part of the framework based on the optimisation function provided decides the best zone to place another charging station. Precision of the framework is (i.e., the place where another charging station should be deployed) is dependant on the distance that clusters are based on.

Last category in research in this field are simulation based research. Those research do not use real-world data, only some information to tune the simulation. All the relevant data is generated by simulation itself.

Sweda and Klabjan [82] have developed and described an agent based decision support system for placement of charging stations. Although, they use real-world data for prices and sales number of electric vehicles, most of the parameters are artificially tuned (e.g., driving patterns, state of charge, etc.) with randomness. This study manages to implement social interactions between car owners ant with that it is possible to simulate decision to buy EV and increase the EV population in the system. Another feature of the model is to compare sales of alternative fuelled cars with dependency to fossil fuel prices. This work is based on the area of Chicagoland. The model is tested against two different proposed charging station placements. When comparing results with current state in that area, improvement can be noticed. The major downside of this approach is that it does not offer a possible location for CS, it analyses the placement provided to it. Updated version of the research is provided in full report by Sweda and Klabjan [83].

Authors Lu and Hua [81] developed location-sizing model for charging station. The goal is to optimise the location and the size (i.e., number of plugs) of a charging station, based on the demand. Their model is based on queuing theory and it is continuation on earlier work by Capar et al. [85].

In this Chapter the problem of charging station infrastructure development was investigated, and one of the conclusions is that the behaviour of EV owners is important for strategical planing of the charging infrastructure. Therefore, next chapter will explore the user charging behaviour.

User charging behaviour

Chapter 2.1 explored the behaviour of potential EV owners, and assumed the behaviour of the EV owners based on the behaviour of the owners of traditional fossil-fuelled vehicles. This Chapter explores the user behaviour in more details, since it is not only important for the charging infrastructure providers and the EV manufacturers, it is also important for the power grid management.

Qian et al. described [86] four different scenarios of user charging patterns with the goal of modelling the load demand of energy grid. The first presented scenario was *uncontrolled domestic charging* which is characterised with no incentive for owners to charge off the peak hours. Second scenario is *uncontrolled off-peak domestic charging* where incentives to charge the EV in off peak hours have been introduced. *Smart domestic charging* is defined as charging accordingly to the real-time electricity rate to decrease the cost for EV owners and to decrease the load on the energy grid. The last scenario is presented as *uncontrolled public charging throughout the day* where certain share of EVs charge at working place on the public chargers. Besides describing the charging patterns of the EV owners, this research compares that behaviour with the load of energy grid.

Koroleva et al. [87] have introduced their research in progress about exploring the demand response of EV owners in response to price of the electricity. Factors that authors considered in their model are: range anxiety, uncertainty about the travel, risk attitude, and social influence. The model uses simulated EV environment to observe driving and charging behaviour of EV owners. In the future authors plan to implement the mobile application that would use that model to visually describe patterns when certain factors change.

To determine a load on energy grid, researchers Taylor et al. [88], in the scope of a larger project, have developed a framework that is based on the data acquired by the National Household Travel Survey [89] (NHTS). Based on the travelled distance, battery state of charge is estimated and assuming that PHEV owner charge the vehicle to the full capacity, load on the energy grid can be calculated. Interesting observation in this work is about the travelled distances and the times of home departures/arrivals. The longer the travelling time is, the earlier is the time of departure. The energy grid is under heavier load around 5 PM which correspondent with the times of PHEV owners arriving to home from work - this leads to conclusion, that PHEV owners are likely to charge their vehicle when they arrive to home.

Like the previous study, Kelly et al. [90] are basing their research on the data provided by National Household Travel Survey and also describes users charging behaviour at home based on different parameters. The peak in energy grid load is highest around 8 pm, and noticeably higher on weekdays than on the weekends. Load on the energy grid caused with EV charging is never 0, since at all times cars are charging. After analysing the impact of battery capacity on the load, authors concluded that increased battery capacity does not only increase the magnitude of the load on the energy grid, but also shifts it in time (i.e., peak will occur later than with the batteries with smaller capacity). From the demographic aspect, authors concluded that the households with highest income generate peaks in the energy grid load 41% higher that the households with lower income and the households with lower income have earlier peaks.

Regardless of the driver sex, based on the sample provided by NHTS, older population generate the peak in the load earlier than the younger people.

Dealing with the same problem as previous studies (i.e., energy grid integration), Shao and Rahman [91] also derived conclusions about the EV owners charging behaviours. Using the same data (i.e., NHTS) that indicates that cars are parked for more than 90% of the time and that arrivals to home from work are in different times of the day, authors calculated (again based

Table 2.4: EV owners charging behaviour and patterns

Observed dependency on charging behaviour	**Observed behaviour**	**Peak hours**	**Research**
Grid load	uncontrolled domestic charging, uncontrolled off-peak domestic charging, smart domestic charging, and uncontrolled public charging	none	[86]
Travelling distance	The longer the travelling time the earlier the departure is	5 PM	[88]
	Load on the energy grid caused by EVs is never 0, households with greater income cause greater load, older population generates peak earlier than younger population	8 PM	[90]
	Cars are parked more than 90% of times	6 PM	[91]
Charging times	The charging pattern differs between weekdays and weekends, classification of charging session as: charging near home, charging near work, and park to charge	none	[92]
	Two peaks in charging utilisation, in the morning charge near work, and in the evening charge near home. Drop in charging utilisation during the summer	8 AM and 5 PM	[93]
Driving pattern and battery state-of-charge	Extended driving distance can be achieved with reducing the amount of accelerating and de-accelerating	none	[94]
Travelling distance and driving duration	On average users charge 3.1 times a week when the remaining battery capacity is under 30% or under 15%	none	[95]

on the distance travelled and battery state of charge) that the peak occurs at 6 PM with one hour variance.

As opposed to the previous research, next studies does not describe patterns of EV owners charging and driving behaviour as a consequence of solving different problem, but as a problem on its own.

Develder et al. [92] conducted a research that is based on determining EV owners charging patterns. Two different real-world datasets were used, each one belonging to the different EV charging infrastructure provider (ElaadNL and iMove). Based on clustering the arrival and departure times of EV to the charging station, charging session has been classified as *park to charge* when charging times are scattered through the day and the duration of charging session is not much longer than the time needed to charge the EV, *charging near home* sessions are characterised with departure times in the morning, and with the arrivals in the evening. Lastly, charging sessions have been also classified as *charging near work* where departure times are in the evening and the arrival times are in the morning. Besides this conclusion, with simple statistics, authors also concluded the pattern differences between weekdays and weekends. The contribution of this work is not only in the previously stated conclusions, but in the fact that previously stated conclusions were drown for two infrastructure providers and compared between them.

Frenkie and Krems [95] investigated the EV owner driving and charging behaviour using the data collected from *travel and charging diaries* from EV owners provided by EV and private charging station. The dataset contains only information from Monday to Friday, since weekends have atypical patterns. The average distance per user for a day is 38 km, while the maximum distance travelled without recharging is 124.9 km. The charging patterns are different than in the most studies, since this study uses private charging stations that are available to the EV owners, and they can charge their car when needed, not when the opportunity arrives. On average, users charged 3.1 times per a week, while the charging event occurred when the remaining capacity is around 30% or below 15%, which is also when the car system notifies the owner about the state of charge.

Bingham et al. [94] used the data collected from the Smart ED platform (i.e., platform for collecting the data from pure electric driven two-seat passenger car). Based on the data it was calculated that battery consumption is equivalent to 1.275% of the battery state of charge, which leads to conclusion that on average, the EV in this case study can travel 78.4 km on full battery (i.e., from 71 km to 88 km). Authors concluded that with reducing the amount of accelerating and decelerating significant amount of energy can be saved, which would extend the driving distance of EV.

Pevec et al. [93] have reported as a part of their contributions the statistics which depicts EV owners charging behaviour on the case of Netherlands, based on the dataset provided by one of the charging infrastructure provider in Netherlands (i.e., ElaadNL). This research describes utilisation of EV charging stations through different time intervals (i.e., hourly, daily, and yearly), on the hourly basis there are two peaks in the utilisation levels, around 8 AM and 5 PM, which corresponds with the time of EV owners arrival to work and to home from work, also, the utilisation of parking spaces follow that pattern with the drop in utilisation right before the peaks in the charging stations utilisation - EV owners and on the road, thus parking space is unoccupied. On the daily basis, authors concluded that there is no difference in utilisation patterns on weekdays, but the weekdays greatly differ from weekends where utilisation has only one peak midday. On the yearly basis, utilisation has significant drop during summer, when people usually go to a vacation. Beside the user charging behaviour this research also describes utilisation from charging station perspective (e.g., is charger located near home, or near workplace, how utilised are specific chargers, etc.). Figure 2.7 depicts comparison of charging station and parking spot utilisation per hour of the day where previously described behaviours can be observed.

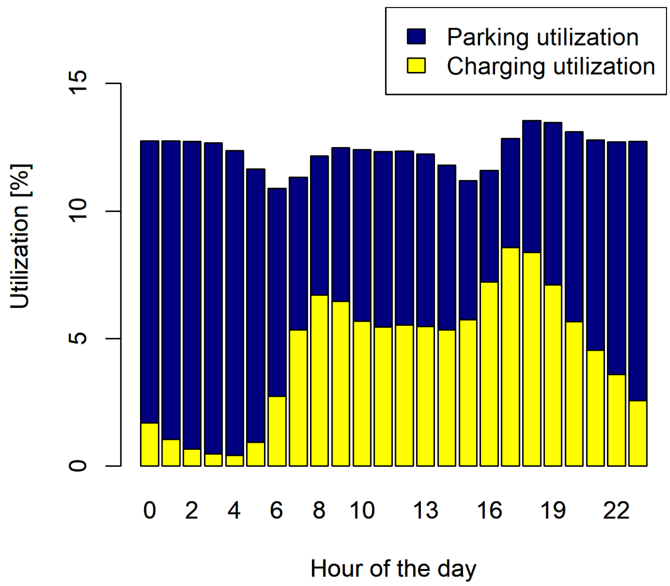


Figure 2.7: Comparison of hourly charging station and parking spot utilisation, taken from [93]

Babic et al. [96], [97] in their research have modelled the willingness to pay for charging service. The model used three control variables: *charging speed*, *referent electricity price*, and *state of charge*. Based on the randomise values for control variables, users answered the survey (deployed via Qualitrics) with price they are willing to pay for the charging service (i.e., answers were collected using Mechanical Turk, crowd-sourcing platform). After collecting the data, multiple linear regression model was developed with the goal to analyse influence of certain variable and the combination of variables on the willingness to pay for charging service. As a continuation of this research, Dorcec et al. [98] extended this methodology with the information about the *time-of-the-day* when EV is being charged. This research as well as previous ones, confirmed the hypothesis that referent price and state of charge have great role in EV owners willingness to pay for a charging service.

One of the most common conclusions in this research area are about user charging times, i.e., when are they charging their car, and for how long which is important for managing the electricity demand and supply. Besides the demand and supply this information can also be used for smart charging station placement [93]. More interesting observations related to user charging behaviour are represented in the Table 2.4.

2.2.3 Vehicle-To-Grid

Vehicle-to-grid (V2G) is a concept of a process in which electric vehicles provide power to the energy grid while parked and connected to a charger, since most of the time, the car is parked and thus, battery unused (Clement et al. [99]). With this method, owners of EVs can return some of the cost, since providing electricity to the grid would be compensated (e.g., free charging, money) (see Figure 2.1—bidirectional energy exchange between EV-CS and CS-energy grid). A simple scenario of V2G technology is as follows when there is a high demand for electricity, electric vehicles that are parked and connected to the charger would discharge and when overall energy consumption is low, they would charge. The vast majority of work in this area is focused on the implementation of V2G technology. However, some researchers are focused on scheduling and the impact of the realisation of that technology.

He et al. [100] have developed an optimisation framework for scheduling EV charging and discharging times. First, they solve the problem of minimisation of the cost on a global scale. This approach has proven to be inefficient, since, it assumes that the arrival times and load during the day is known in advance. The second problem was defined on a local scale (i.e., EVs that perform charging and discharging in one parking lot). This approach is applicable on a larger scale, and is resilient to dynamic EV arrival. The authors tested their framework on a case study involving the data Toronto on 21 August 2009. The simulation results indicated that the local scheduling can achieve results close to those on a global scale.

Wang et al. [38] have defined V2G EV as an electric vehicle that has low driving time and high parking time, which ideally describes personal vehicles. The goal of this study was to analyse the impact of EV charging on energy grid load. Authors propose three models: uncontrolled charging where user randomly charges EV, controlled charging by tariff structure (charge during off-peak hours), and controlled charging/discharging (charge during off-peak, discharge during on-peak hours). The first model as expected has proven to be the worst during peak hours, while the second and third models improved the load of the power grid during peak hours. The third model was able to efficiently exchange energy with the power grid and further flatten the load curve.

Soares et al. [101] utilise Particle Swarm Optimisation (population-based stochastic optimisation, similar to the genetic algorithm, Kennedy [102]) to tackle the problem of energy management with a high number of V2G capable EVs. This paper introduces a method that is for the order of magnitude faster than standard non-linear programming, and can find an optimal solution in a matter of seconds, which is of great importance for the day-ahead planning.

In this area of research, there are some studies that focus on energy grid load balancing with agent-based modelling: Kahlen et al. [103], Vytelingum et al. [104], Kamboj et al. [105], Valogianni et al. [106], and Ramchurn et al. [107]. All those studies have defined their own models with agents (e.g., car, electricity provider) with different behaviour (e.g., electricity storage provider has a goal to maximise the cost, EV owners charge randomly). More extensive research on vehicle-to-grid EV integration is provided in research by Mwasilu et al. [108].

Currently, vehicle-to-grid technologies are tested in Netherlands with the collaboration with Stedin, GE, Renault, and ELaadNL [109], and in USA, PG&E are converting company-owned Prius to V2G PHEVs at Google campus, while Xcel Energy is converting six Ford Escape Hybrids into V2G capable vehicles as described by Fang et al. [110].

2.3 Reflection on the state-of-the-art literature

Throughout this state-of-the-art review, EV-related studies from fields of green transportation, energy informatics, and economics are reviewed and summarised in a systematic way by using the data science perspective. The described research area is gaining an increase in the interest with the growing trend of EVs on the market [19]. Up until now, the data science approaches, methods, and tools in the domain of EVs were present only in a small number of studies, since the research focus was mainly on the electrical engineering aspect (i.e., the number of EVs was not large enough for implementing solutions based on the data science and there was no enough data). However, the situation is changing what can be noted from a growing number of EV-related data science research papers. Consequently, data science is becoming a highly relevant approach for green transportation, energy informatics, and EV-related economics studies. Researchers are actively cooperating with the industry since there is no conventional way to gather the EV-related data and the private, i.e., company-owned, data is the most used source in various studies (e.g., [92, 111]). Following paragraphs will consolidate main scientific observations for research problems covered in the paper: EV acceptance, EV market penetration, charging station deployment, and EV owner charging behaviour.

Based on the insights in Chapter 2.1, EV acceptance is usually tackled with conjoint analysis with different factors considered, e.g., range anxiety, education, age, and income. The most important factors in EV adoption are proven to be government incentives and high availability of charging stations which consequentially lowers range anxiety. Negative influence on the EV adoption rate is mostly long recharging times and low range with a fully charged battery. The second part of Chapter 2.1 deals with the research problem of predicting EV future sales. Researchers in the sales forecast field mostly use analysis based on the historical data and well established statistical approaches or simulations that mimic potential owners' adoption rate and other complex EV environment interactions. Some of the studies analysed in this state-of-the-art review, i.e., those that are dated before 2015, have accurate predictions for the near future and very optimistic predictions for the period of the next 10 years (i.e., growth around 30–40%).

Chapter 2.2 deals with the charging station deployment and user charging behaviour, which has proven to be valuable information for deciding the location for new charging stations. Both research problems employ similar methods to tackle their respective challenges: data analysis, machine learning, mathematical programming, and simulations, with the emphasis on the latter two. Majority of studies about EV owners charging patterns have similar conclusions: EV owners are most likely to charge their car when they arrive to work and to home from work, i.e., peaks in the charging station utilisation are around 8 A.M. and 5 P.M. Besides the charging station deployment, charging behaviour is an important aspect in research related to energy grid load demand optimisation. The next observed challenge, the one dealing with the deployment of charging stations, is nowadays the most important since it directly impacts EV adoption and consequentially the development of EVs. While being important, the EV charging infrastructure is generally underdeveloped due to short existence. Lack of data in this research area is the reason why researches are mainly employing methods of mathematical programming and simulations. For now there is no generally applicable method for deployment of charging stations, since, to the best of the author's knowledge, the existing studies are specific and cover either specific area, i.e., due to simulation restrictions, or specific case, e.g., macro/micro deployment or deployment along the highways. Finally, one of the greatest challenges in this domain is the adaptation of existing energy infrastructure to accommodate the EV charging needs. This challenge is being tackled by the smart charging research, partially discussed in the Chapter 2.2.3. In order to offload the energy grid, it is important to determine in which time intervals the electric vehicle should be a charge, should it be used as energy storage during the peak load times, and how to manage the EV battery to satisfy both the owner's needs and the energy grid.

Based on the presented review, it can be concluded that data science should be today widely used to solve various EV-related challenges. The EV-related data is nowadays generated from numerous sources such as road sensors, vehicles, and EV charging stations. Furthermore, industry more and more provides researchers with otherwise private data and catalyses the development of high-quality data-driven research. Of course, both researchers and industry need to be careful about what and how data can be shared and analysed not to compromise data and end-user privacy, where data (pseudo-)anonymisation methods will play an important role. However, it is not only that a data-driven approach is nowadays possible for the EV-related research, but such an approach is sometimes necessary and very often it generates beneficial added value. There are various emerging research problems that cannot be tackled using traditional methods, such as mathematical programming. An example is the smart charging station management, i.e., deploying, removing, and re-allocating charging stations. There are numerous research initiatives that aim to solve this problem by not using real-world data that requires setting many assumptions, making them less accurate and consequentially lowering their applicability in real-world scenarios.

Chapter 3

Key concepts related to charging infrastructure development

This Chapter explains the key concepts that the EVCI framework was built upon. Namely, it explains *range anxiety* research that is crucial for clustering method, i.e., the distance on which the charging zones are based (see Chapter 4.2) and the analysis of *places of interest* (PoIs) which have significant impact on the prediction of charging station utilisation, as described in Chapter 4. PoIs are also one of the main components for the macro development aspect of EVCI framework, and their analysis is significant for the charging station placement when the data about the charging transaction is not available.

3.1 Range Anxiety

Range anxiety, EV driver's fear of running out of electricity before reaching another available charging station ([12]), is one of the most important factors that influence the thinking of new-vehicle buyers when deciding whether to purchase a traditional internal combustion engine (ICE) vehicle or EV ([13]). The range anxiety can be lowered either by increasing the EV autonomy or by developing the existing charging infrastructure.

This Chapter focuses on the charging infrastructure aspect of range anxiety by identifying a pair of research questions focused on assessing variables that impact the range anxiety. The first question asks the following: *"How do existing EV owners, as well as potential EV owners, perceive* ***charging station*** *infrastructure in comparison to the existing* ***gas station*** *infrastructure, considering the distance between two neighbouring chargers and gas stations?"*. Answering this questions enables us to understand the relationship between the level of charging station infrastructure development and range anxiety, as well as to make connections with the gas station infrastructure which is in the significantly higher maturity phase compared to charging station network. The second question asks the following: *"To what extent do dif-*

ferent key EV parameters influence the range anxiety among potential EV owners, and how does that compare to existing EV owners?". Answering this question provides understanding of the relationship between the state of charge (SoC) (i.e., remaining capacity of EV battery) and EV driver's decision to (not) charge the vehicle. Furthermore, this research question also provides understanding whether the SoC or driving range (i.e., remaining range EV can reach) have a stronger influence on range anxiety. Both questions are answered by analysing data collected through the specially designed survey questionnaire, aimed at both potential EV owners (who do not own an EV personal transportation vehicle) and existing EV owners. By using a specially-designed survey, responses are collected from more than 200 (potential) EV owners. The survey had three parts: (i) demographic questions; (ii) a questionnaire comparing charging station and gas station infrastructure; and (iii) 5 arbitrarily generated scenarios through which survey respondents gave opinions about their willingness to charge. This enabled categorisation of survey respondents based on different individual characteristics (e.g. age), contextual information (e.g., settlement type) and EV-related parameters (e.g., EV ownership).

3.1.1 Methodology

This Chapter describes the methodology used to carry out the research. In principle, the methodology follows the survey-design work ([112]) and *Cross-industry standard process for data mining* (CRISP-DM) methodology ([113]). The *end-to-end* methodology is depicted in Figure 3.1 and described in the following paragraphs, together with the detailed description of the survey design.

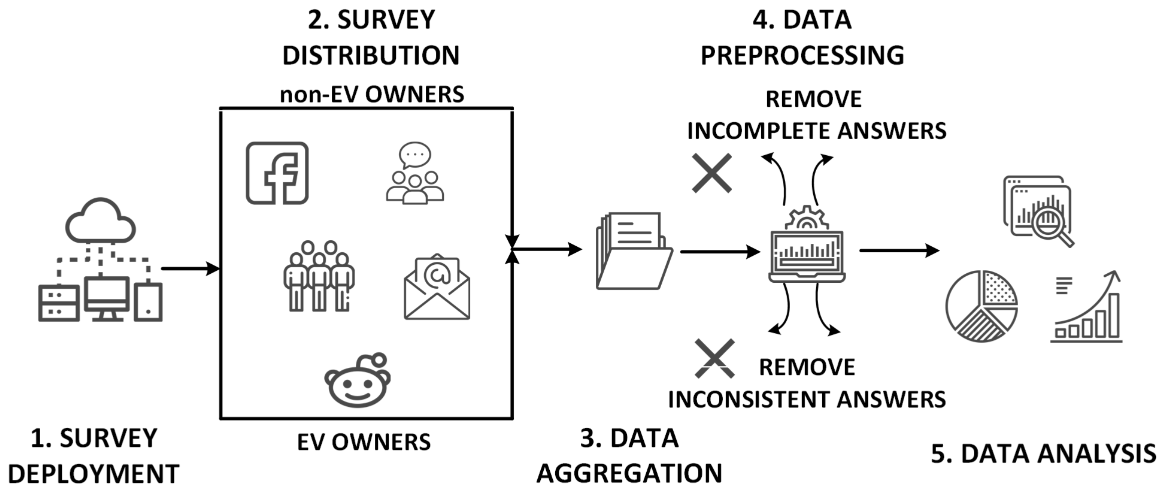


Figure 3.1: Research methodology

Data Flow

The questionnaire was implemented as an online survey using the Limesurvey tool which can be used both as a service, or deployed on one's private infrastructure. It was decided to use the latter approach for **survey deployment**, since access to the source code as well as the flexibility in the access control and integration with established Web domain is needed.

The second step of the methodology, *survey distribution*, was to distribute the aforementioned survey among a diverse set of participants. In particular, the survey was distributed targeting two different populations: (i) non-EV owners; and (ii) EV owners. To better cover the non-EV population, various communication channels were used to maximise the reach and achieve heterogeneity among survey respondents in terms of demographics (e.g., age, gender, income, settlement hierarchies considering population density, or knowledge about EVs). More specifically, Facebook, various forums, Reddit, and a word-of-mouth approach. For the group of participants who are EV owners, besides the previous communication channels, specialised EV-related forums, companies that provide electricity and work on charging station infrastructure development, such as HEP* Croatian electricity provider, and Facebook groups containing EV owners from all over the world were used as a communication channels. This approach for survey distribution ensures that enough people participate in the survey, both EV owners and potential EV owners, i.e., drivers that still do not own an EV.

The next step of the methodology, **data aggregation**, includes the aggregation of the responses into a single dataset appropriate for further analysis, as well as the separation of the participants into one of the groups based on EV ownership.

The data aggregation phase is followed by the **data pre-processing** phase, where answers that are incomplete (e.g., when a participant left the survey before finishing it), as well as inconsistent answers (e.g., *effortless* answers where all the reported values are the same) are removed. This phase removed specific records from the dataset and transformed the variables in order to make analysis possible. The described data pre-processing step ensures the availability of a high-quality dataset in the last phase of the applied methodology (i.e., **data analysis** step).

Survey Design

The survey consists of the following parts: (i) demographic questions; (ii) a questionnaire comparing charging station and gas station infrastructure; and (iii) 5 arbitrarily generated scenarios through which survey respondents give opinions about their willingness to charge. All questions were asked in English.

The first group of questions presented to the participants concerns a *demographic* set of questions. The first part of this question group contains standard questions (see Table 3.1), e.g.,

*https://www.hep.hr/

gender, country, age, and income. Answering all questions was not mandatory, e.g., respondents did not have to report their annual income. The second part of the demographic question group is oriented towards assessing the participants ability to drive as well as to better understand what type of vehicle the participant owns. Lastly, the third group of questions in this category are domain specific and they serve to separate EV owners from non-EV owners. Technique of hidden questions was used, meaning that questions 13 through 15 (i.e., EV-related questions) are not be visible to someone who does not own an EV.

The second group of questions is about the participant preferences regarding the development of the **EV charging infrastructure** and its relative relationship with the **existing gas station infrastructure**. Survey takes into account the infrastructure context as well as some information about the settlement type in which the participant lives. All questions from this group are listed in Table 3.2. This set of questions does not only provide valuable insights into the development of existing gas station infrastructure considering settlement hierarchies, but also measures how the familiarity with the existing transportation infrastructure impacts preferences regarding the *would-be* charging infrastructure.

The last set of questions, which is repeated five times for five hypothetical scenarios, is comprised of only two questions per scenario as presented in Figures 3.2 and 3.3. Each participant is presented with five randomly generated scenarios to assess the range sensitivity considering the key EV parameters, namely *state of charge* and *remaining range*. Again the technique of hidden question concerning the range one is willing to travel to charge was employed. In particular, that question is only presented to a participant if the answer to the previous question, about the participant's willingness to charge in the given hypothetical scenario, is affirmative (the example of the full question can be seen on Figure 3.4). The exact text of the first question is given below in Figure 3.2:

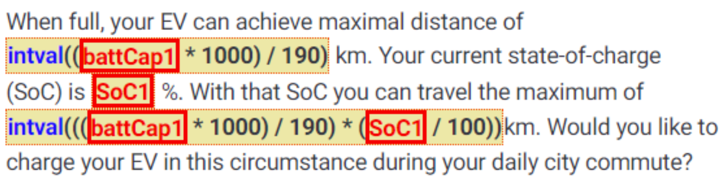


Figure 3.2: First question, coded in LimeSurvey tool

The expressions inside square brackets are not shown to a survey participant. Instead, the expressions are replaced by values which are computed based on arbitrarily-created data relevant for each scenario. The **battCap** variable represents the nominal EV battery capacity, randomly selected between 16 kWh and 60 kWh, an interval that encodes the battery capacity of the most prevalent EVs ([114]). Next, the **SoC** variable is used to describe the EV's *state of charge*. Please not that the expression has the constant with the value of 190, calculated based on the average range of common electric vehicles per kWh ([114]). The participant will be asked to answer question for five scenarios. Each scenario follows the same structure, however, the changes are in the way the SoC variable is sampled. That said, the first scenario will draw the SoC variable between 5% and 100%, representing the huge majority of realistic SoC cases. However, in each following scenario, the upper-bound SoC amount is curtailed by 20% to encourage scenarios that would induce range anxiety. If the survey participant answers the first question affirmatively (i.e., EV driver wishes to charge based on the hypothetical scenario) then the second question about the range preference is prompted as depicted in Figure 3.3.

What is the acceptable additional distance (in km, 1 km = 0.62 miles) to travel to the charging station which may or may not be occupied, taking into consideration the time that is needed to cover that distance? (Example: for 10 km in Europe, average time is 25-35 minutes) In this situation, you must carefully consider your answer since you are either unsure how far the next charging station will be or whether the next station will be unoccupied!

Figure 3.3: Second question, coded in LimeSurvey tool

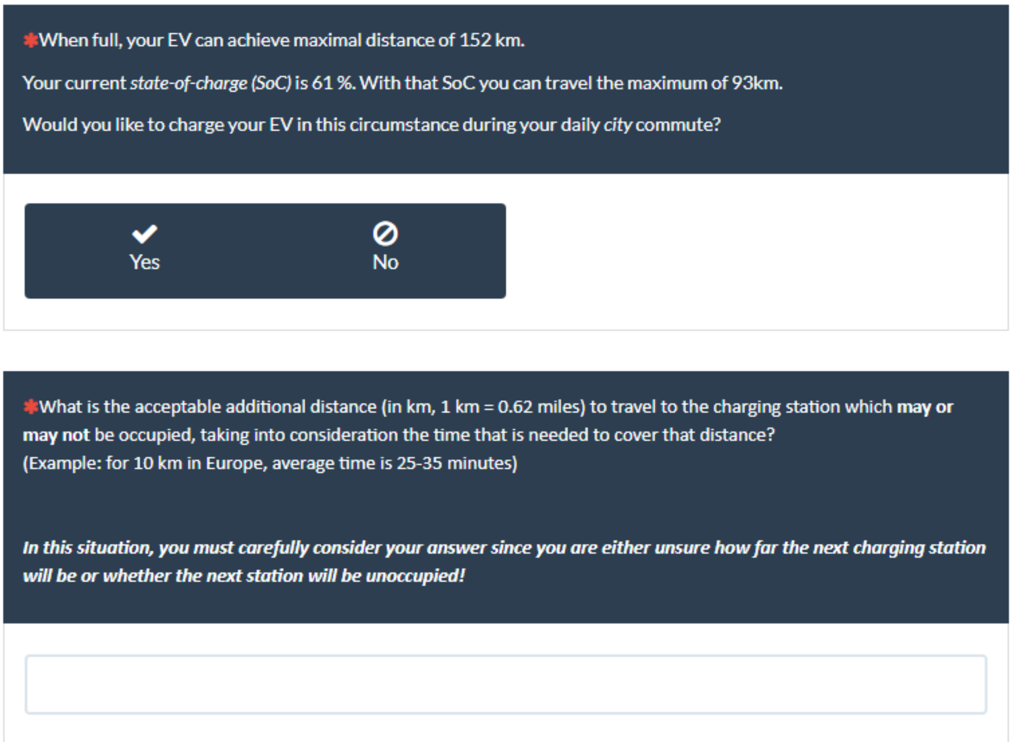


Figure 3.4: Example of the question about distance preference

This question is used to judge how a participant perceives the distance by emphasising the terms “*additional distance*", “*time that is needed to cover that distance*", and the fact that the charger “*may or may not be occupied*", as non-EV owners who are used to a high availability of traditional gas stations potentially have unrealistic expectation concerning the time needed to travel a specific distance. Also, we wanted to ensure that the participants are aware of the fact that the charging station may be out of order or occupied so they think ahead and consider the distance needed for travelling to other available charging station without running out of electricity. The same survey respondent could have answered this second question multiple times (a maximum of five times, one for each affirmative answer to the first question in this set).

3.1.2 Results

This Chapter describes the results of the data analysis phase concerning the demographics, desired distances between neighbouring EV charging stations, and the range preferences considering key EV parameters.

Demographic Data Analysis

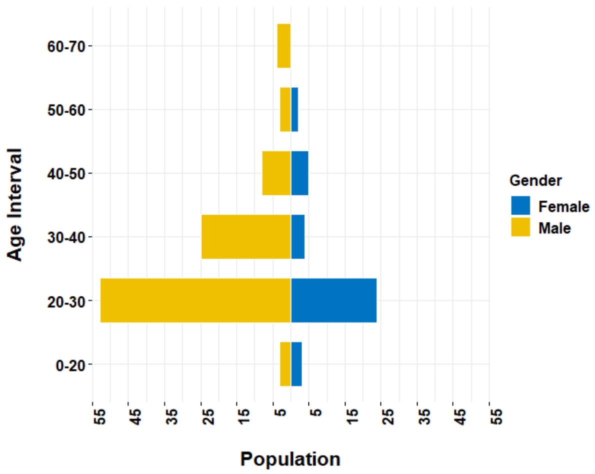
The survey described in Chapter 3.1.1 was taken by 274 participants. The first group of participants, the **non-EV owners**, consisted of 170 participants, while the second group of participants, the **EV owners**, consisted of 104 participants. After the phase of the initial data processing, 61 answers were removed for one of the reasons, as follows: (i) incomplete answers, e.g., when a participant did not finish the survey; (ii) effortless answers, e.g., when a participant consistently provided the same answer, disregarding the differences in the presented scenarios; (iii) inconsistent answers, e.g., for battery capacities that do not differ more than couple kWh, or SoCs that result in remaining ranges being not more than a few kilometres apart, some participants answered with extreme values (e.g. the lowest possible value in one scenario, the opposite in the another); and (iv) outliers, e.g., answers that have significant deviation from the dataset mean. Removing outliers is a common procedure for noise removal ([115]). The final number of participants considered in the data analysis is then 213: 134 non-EV owners (i.e., potential EV owners) and 79 EV owners. Table 3.3 shows some demographic information concerning the participants.

Achieving a substantial sample size is a challenging endeavour in research setting given the open-call and voluntary nature of the survey. A question that naturally arises is whether the sample size is enough for research purposes. This was assessed with a power analysis. In particular, a power analysis was performed for an F test in anticipation of the fact that a multiple regression model will be built having two predictors (see Table 6). The null hypothesis in the F test states that both estimated coefficients are equal to zero, whereas the alternative hypothesis states that not all estimated coefficients are equal to zero. In this setting, power (β) is influenced by the effect size (f^2), significance level (α), and the sample size (n). After rearranging the underlying equation, one can then determine the sample size by having a fixed effect size, significance level, and power. This calculation relies on the traditional values of $\alpha = 0.05$ and $\beta = 0.8$. As for the effect size, given the above discussion on the challenges faced by data collection process, a sample large enough to be able to detect at least medium effects is desired, which according to [116] translates into an effect size of $f^2 = 0.3$. The power analysis informs that a sample size of at least $n = 36$ participants is needed given the fixed parameter values. Both the number of non-EV owners and EV owners (respectively, 134 and 79) are considerably larger than what the power analysis suggests. In fact, with the smallest sample ($n = 79$), even smaller effect sizes can be detected, such as $f^2 = 0.13$, which in turn requires $n = 78$.

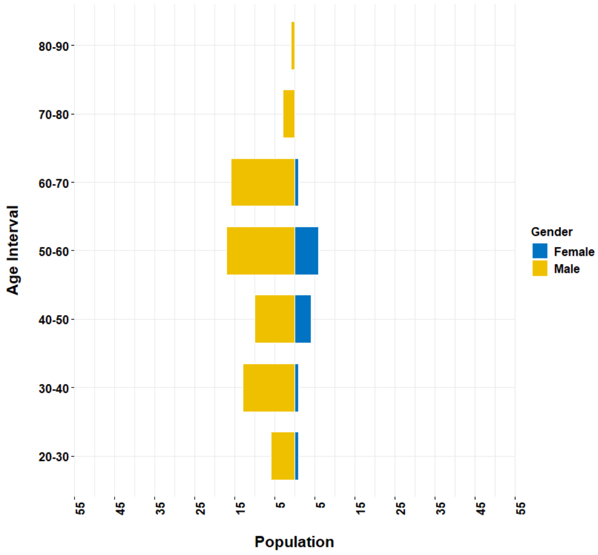
The demographics of non-EV owners are consistent with those of individuals that show increased interest in electric vehicles ([31]), in a sense that the majority of the participants are well educated and in the stable working relationship. Our dataset is also consistent with the fact that the survey was distributed on vehicle enthusiast forums where the majority of the population is male. This shows as 70% of participants in this survey are also male. Since we used the Facebook as one of the means for survey distribution, our pool of participants is mostly 20-40 years old, which is consistent to the age of the majority of Facebook users. The detailed overview of aforementioned demographics of non-EV owner participants is shown in Figure 3.5a. We note that the demographics of EV owners are significantly different than non-EV owners in terms of age and gender (Figure 3.5b). In particular, most of the EV owners (85%) are male, and more than 85% are older than 35 years old. This distribution of age can be arguably explained by the novelty of EVs on the market and the fact that they are traditionally more expensive than second-hand ICE vehicles. Therefore, it is expected that one must have a stable life (secured job and income) to afford an EV.

A crucial information about the survey participants is their knowledge about EVs and their driving experience. EV owners, naturally, all have experience with both driving and owning EVs, while around 90% of the non-EV owner participants have basic understanding of EV concept, but more than 80% of them have a driving license. This is important information since this study heavily relies on the distance perception between neighbouring gas stations. One should expect that the experience of driving a car increases the accuracy of that approximation.

The majority of the non-EV owner participants are from Croatia, i.e., more than half of the dataset, where the charging infrastructure is rather scarce. Other participants are from 14 different countries, e.g., US, UK, Norway, and other regions where EVs are more common option and, therefore, the infrastructure is developed to accommodate the charging needs. Aforementioned distribution of countries is beneficial for this study, since arguably, the range anxiety will be more emphasised in regions where the charging infrastructure is scarce and underdeveloped. More than 75% of the participants who own an EV are from either the United States of America or from the United Kingdom. This is rather expected since the EV market penetration in those countries is significantly greater than in most of the rest of the world.



(a) Non-EV owners



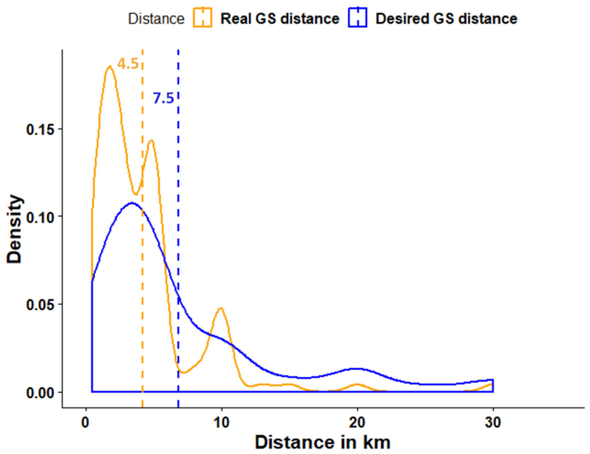
(b) EV owners

Figure 3.5: Demographics data

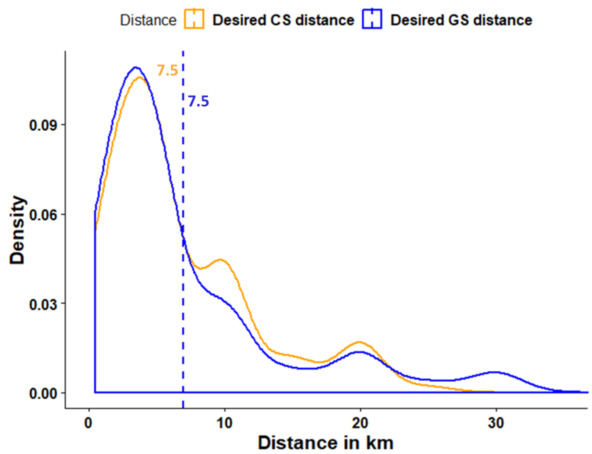
Analysis of the Desired Distance to a Neighbouring Charging Station

The analysis of the perceived distance between two existing neighbouring traditional refuelling stations and comparison with the among the two neighbouring charging stations is an important aspect for decision makers in the charging station infrastructure development domain. As shown in Figure 3.6a, non-EV owners' opinion regarding the traditional refuelling infrastructure is that, currently, there are too many gas stations, and they are too densely distributed. In Figure 3.6b, the relation between desired neighbouring gas station distances and charging station distances is compared. Evidently, potential EV owners would like the charging station infrastructure to be deployed and accessible as the traditional refuelling infrastructure is. The mean distances are represented by the dashed lines in both Figure 3.6a and Figure 3.6b. For example, the **mean desired distance** between neighbouring charging stations, for non-EV owners, is around **8 km**. Figure 3.6c and Figure 3.6d depict the previously described relations from the EV owner's point of view. EV owners reported almost the same distance between two neighbouring gas stations as the non-EV owners. However, EV owners would prefer a closer distance between the charging stations than the non-EV owners. Arguably, the reason behind the aforementioned difference between the desired neighbouring charging station distances lies in the fact that EV owners are more knowledgeable regarding EVs and have hands-on experience driving an EV.

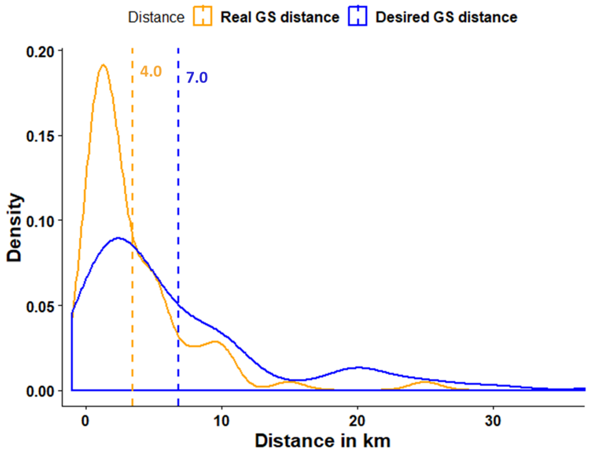
Data analysis points to the fact that more than 20% of the participants prefer the charging station infrastructure more densely distributed than the traditional refuelling infrastructure is, while about 50% of the participants would like the charging station infrastructure to be deployed as the traditional refuelling infrastructure is, meaning that they are satisfied with the availability of the gas stations today. Taking into consideration the average value, the results



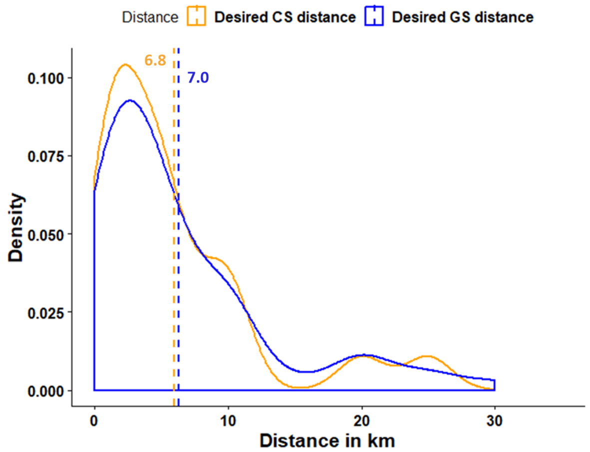
(a) Comparison between real and desired neighbouring gas station distance (non-EV owners).



(b) Comparison between desired neighbouring gas station and charging station distance (non-EV owners).



(c) Comparison between real and desired neighbouring gas station distance (EV owners)



(d) Comparison between desired neighbouring gas station and charging station distance (EV owners).

Figure 3.6: Comparison between real/desired neighbouring gas/charging station distances.

showed that two neighbouring charging stations should be *0.12 km* less far apart than the gas stations are, as approximated by the participants. Comparison of the actual and desired charging station infrastructure in this research is not included. The reason by this approach lies in the fact the charging infrastructure is significantly scarce in majority of countries, meaning, participants from those countries would not be able to accurately approximate the distance between neighbouring charging stations so the quality of collected data would be poor.

Furthermore, participants were asked about the size and type of their area of living, i.e., whether they lived in a village, town, large town, city, large city, or metropolis (see Table 3.4). Strong relationship between range preferences concerning neighbouring charging stations and the settlement hierarchy was noticed. In particular, participants that live in small, rural places are prone to accepting greater distances between neighbouring charging stations than participants from larger/urban places. As can be seen in Figure 3.7a and Figure 3.7b, the previous statement applies to both non-EV owners and EV owners, with some minor exceptions likely due to a non-even distribution of participants across the settlement hierarchies. Another interesting finding is that non-EV owners would like the distance between two neighbouring charging stations to be less than **7.0 km**, while EV owners are satisfied with the distance of **6.8 km** on average. Taking into account the aforementioned points, and the fact that we defined range anxiety as a fear of running out of electricity before reaching another available charging station, this (i.e., the preferable distance between two neighbouring charging stations) is the metric that is decided to use to formally define range anxiety. Besides the aforementioned the range anxiety can also be defined as a fear of longer EV-based commutes since the driver might felt uncertainty about reaching the destination since the charging infrastructure is globally underdeveloped. However, the mean value for the preferred distance between two neighbouring charging stations is highly dependent on the settlement hierarchy. This is illustrated in Table 3.5, where the preferred distances for both potential and current EV owners across all settlement types are displayed.

Figures 3.7a and 3.7b show that there is a considerable variance in the preferred distance between neighbouring charging stations for different settlement hierarchy levels. A potential suggestion when using the values in Table 3.5 is to create ranges surrounding mean values, e.g., distance preferences may vary up to one standard deviation. From the smallest to the largest settlement hierarchy (see Table 3.4), the standard deviation values for EV owners are, respectively, 5.3 km, 6.6 km, 9.2 km, 3.7 km, 6.6 km, and 1.8 km, while for the non-EV owners the standard deviation values are 6.1 km, 6.6 km, 7.6 km, 3.1 km, 4.2 km, and 2.2 km. Under this interpretation, the preferred distance between two charging stations for a potential EV owner from, say, a metropolis is equal to 5.0 km $+$ [1.8 km]. It can be noticed that only the upper bound was used and not the lower one. The main reason is that, we assume, from the business perspective, there is no need to deploy charging stations more dense than the average.

Table 3.1: Set of demographic questions with potential answers and preconditions.

#	QUESTION	ANSWERS	CONDITION
1	What is your gender?	Male; Female	
2	What is your country?	List of all countries	
3	What is your age?	Number between 1-100	
4	What is your working status?	Student; Employed; Unemployed; Retired	
5	What is your annual net income? ($)	Number	
6	Do you have a driving licence?	Yes; No	
7	Please evaluate your familiarity with the concept of electric vehicles	Never heard of it; Heard of it, but I am not familiar; I know something; I am very familiar	
8	How many cars have you owned so far?	Number	
9	In your opinion, what should be the maximal distance between two charging stations in a city (in km, 1 km = 0,62 miles)?	Number	
10	Do you own a car now?	Yes; No	
11	How many vehicles do you have in your household?	Number	If Question#10 = 'YES'
12	Do you own or have an EV?	Yes; No	If Question#10 = 'YES'
13	What model is your EV (e.g., Nissan Leaf)?	Open text	If Question#12 = 'YES'
14	What is the capacity of your EV battery (kWh)?	Number	If Question#12 = 'YES'
15	At what state of charge (remaining battery) do you usually charge your EV? (In percentage)	Number	If Question#12 = 'YES'

Table 3.2: Range preferences considering settlement hierarchy.

#	QUESTION	ANSWER
1	How would you describe the place where you live?	Village (population less than 1,000); Town (population between 1,000 and 20,000); Large town (population between 20,000 and 100,000); City (population between 100,000 and 300,000); Large city (population between 300,000 and 1 million); Metropolis (population between 1 million and 3 million)
2	What is (approximately) the average distance between neighbouring GAS STATIONS in the area you live in (in km, 1 km = 0.62 miles)?	Number
3	In your opinion, what should be the maximal distance between two neighbouring GAS STATIONS in the area you live in (in km, 1 km = 0,62 miles)?	Number
4	In your opinion, what should be the maximal distance between two neighbouring CHARGING STATIONS in the area you live in (in km, 1 km = 0,62 miles)?	Number

Table 3.3: Statistics concerning demographic information.

		Non-EV	EV
Category	**Subcategory**	**% of Participants [N = 134]**	**% of Participants [N = 79]**
Working status	**Employed**	67.5	76.5
	Student	29.0	2.5
	Retired	3.5	20
	Unemployed	0.0	1.0
EV knowledge	**Very familiar**	45.0	96.0
	Know something	45.0	4.0
	Heard of	10.0	0.0
Driving licence	**Have**	85.0	100.0
	Not have	15.0	0.0
Gender	**Male**	70.0	83.5
	Female	30.0	16.5

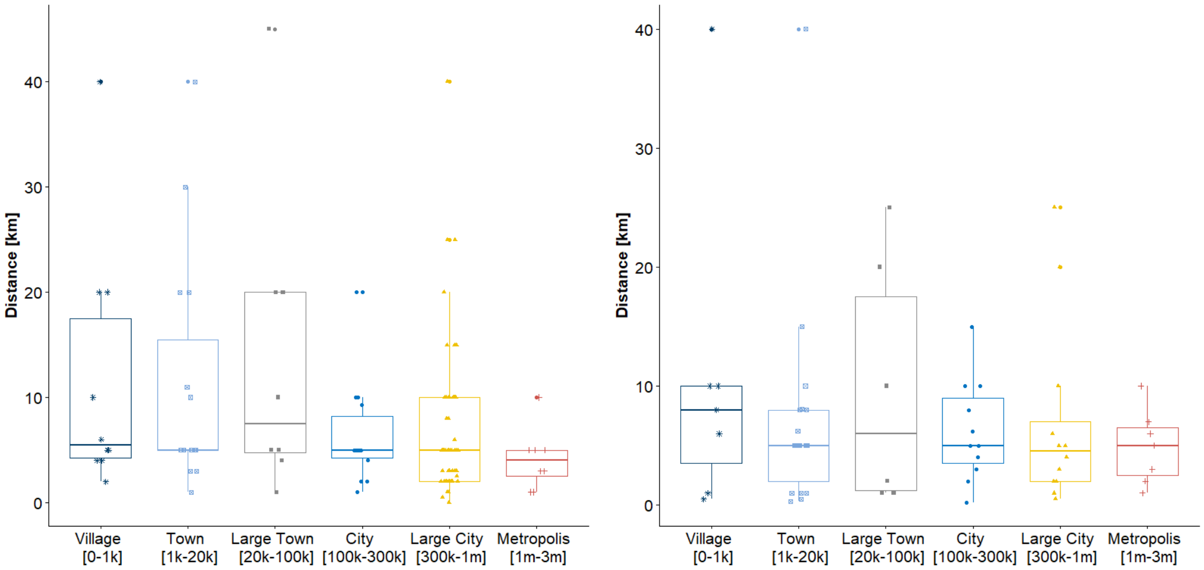
Table 3.4: Settlement hierarchy defined by population size.

Settlement category	**Population**
Village	less than 1,000
Town	1,000 - 20,000
Large town	20,000 - 100,000
City	100,000 - 300,000
Large city	300,000 - 1,000,000
Metropolis	More than 1,000,000

Table 3.5: Preferred distances across all settlement hierarchy levels for both EV owners and non-EV owners.

Settlement type	**EV owner preferred distance (in km)**	**N**	**SD**	**non-EV owner preferred distance (in km)**	**N**	**SD**
Village	7.0	8	5.0	9.0	11	13.4
Town	6.8	24	17.9	6.5	21	19.2
Large town	9.0	11	15.0	7.0	11	13.2
City	6.5	12	3.4	6.6	15	7.2
Large city	6.5	15	13.0	6.5	57	3.0
Metropolis	5.0	9	1.9	6.6	8	4.3

The previously described findings point to the following conclusion: traditional refuelling infrastructure is well-developed in larger/urban areas, which is often not the case in the smaller/rural areas and villages. Therefore, consumers from big cities might tend to be less flexible when considering the desired distances between charging stations than those who live in smaller areas. These, in turn, might be used to a smaller and more sparse refuelling infrastructure. However, the sample is not representative for all settlement hierarchies, which is one of the limitations of this research.



(a) Non-EV owners (b) EV owners

Figure 3.7: Comparison of desired distances between neighbouring charging stations considering the settlement hierarchy.

Range Anxiety through Key EV Parameters

The **key EV parameters** are defined as: (i) *state of charge* (SoC), i.e., the percentage of battery left; and (ii) the *remaining range*, i.e., the range that the vehicle can cover with the aforementioned SoC.

Each participant was asked to assess their own range anxiety, i.e., how far (s)he is willing to drive to reach another available charging station. The same question was repeated up to five times to each participant, each time with a different hypothetically generated scenario. Therefore, the collected dataset contains up to five responses from the same participant. Those answers cannot be considered as independent as they are rather interdependent. However, they are independent from the answers received by other participants. Taking aforementioned into account, to analyse the impact of key EV parameters on range anxiety, a *mixed-effect model* was used where a randomness was added to account for the significance of the individual responses. Mixed-effect linear regression formula is described as follows:

$$\begin{aligned} distance\_to\_travel_{ij} = \beta_0 + \beta_1 * SoC_{ij} \\ + \beta_2 * driving\_range_{ij} \\ + participant\_id_j + \varepsilon_{ij} \end{aligned} \tag{3.1}$$

In Equation (3.1), SoC_{ij} and $driving\_range_{ij}$ present the independent variables, i.e., variables with predictable impact on a variable that we want to predict. The subscript ij represents the i-scenario faced by participant j. The random effect is represented by $participant\_id_j$, an independent variable that captures variability among participants. In this model, the randomness is an interceptor which is unique for each participant, making participant's responses mutually dependent but also not dependant with the responses from all other participants. The above said, two separate regression models were built following Equation (3.1), one for each group of participants. The resulting coefficients are displayed in Table 3.6.

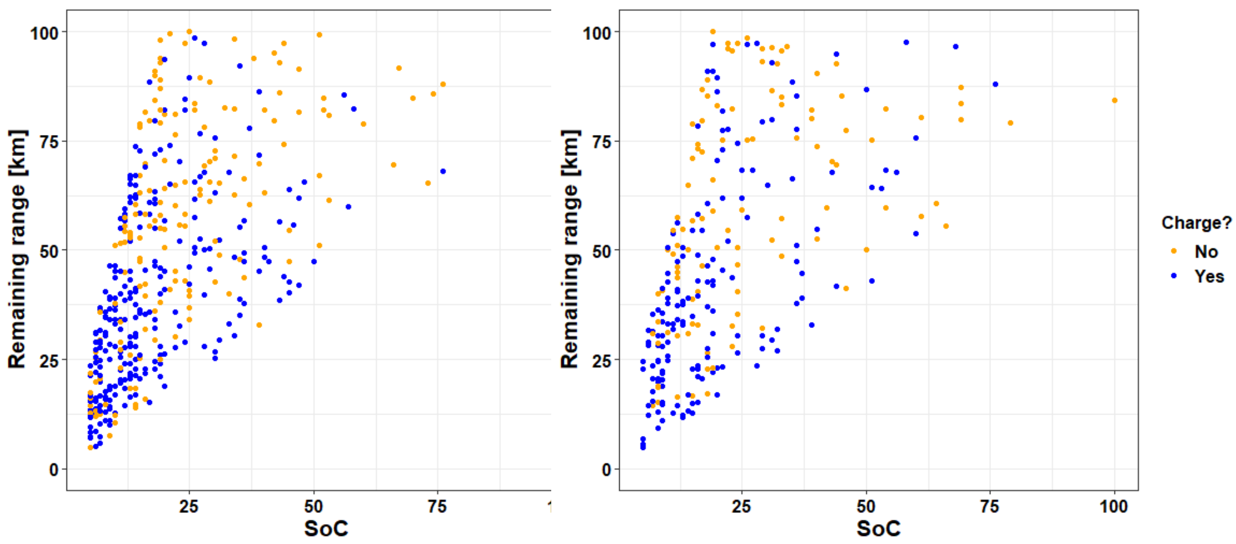
Table 3.6: Description of the obtained mixed-effect models.

non-EV owners			**EV owners**		
Random effects					
Groups	Name	SD	Groups	Name	SD
participant_id		13.27	*participant_id*		5.63
Residual		14.73	Residual		4.14
Fixed effects					
Intercept (β_0)	*SoC* (β_1)	*driving_range* (β_2)	Intercept (β_0)	*SoC* (β_1)	*driving_range* (β_2)
-1.84	0.08	0.22	6.08	0.04	-0.002

The results described in Table 3.6 lead to the two remarks. First, for non-EV owners, each increase in the *SoC* unit will increase the average distance a participant is willing to travel to another available charging station by 0.08 *km* on the average, if everything else is constant. Similarly, if everything is constant, for each increase in the unit of remaining *driving_range* the distance one is willing to travel to reach another available charging station will, on average, increase by 0.22 *km*. Second, for EV owners, the results point to the fact that both variables the *state of charge* and the remaining *range an EV can cover* have much weaker impact on the distance one is willing to travel to reach another available charging station. Specifically, if everything else is constant, increasing one unit of *SoC* results in an average increase in distance by 0.04*km*, while in the case of the remaining *driving_range*, that distance would decrease insignificantly.

To study the importance of variables involved, model with two variables was compared against the baseline model using the analysis of variance (ANOVA) test. The baseline model contains only one of the variables. The evidence suggests that for non-EV owners the *SoC* variable is not significant for the prediction of the range that one is willing to travel, while, on the other hand, the *driving_range* variable is significant with the p-value of $4.449e-10$. One possible explanation for those conclusions is that those the aforementioned variables are somewhat related, in a sense that lower SoC will contribute to the lower driving range. For the EV owners, neither of the variables has a significant impact on the model. However, they confirm certain trends regarding the key EV parameters, i.e., participants are willing to travel further the more SoC they have. To ensure that there is no multicollinearity between independent variables, the *variance inflation factor* (VIF) was calculated to be 2.0, leading to the conclusion that the standard error is only 1.4 times larger than if the predictor variable (SoC) had 0 correlation with the other predictor variable (remaining range). In terms of goodness-of-fit, we calculate two r-squared measures based on the work by [117]. In particular, marginal R-squared provides the variance explained only by fixed effects, while conditional R-squared provides the variance explained by the entire model, i.e., by both fixed and random effects. Both conditional r-squared values show that our models fit well our data.

The presented range anxiety model is illustrated in the next example considering non-EV owners. Assume that a person considers purchasing a BMWi with the battery of 50 kWh capacity (i.e., nominal distance that such EV can cover is around 210 km). If that individual would found himself/herself in a hypothetical scenario having the SoC at the 20% level (i.e., the remaining range is 42 km), he/she would agree to travel for 8.4 km more to reach the charging station in order to charge.



(a) Non-EV owners (b) EV owners

Figure 3.8: Comparison of willingness to charge considering SoC and remaining range

As Figure 3.8a shows, non-EV owners care less about the state of charge than the remaining range that they can cover. This conclusion is expected since two vehicles with the same SoC can cover significantly different distance, e.g., Nisan Leaf with 30 kWh battery capacity and with 15% SoC can cover up to 24 km, while Tesla Model S with 95 kWh on the same SoC can cover more than 70 km. EV owners have different perspective, as can be seen in Figure 3.8b, where those that are willing to charge are more scarcely distributed between 0 and 50% SoC, as well as between 0 and 100 km of the remaining range. The main reason behind this phenomenon is the fact that some EV owners own a private charging station, and others have accessible chargers near their workplaces, and for that reason they do not react as expected to different values of the SoC and the remaining range. Uneven distribution of EV owners and non-EV owners should also be considered as one of the factors behind this conclusion.

Reflection

As the result would suggest, evidently, non-EV owners are more affected by the key EV parameters than the EV owners when determining the distance they are prepared to drive in order to find other available charging station, i.e., by their answers regarding the available SoC and range that they can cover. Furthermore, remaining driving range has a stronger impact than the SoC for non-EV owners. This particular challenge can be tackled through ads targeting the education of the potential EV owners on the topics of the nominal range that the EV can cover and the distances one is approximately covering in a week drive, since today EVs mostly have the battery capacity large enough to satisfy an average customers *day-to-day* commuting needs. However, even if the remaining range variable is more significant than the SoC, SoC gives us an important insight into the range anxiety in the context of non-EV owners. Namely, most of non-EV owners are more inclined to charge when SoC drops below 15%, i.e., according to the analysis of the key EV parameters, a level at which most of the EVs prompt a warning about low battery capacity.

How key EV variables impact EV owners' thinking about charging is undetermined. The reason behind this is the fact that this survey is universal for both non-EV owners and EV owners, i.e., not specifically made for EV owners. EV owners have experience in driving an EV and they have different habits when it comes to charging. Since we targeted EV owners through various EV specialised forums, they often left us comments about the survey. Majority of those comments were addressing the fact that early adopters tend to own a private charger and that they never let the SoC fall below 30%. Therefore, some of the EV owners were willing to charge whenever they have an opportunity, since that is what they are used to do as they plug in their vehicle whenever they are at home. Furthermore, majority of EV owners that participated in this survey are enthusiasts (consequence of targeting the audience through the EV enthusiasts forums) that own a private charger. Majority of EV owners are early adopters that live in the smaller settlements, often with the population below 300,000, and therefore they are accustomed to drive further to reach a gas station and they would not mind the same in the case of the charging station.

One of the greatest challenges of the presented research is participants perception of the distance. Some participants reported that the acceptable distance to travel is more than 50 km, while minority of participants stated that they are willing to travel for the distance that equals their whole available driving range to find a charging station which could be out of order or occupied. This attitude is not a surprise as some of the survey respondents may be more prone to taking risk than the others. However, to solve the aforementioned issue, answers that greatly differ from the dataset mean value were removed in the process of the outlier detection and removal. The outlier removal was performed with great attention to settlement hierarchy, since majority of non-EV owners participants were from larger settlements and they dictate the mean of the dataset, while the participants from smaller settlements are expected to be willing to travel for greater distances.

Interesting observation is that, despite aforementioned differences between non-EV owners and EV owners regarding the charging habits and settlement hierarchy, both groups of participants have similar approximation of distances between existing neighbouring gas stations. Furthermore, both participant groups also reported similar desired distances between two neighbouring charging stations, leading us to conclusion that the significant underdevelopment of the charging station infrastructure is still the main cause of the range anxiety phenomenon.

The research presented in this Chapter has a number of limitations, some of which are related with the characteristics of the respondents who participated in the survey, while others are related to the statistical approach used to analyse and interpret the survey results. The most important limitation arising from the survey respondents perspective is the fact that the majority of survey participants who are EV owners are located in the USA or UK, while the majority of non-EV owners are from Croatia. Although, at least partially,the information about the survey respondents location context through their settlement sizes was captured, in order to fully remove biases rooted in different drivers cultures and characteristics based on their geographical location a follow up survey which would include a more comprehensive respondent pool would benefit the generalisability of the conclusions. The most important limitations arising from the statistical approach used are: (i) existence of the almost linear relationship between SoC and remaining distance; and (ii) usage of the linear model to explain range anxiety based on SoC and remaining distance, which resulted in partially non significant results. Regarding the former limitation, deeper statistical analysis on the collected survey responses provided grounding for having both SoC and remaining distance in the model, what can potentially be explained with the way how (potential) EV owners interpret those two parameters. However, again the more comprehensive study focused specifically on this research question should be done to confirm the assumption. Regarding the latter limitation, it would be beneficial to extend statistical modelling beyond linear to explore whether more complex modelling approaches would result with the higher percentage of statistically significant results.

Analysis of data gathered from respondents to the specially created survey enabled answering both research questions presented in Chapter 3.1. Both EV owners as well as non-EV owners share the opinion that the gas station infrastructure is overdeveloped, i.e., neighbouring gas stations can be further apart than they currently are. Moreover, both participant groups choose the average desired span between neighbouring charging stations around 7 km, which corresponds with the preferred distance between neighbouring gas stations. Another important conclusion comes from grouping survey respondents based on the settlement type - survey respondents from smaller settlements are satisfied with longer spans between neighbouring charging stations when compared to respondents from larger settlements, what also reflects current topologies of the gas infrastructure network. Regarding the impact of key range anxiety variables on non-EV owners, we identified that SoC has more influence compared to remaining range when non-EV owners decide about whether to charge, while on the other hand remaining range has more impact when deciding about the distance non-EV owner wants to travel for reaching an another charging station. EV owners show the same trends as the non-EV owners - they want to travel further to find another available charging stations when their EV's driving range is higher, as well as they are more prone not to charge when their EV's SoC is higher. However, EV owners are less sensitive about the key EV parameters, since they have a real-life experience with EVs. This also leads to the conclusion that experience of owning an EV greatly influences the range anxiety.

For the future work in this area, a plan is to customise the survey based on the feedback that was received from the EV owners, e.g., it is important to know if someone owns a private charger. This piece of information can greatly influence their responses considering the preferred distances, as well as their perception of the key EV parameters. Another interesting aspect of understanding the range anxiety identified in this paper is the influence of settlement type (potential) EV owner is living in. Finally, the plan is to mitigate some of the identified limitations of this paper in the follow up research, including distribution of the extended survey among geographically more balanced respondents base, as well as use more complex statistical approaches for interpreting collected data in order to achieve even more statistically significant results.

3.2 Geo-spatial charging station and PoI analysis

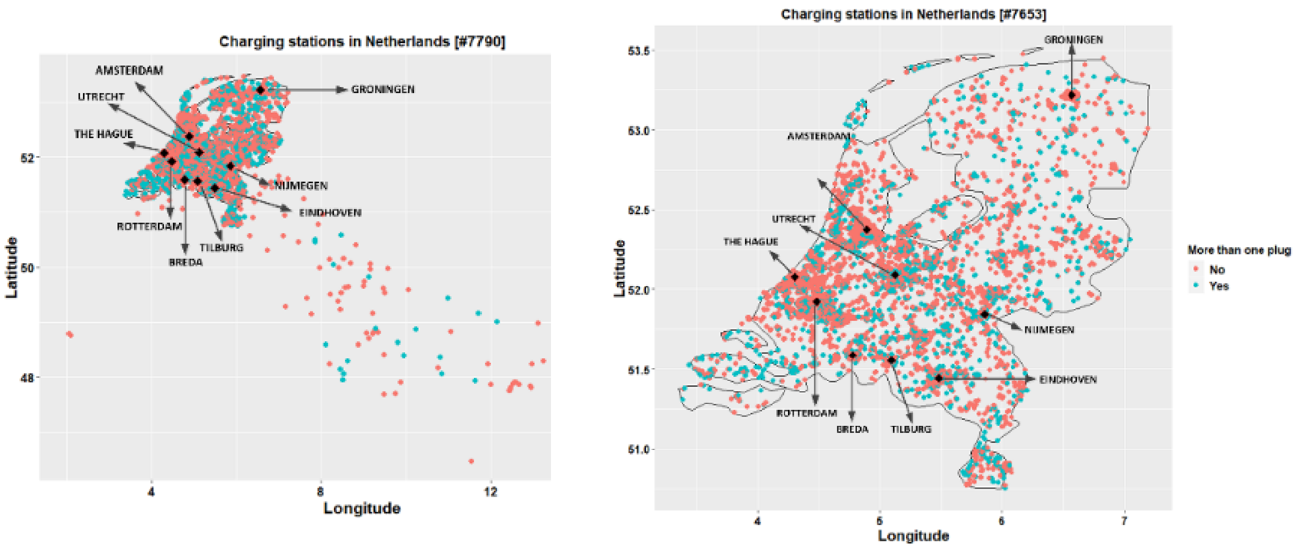
As the range anxiety, the geo-spatial analysis is one of the key concept that the EVCI framework is based upon. The following paragraphs will explain the methodology of the research, as well as the *key performance indicators* that are defined within the scope of this thesis for the better understanding of the charging station infrastructure state of the development.

3.2.1 Data collection

The methodology of the research is based on data collection from multiple heterogeneous sources and on the data analysis. The following text describe main sources of data, as well as necessary steps in order to obtain the data in format appropriate for further analysis.

Charging station infrastructure

The data about the charging station infrastructure can be obtained through several different sources. The most valuable source is the *charging point operator* (CPO) as the CPO has all information about the charging station and charging transactions. However, this source is not a publicly available one, and does not operate on global scale, i.e., one CPO is usually in charge of the infrastructure in a specific area. The solution that is fit for this type of research is the one provided by the *Open Charge Map* † (OCM). OCM API provides access to all charging stations that are covered by their service, which accounts for most charging stations in the world. The OCM API provides following information for each charging station in their database: unique identifier, address, geo-coordinates, address and contact number of the owner, connection type, usage type, number of chargers, status of the charging station, and general comments. The main challenge of the OCM API is that on occasion it returns more records than it should, i.e., some of the charging station are not located in the Netherlands, as showcased on the Figure 3.9.



(a) Before processing (b) After processing

Figure 3.9: Charging station data obtained via OCM API

To solve the aforementioned challenge, reverse geocoding is used where for each geo-coordinate the country is identified and, based on that information, the dataset is cleaned from the misplaced charging stations (see Figure 3.10). Request for all chargers in the Netherlands returned 7790 charging stations, however, after cleaning the dataset, there are only 7653 charging stations.

†https://openchargemap.org/site/develop/api

Places of interest

Places of interest (POI) are information of great value for both micro and macro development of charging stations. More about the gathering of the PoI data is explained in the Chapter 4.7.2.

Based on the previous work by Wagner et al. [118] and Chen et al. [73], hierarchy of PoI categories is defined as depicted in Figure 3.11.

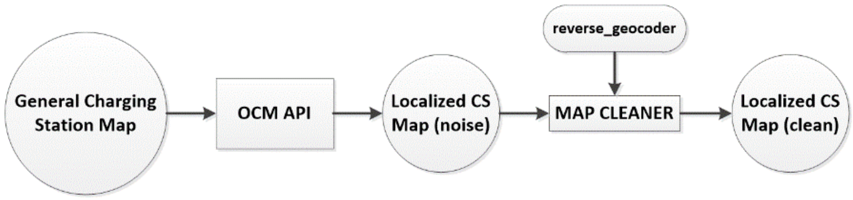


Figure 3.10: Methodology used for retrieving localised charging stations without the noise

The raw data contains specific PoI categories, and therefore, the classification towards abstraction is necessary in order to group specific establishment by common characteristics.

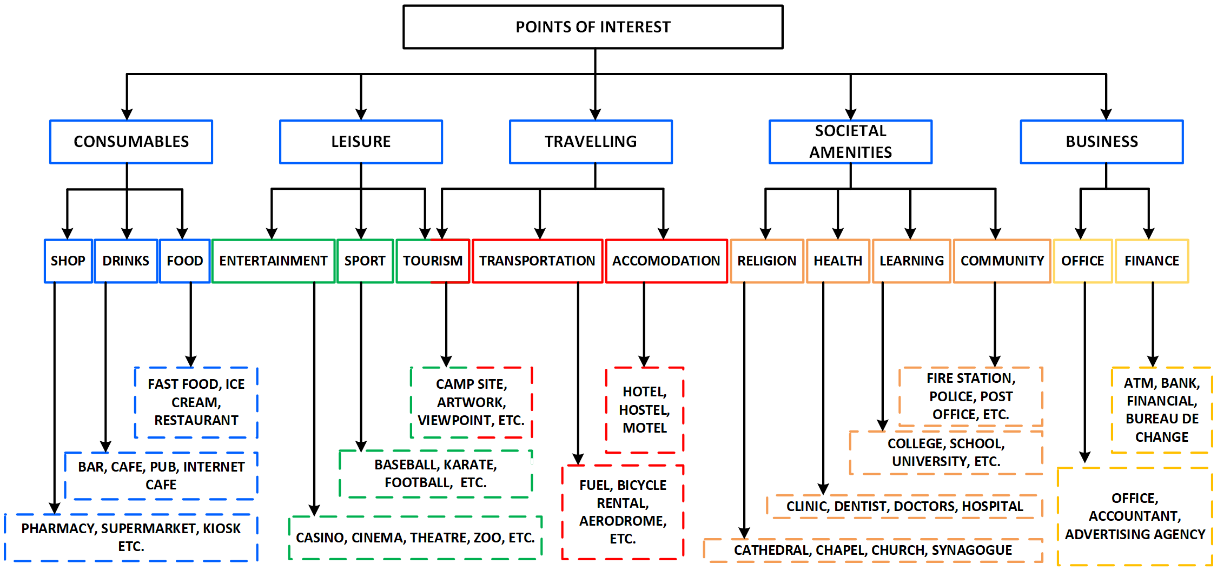


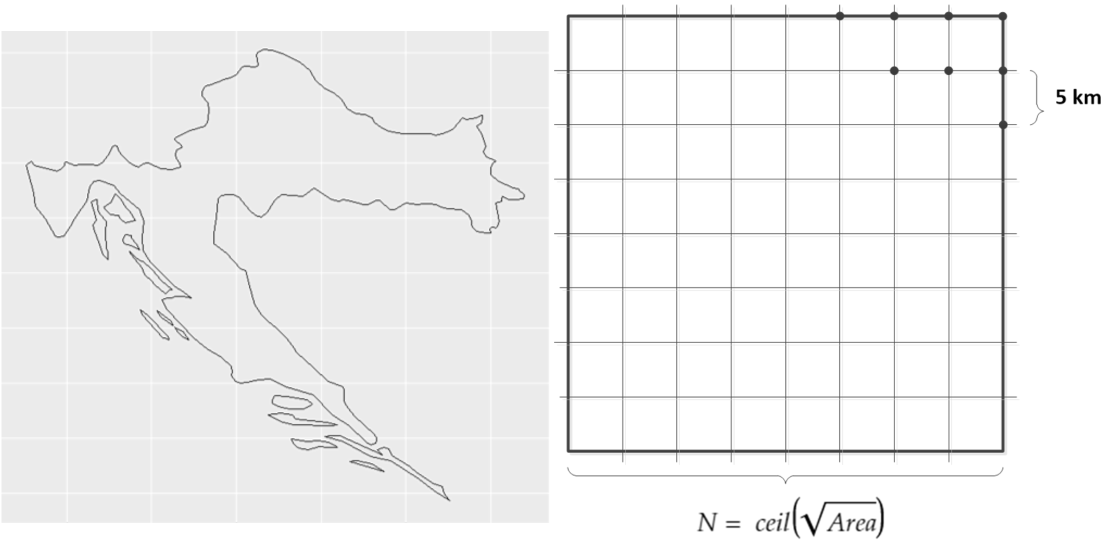
Figure 3.11: PoI hierarchy

3.2.2 Key performance indicators for charging station infrastructure development

After all the data is collected and processed, two KPIs are defined in order to provide an insight into the charging station infrastructure development: *(i)* charging station density and *(ii) charging station scarcity*. Aforementioned KPIs, although have no significant impact on the decision to place new charging station, are of great importance when deciding which component of the EVCI framework should be used, micro or macro development decision support system.

Charging station density

Charging station density is an indicator for how densely the area is covered with charging stations, more specifically, how the number of available charging stations corresponds with the size of the area. In order to get this information, the selected area firstly has to be transformed into rectangular shape so the grid can be created. The grid should be created taking into a consideration range anxiety, i.e., all grid intersections should be at the distance defined by the range anxiety, as shown in Figure 3.12.



(a) Croatia country shape

(b) Grid based on a Croatia area

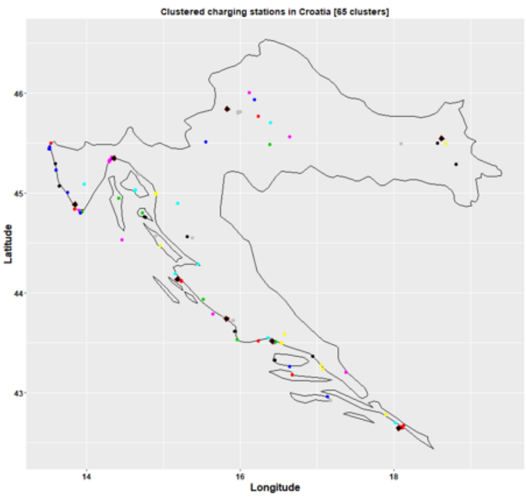
Figure 3.12: Creation of a grid for charging station density KPI

The length of the square side can be calculated as in Equation 3.2. The number of the intersection on the grid corresponds with the number of charging stations that should be present in order to fully cover the area in a way that wherever the EV is currently located, the closest charging station will always be in the distance lower than the one defined by the range anxiety. The ideal number of charging stations is defined in Equation 3.3

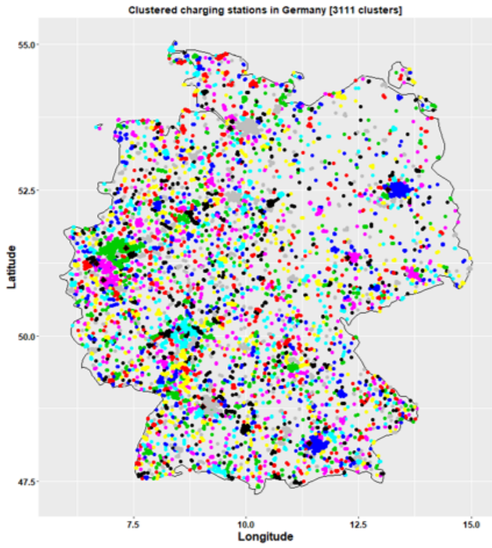
$$\mathscr{L} = ceil(\sqrt{Area}) \tag{3.2}$$

$$\mathscr{N} = ceil\left(\frac{\mathscr{L}}{range\ anxiety}\right) \tag{3.3}$$

The ideal number of charging station, obviously, is not the correct calculation. In the example of Croatia, there is no need to place the charging stations around the mountain area since no one lives there or commute through that specific area. However, if the ratio between the the ideal number of charging stations and real number of charging stations is observed (see Figure 3.13), it can be seen that aforementioned metric is informative regarding the charging station infrastructure development, i.e., charging stations in Croatia are barely visible, while the charging stations in Germany all all over the country.



(a) Charging station density in Croatia 4.03%



(b) Charging station density in Germany 81.82%

Figure 3.13: Comparison of charging station density Croatia vs Germany at the end of 2019

Charging station scarcity

Charging station scarcity, same as the charging station density is a KPI that is not intended to be use in the EVCI framework itself, rather as an indicator which mode of the framework should be applied. Charging station scarcity takes into consideration the number of charging zones (defined in Chapter 4), as well as the number of chargers in a certain area. The charging station scarcity $\mathscr{S}$ can have value $\mathscr{S} \in [0,1]$ where $\mathscr{S}$ is defined as follows:

$$\mathscr{S} = \left(\frac{N_{ChargingZones}}{N_{ChargingStations}}\right) \tag{3.4}$$

Obviously, from the interval that the charging station scarcity can take the value, as well as from the Equation 3.4, when the KPI charging station scarcity is close to 0, that KPI points to the conclusion that majority of the charging stations are grouped into one charging zone. On the other hand, if the KPI is close, or equal to 1, that means that each charging station is its own charging zone, and that they are very scattered throughout the area. Scatter value for the case of Croatia is around 0.7, i.e., 65 charging zones divided by 93 charging stations 3.4, while for the Germany it is around 0.26. From the Figure 3.13 it can be seen that, in the case of Germany, large groups of charging stations are belonging to the same charging zones, while multiple charging zones exist. On the other hand, in Croatia, there are no charging zones with significant number of charging stations. This conclusion can be drown from the charging station scarcity KPI. Of course, some adjustments to the formulae must be made in order to include the range anxiety as a variable that the scarcity is dependant on.

3.2.3 Results

The geo-spatial analysis have multiple outcomes. First of all, the methodology for acquiring data related to charging stations and places of interest was developed in a way that all the data is up-to-date with the current situation in the world, i.e., OSM API returns only the latest data, as well as to not depend on third parties, i.e., charging station operators. Another important outcome is the classification of PoIs by the categories. Raw data contains more than 100 PoI categories. This is not efficient in terms of computational performance, as well as timewise, therefore, they have to be grouped by the common characteristics. This research extended existing model in a more comprehensive and detailed model explained in Chapter 3.2.

In the scope of this thesis two KPIs related to the development of the charging station infrastructure are defined: charging station density and charging station scarcity. As explained in the previous Chapter, when those two KPIs are combined, they can serve as a good indicator of the state of the charging station infrastructure development. Finally, the geospatial analysis was performed for all countries in the Europe, and the results summary are presented in the Table 3.7, more detailed analysis is showcased as a part of Appendices. Section 7.2 demonstrates each country included in the analysis in the context with all other countries, as well as the individually. Based on the analysis performed per country, each country can be ranked, considering other countries, regarding the charging infrastructure relevant KPIs. Table 7.1 presents each country scores for relevant KPIs, as well as a total score. The lower the score is, the charging station infrastructure is potentially more developed.

Table 3.7: KPIs for European countries

KPI	MEAN	MAX	MIN
Area km^2	168,000	783,562	316
GDP per capita USD	34.80	113.95	5.26
Ideal number of CS	6,800	31,684	16
Number of chargers	1,189	11,866	2
Number of charging zones	308	3,111	2
Number of PoIs	161,491	1,339,230	5,084
Number of PoIs close to CS	27,000	339,030	80
Population	17,605,000	82,887,000	355,620
Scatter value	0.50	1	0,05

Aforementioned KPIs can be used to decide which component of the EVCI framework should be used for the charging station placement decision, macro, or micro development. For example, if the charging station density is high, while the scatter value is low, one can conclude that the charging station infrastructure is developed, and the micro development can be used. On the other hand, if the scatter value is high, i.e., charging zones are far apart, and the charging station density is low, i.e., not many charging stations in a large area, the macro development can used to decide where a new charging station should be deployed.

Now that the key concepts that EVCI framework is based upon are introduced, next chapter will in details describe functionality of the aforementioned framework, as well as all modules that the framework is based upon.

Chapter 4

Data-driven framework for developing EV charging infrastructure

The Electric Vehicle Charging Infrastructure extending framework * (EVCI framework) † is a conceptual model and implementation of decision support system (DSS) for the charging station deployment. The framework relies only on real world data and is not dependant on any assumptions and simulations which reduces the risk of increased error rate.

The EVCI framework is divided into two independent logical parts: *(i)* macro development and *(ii)* micro development. Each part should be used depending on the situation with the charging station infrastructure development level and on the data that is available.

Macro development is intended to be used when the transaction data, i.e., the data about the charging transactions, is not available and when the country has underdeveloped charging infrastructure which consequently influence the aforementioned. Macro development is dependant on publicly available data about the location and categories of places of interest (PoIs) and towns in a country, as explained in Chapter 3.2, and on the location about public charging stations. This component of framework works with three different objective functions: *(i)* connect large cities with charging stations, *(ii)* connect two largest charging zones with charging stations, and *(iii)* connect two closest charging zones with charging stations. Macro development is based only on geospatial analysis.

Connection of big cities is the first step in developing charging infrastructure, since the inter city travel is one of the major challenges considering the battery capacity and the range that EVs can nowadays cover. Deployment of charging stations between two large charging zones is also an important step since those two charging zones are most likely populated with significant amount of EVs and if the zones are far enough, there is high probability that the chargers along the way will create more charging zones, as explained in the following Sections. The final

*http://161.53.19.71:9000/evci/

†For detailed description of EVCI framework component, see Appendices 7.1

objective function is based on placing the smallest amount of charging stations to connect two charging zones, i.e., two closest charging zones. The distance along the shortest path between aforementioned entities where charging stations should be placed is derived from the detected range anxiety, as explained in Chapter 3.1.

Another important parameter in this EVCI framework mode is the number and location of PoIs. When considering big cities and connection between them, usually it is a highway, and on highways it is not a good business decision to place charging stations every 7 km from each other. The EVCI framework provides the decision based on the PoI location, i.e., how many charging stations along the way should be grouped around the significant amount or category of PoI, instead of being placed at each 7th km.

Another, more complex mode of this framework is micro development and it intended to be used in a case where charging infrastructure exist and is developed, since it is based on the charging transactions. This mode makes a decision for a charging station placement on a resolution of a charging zone on a predefined area, e.g., country or town. Micro development is based on the calculation of utilisation of charging stations in the charging zones. After the calculations are made, next step is to predict the utilisation when another charging stations are placed and compare those results in order to maximise overall utilisation, as explained in the following paragraphs.

A charging station is a place where EV owners can park and charge their vehicles. Each charging station can be equipped with only one charger plug (CP) and only one parking spot (PS), as in Figure 4.1a, or with multiple charger plugs and parking spots, as in Figure 4.1b, where the number of plugs is equal to the number of available parking spots. In this thesis, the *charging utilisation* KPI (U_{ch}) is considered, which is computed per geographical segmentation called *zones*. For example, the charging utilisation in a certain zone is the likelihood that any charging plug in that zone is being used at any arbitrary time. It is assumed that all charging plugs in the same charging zone are equally likely to be busy (i.e., that there is a car being charged there). Aforementioned KPI is used in three different objective functions in order to decide on a location for a new charging station within a specific area on a zone resolution: *(i)* maximisation of the overall charging station utilisation, *(ii)* populate charging station unpopulated areas, and *(iii)* hybrid approach between previous two. Objective functions are in more detail explained in Chapter 4.7.1.

The EVCI framework in its entirety is depicted in Figure 4.2 and following Sections will explain the main components of the framework.

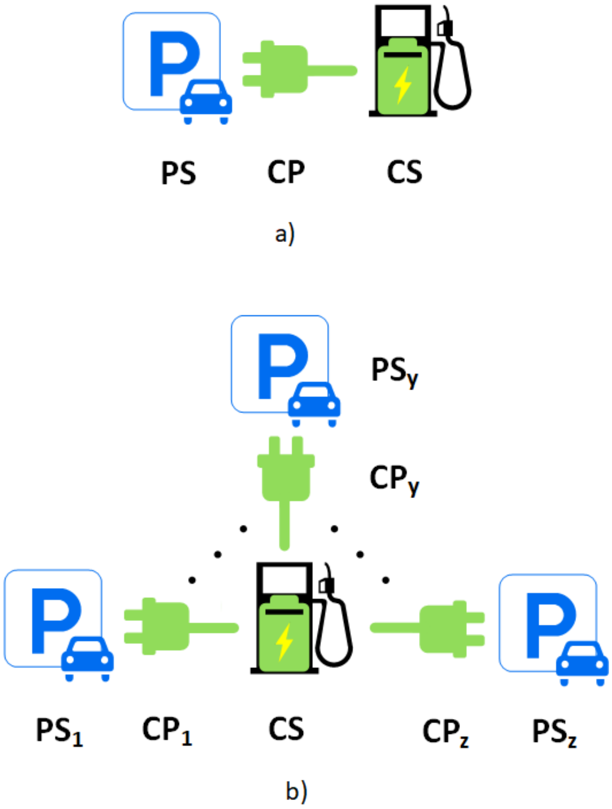


Figure 4.1: a) charging station with one plug. b) charging station with multiple plugs.

4.1 Data sources

The EVCI framework uses exclusively real-world data to assess the potential location for a new charging station. Although the data in this field is often challenging to obtain, it provides more accurate results than those from the simulations, since real-world data clearly states the real-world behaviour of EV and potential EV owners. The most challenging dataset to obtain is the dataset about the charging transactions, since it is usually owned by the service or infrastructure provider, and therefore considered as proprietary data. Charging stations transactions data can, however be obtained as a sample dataset, although for the full dataset cooperation with charging infrastructure service or infrastructure provider is needed.

Figure 4.3 depicts all data sources, described in following sub chapters, used in the EVCI framework before and after the data processing. The data processing phase is the most important step for high quality results of the EVCI framework. The EVCI dataset consists from the data from 5 heterogeneous data sources. For the creation of the EVCI dataset based on the charging transactions, the core data is EV charging infrastructure operator's dataset, although the CPOs are not the only owners of the dataset, the dataset can also be the property of an Emobility Service Providers (EMSPs). The core dataset is extended with geographical data, i.e., data containing information about *places of interest* (PoIs), *distance between charging stations*,

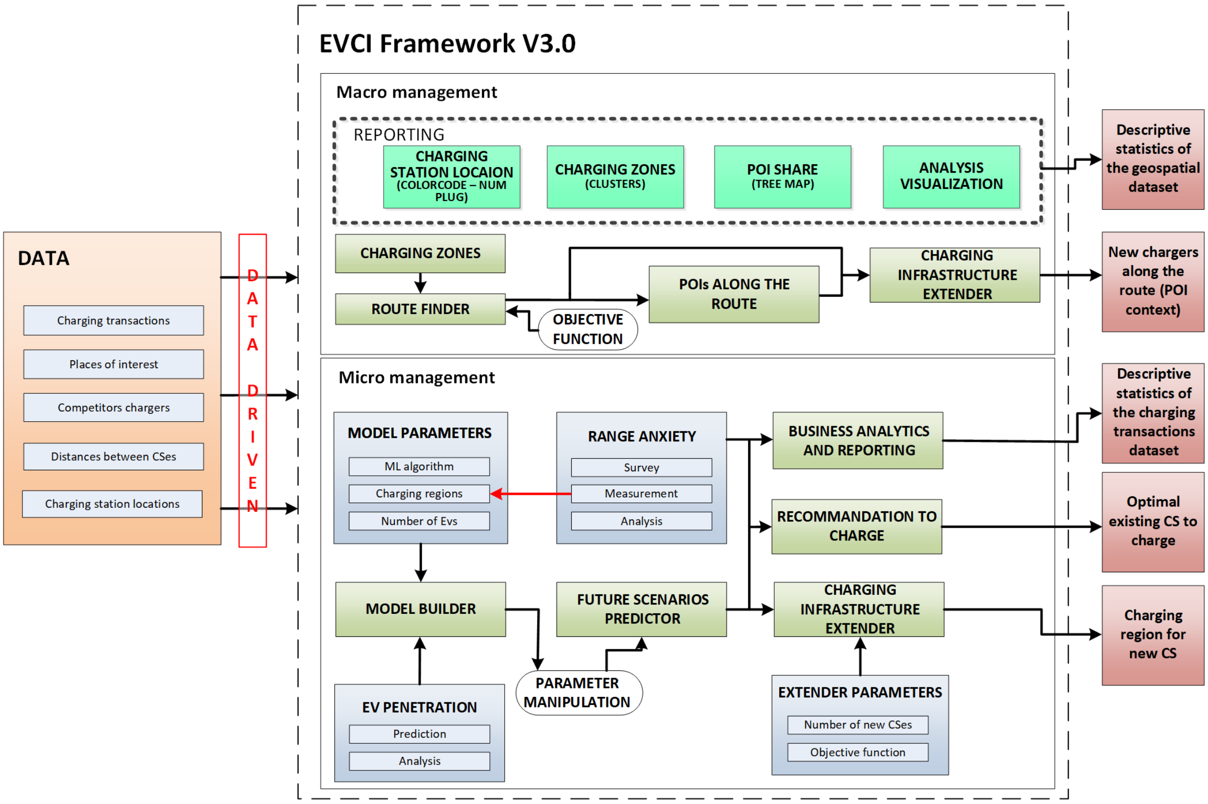


Figure 4.2: The Electric Vehicle Charging Infrastructure extender (EVCI) framework

and with information about the number of *competing charging stations*. The expanded dataset gives further insights into the environment of each charging station in the core dataset and, consequently, it enables better analysis based on richer contextual insights. The EVCI dataset that is based purely on geospatial information about the charging stations and PoIs.

4.1.1 Historical transaction data

The core dataset consists of charging transactions for charging stations through the time.The taxonomy is derived from the multiple datasets that use similar taxonomy, i.e., ChargePoint is usually used to describe an unique charging station. Besides the conclusion from different datasets, Open Charge Point Protocol (OCPP) defines some common variables, such as TransactionStart and the TransactionStop to define the time span when the charging transaction occurred [119]. For the EVCI framework, the important information in that dataset are as follows:

- *TransactionID* - unique numeric identification of a transaction (e.g., 1391709);
- *ChargePoint* - identification of a charging station (e.g., AL100);
- *Connector* - numeric value representing the number of chargers available in a charging station (e.g., 1);
- *StartCard/StopCard* - identification of the user's ID card used in the beginning and end

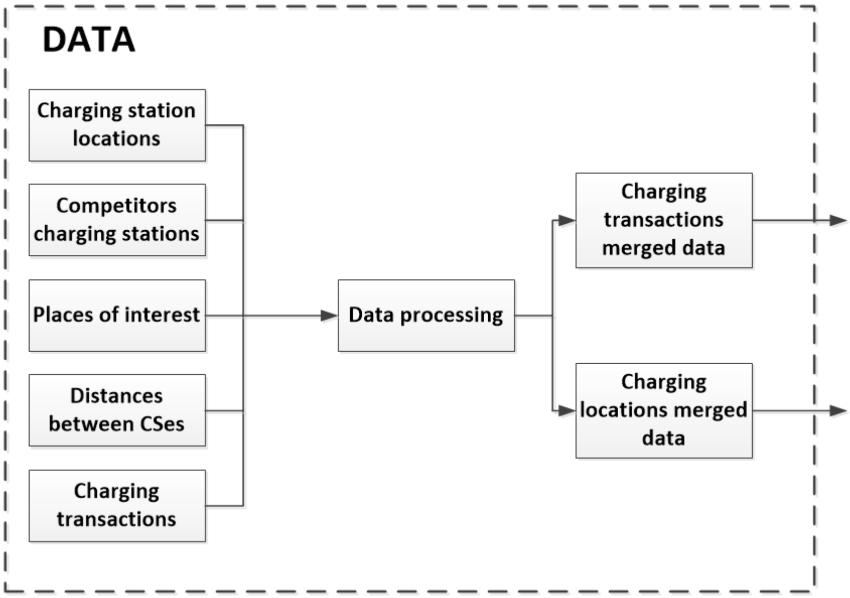


Figure 4.3: Data component of the EVCI framework

of a charging session (e.g., 0488D392 213180);

- *UTCTransactionStart/Stop* - time the charging session started/stopped (e.g., 2016-03-07 16:54:10);
- *ConnectedTime/ChargeTime/IdleTime* - the time (in hours) the vehicle was, respectively, connected to the charger, charging, or idle (e.g., 4.3834, 3.5003, and 0.8831); and
- *Lat/Lon* - latitude and longitude coordinates of a charging station (e.g., 53.19865 and 5.792520).

Each transaction is defined by all actions from the time when an EV owner plugs the EV to the charger (*UTCTransactionStart*) until the EV is unplugged (*UTCTransactionStop*). A charging session starts when an EV owner initiates the transaction with his/her charging card. As soon as the transaction starts, the car begins to charge. After the car is charged to a desired level, it stays in idle mode (i.e., not charging) connected to a charger until the EV owner ends the transaction with his/her charging card.

Based on the transaction variables, we generate an hourly time-based version of the original dataset. This dataset transformation facilitates the study of temporal charging behaviours for different time intervals. Moreover, it introduces more instances for the machine learning algorithms. For example, if a transaction starts at 5 AM and ends at 1 PM, that single line in the core dataset is replaced with 8 rows corresponding to each hour in which the transaction was active.

4.1.2 Places of interest data

Another significant source of data in this research is Open Street Map ‡ since it provides information about different places of interest (PoI). PoIs are distributed across 14 categories as follows: *shop*, *drinks*, *food*, *entertainment*, *sport*, *tourism*, *transportation*, *accommodation*, *religion*, *health*, *learning*, *community*, *office*, and *finance*.

PoIs have been shown to be of importance in developing charging station infrastructure [111] especially PoIs that are in the radius of 500 m from the charging stations have a significant impact on charging station demand [118]. Since two charging stations can be deployed close to each other (i.e., distance lower than 500m), algorithm for identifying PoIs takes that into consideration so that no duplicate PoIs are in the EVCI Dataset. In other words, even if one PoI is in between two charging stations that have the distance between themselves lower than 500m, that PoI will not have a duplicate entry in the dataset. Therefore, PoI categories are suggested in the hierarchy as depicted in Figure 3.11, based on previous research [73, 118]. OSM API ensures that the PoI data is refreshed daily and therefore up-to-date.

4.1.3 Distances between chargers and places of interest data

The distance between charging stations is needed for performing a distance-based clustering of charging stations, which results in the charging zones. Clusters (charging zones) are determined based on the *driving distance* between charging stations. To do so, Nokia HERE API § was used. Based on the Nokia HERE API and geographical coordinates of the charging stations, the NxN driving distance matrix was calculated. All the distances in the matrix are in kilometres. Besides the driving-distance matrix, the *aerial distance* matrix was also created using the Haversine formula [120]. Both distance measures are evaluated and the results are reported in Chapter 4.2.

To calculate the distances between charging stations, as stated before Nokia HERE API is used, which relies on the REST service. This is time intensive and requires large number of requests to create upper-triangular matrix, that can later be transformed into the distance matrix. As can be inferred from the Equation 4.1, the number of requests has polynomial dependency.

$$numberOfRequests = \frac{numberOfChargers \times (numberOfChargers + 1)}{2} \tag{4.1}$$

For the case of Croatia, that has only 94 charging stations, a little more than 4,000 queries is needed, while for the Germany that has more than 11,000 chargers, more than 70 million requests are necessary to compute the whole distance matrix (see Figure 4.4). To address this challenge, proposition is to only calculate distance for the charging stations which geo-location

‡ www.openstreetmap.org

§ www.developer.here.com

does not differ for more than 0.1. This is the equivalent for around 7.8 km at 45° ± 15° North or South. Using the proposed methodology, the number of requests needed can be significantly lowered, depending on the size of the observed area.

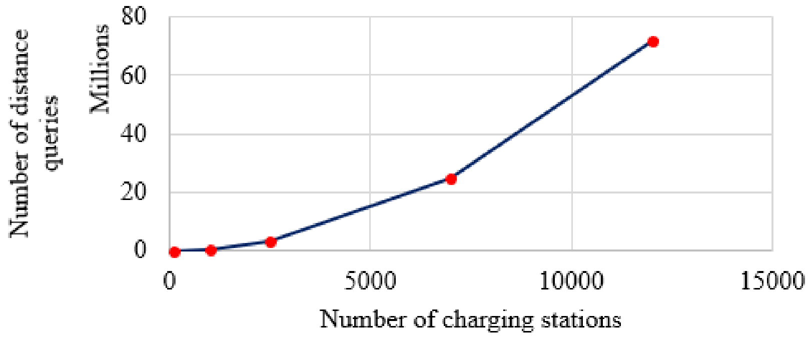


Figure 4.4: Number of requests dependent on the number of charging stations

The distance between charging stations and PoIs was not calculated using the real driving distance for two reasons: *(i)* there is to many PoIs, compared to the number of charging stations, and the calculation of the driving distances would not be efficient time-wise and *(ii):* since the neighbouring PoI is defined by the 500 m distance, there is no room for significant error comparing the driving and *as-a-crow-fly* distance.

4.1.4 Competitors charging station data

Information about the competitors charging stations is highly important for the for the EVCI framework, more specifically, for the calculation of the utilisation, since the more alternatives an user has, the higher the probability he/she will choose one of the competitor's charging stations.

The information about the charging station operator can usually be found on any map of charging stations (e.g., Open Charge Map [¶]), however the access to the API is not always free to use and additional cooperation from the service provider is needed. Information about all charging stations in the Netherlands is, for example, available through the Oplaadpalen API [‖]. In the EVCI dataset, the number of competing charging stations is treated as a separate PoI category.

4.1.5 Data processing phase

Once all the data sources are present, each dataset needs to be prepared in order to create the EVCI dataset. A proper representation of variables helps increasing the accuracy of the machine

[¶] www.openchargemap.org
[‖] www.oplaadpalen.nl

learning algorithm (e.g., multiple linear regression and XGBoost) and potentially reduces the computational time for making a prediction. One of the key challenges in this step is to define a representative variable for the places of interest. Clearly, a good representation of PoIs must reflect how they affect utilisation of charging stations, as well as how they correlate with the number of charging stations. In this thesis three potential representations are defined: (V1) the absolute value, i.e., the number of a certain PoI category in a zone; (V2) the relative share of PoIs in a certain zone taking into account the total number of all PoIs (see Table 4.1); and (V3) the existence of PoIs, i.e., 1 if the PoI exist, 0 otherwise (see Table 4.1).

Table 4.1: Example of different PoI representation (V1 = absolute number of PoIs, V2 = relative number of PoIs, and V3 = existence of PoI category)

PoI category	**1**	**2**	**3**	**4**	**5**	**6**	**7**
V1	0	1	22	12	11	0	3
V2	0.00	0.02	0.44	0.24	0.22	0.00	0.006
V3	0	1	1	1	1	0	1

Another important factor that needs to be coded into variables is the temporal charging behaviour. We define multiple hierarchical variables to capture the temporal behaviour in the analysis. The EVCI dataset consists of start and end times for transactions (i.e. hour and minutes). To explore how utilisation depend on the time of the day, original variables that describe start and end times of transactions were transformed into a variable called the *category of the day* that can take on only 4 different values:

- morning (from 5 am to 12 noon);
- afternoon (from 12 noon to 6 pm);
- evening (from 6 pm to 12 midnight);
- night (from 12 midnight to 5 am).

Next, long-term temporal behaviour was captured, namely the *day of the week*, having the possible values “Monday", “Tuesday", ..., “Sunday". This is translated into a variable called *isWeekend*, with possible values “YES" and “NO".

4.2 Clustering method

The resolution on which EVCI framework makes a decision on charging station placement, i.e., the part that relies on the historical transactions, is a charging zone. Charging zone is defined as an area in which all charging stations are neighbouring based on the specific distance experimentally defined as described in Chapter 3.1 (see Figure 4.5). Of course, charging zones can not be defined if there is no charging stations in the region.

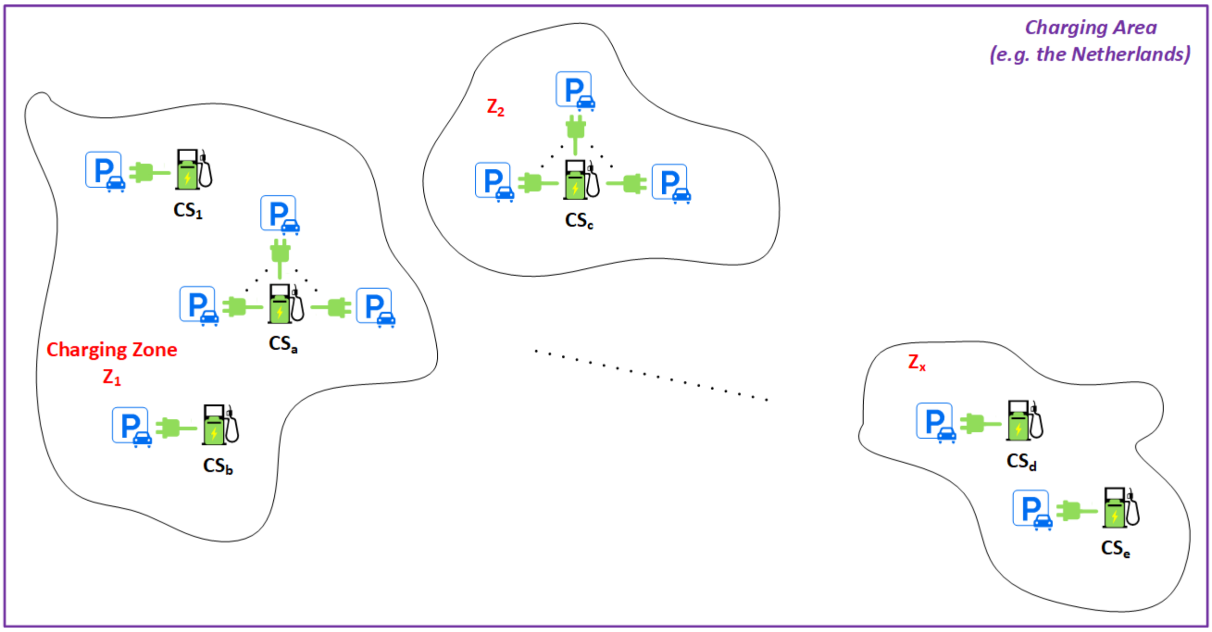


Figure 4.5: Example of charging zones

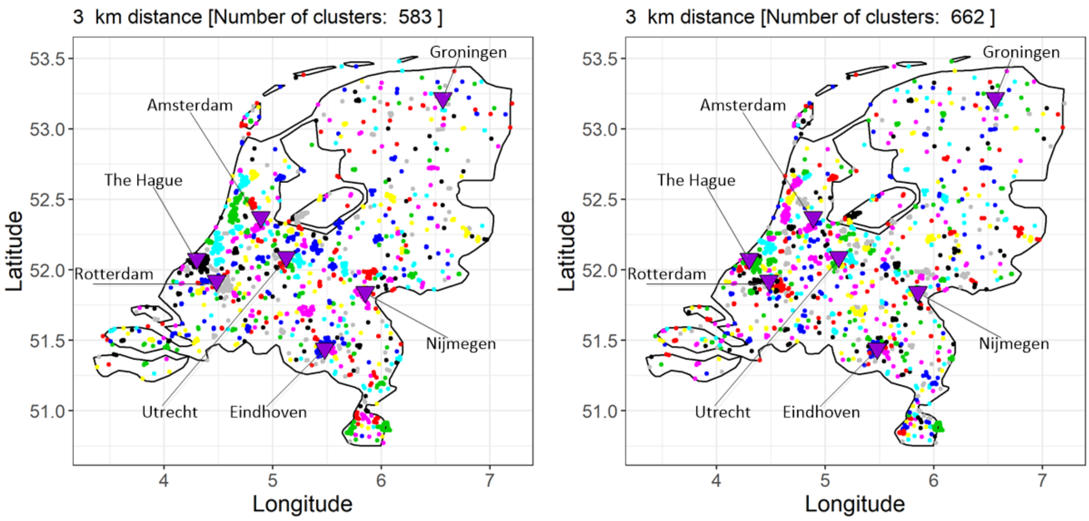
It is well known that the accuracy of predictive algorithms is not only dependent on the underlying machine learning technique, but also on how the variables are represented, as explained in the previous sub chapters. In our solution, predictive accuracy is highly affected by how charging stations are clustered together into charging zones. For that reason, an appropriate selection of a clustering method and its parameter values is required.

Clustering is generally used to group entities together based on similarities among them. In our case, entities are the charging stations and similarity is the distance between them. We employ a *hierarchical clustering* approach that builds a dendogram based on that distance. The basic algorithm of the hierarchical clustering is as follows:

- Compute the proximity matrix for each point in the dataset;
- Let each point in the dataset be a cluster for itself;
- In the next step merge two closest points based on the distance;
- Repeat previous step until there is only one cluster; and
- Cut the built tree on the desired distance.

Hierarchical clustering has proven to be very versatile since it enables easy clustering by any pre-defined distance with just one dendogram being built [121]. For example, if one wants the clustering distance to be 3 km, the dendogram can then be cut at the corresponding level. The function that builds the clusters in this research is based on the minimum distance between the elements of clusters, i.e., we use the single linkage function.

Clusters in this research can be defined *"on-the-fly"*, however, the predefined distance is 7 km since that is the distance which corresponds with the manifested range anxiety, experimentally detected as described in Chapter 3.1.



(a) (b)

Figure 4.6: Difference between (a) aerial-distance and (b) driving-distance based clustering

We use an innovative approach to compute mutual distances. The most widely-used method to compute mutual distances in this field is to calculate the aerial distance between two geographical coordinates, e.g., Haversine distance [72]. We, however, complement this information by computing the *driving distance* between each two charging stations acquired via Nokia HERE API as their mutual distance. Aerial distance-based clustering could result in unrealistic scenarios, e.g., grouping together charging stations around a bay that have small aerial distance, but long driving distance, or even grouping charging stations that are not connected through land. For example, in the Netherlands, two charging stations located near the Oud Valkeveen and the Bikbergen have the aerial distance of 1.6 km, while the driving distance is 2.2 km. On the other hand, the charging station near Oud Valkeveen has only 4 km aerial distance from the charging station located near the Kromslootpark, while the actual driving distance is 16.4 km. Naturally, the driving distance approach is more suitable for the aforementioned applications. After calculating the average distance between all available charging station in the Netherlands that are present in the EVCI dataset for both aerial and driving approaches, it was proven that, on average, the driving distance improves precision, i.e., accuracy of calculated distances, by 31% over traditional aerial-based clustering, i.e., aerial-distance results in 31% unrealistically shorter distances than driving-distance. An illustrative comparison of aerial and driving based clusters is depicted in Figure 4.6, where it can be noticed that the number of clusters is higher when the driving distance-based approach is used. As a reminder, the clustering step in the EVCI dataset generation identifies the charging zone each charging station in the EVCI dataset belongs to.

4.3 Prediction of future EV sales

The EVCI framework is design to work on the real world dataset. However, future data can also be valuable as an input for the analysis of charging station infrastructure needs. If the number of electric vehicles is present in the real world dataset in the form of longitudinal values, e.g., for the period of one year or couple of years, in our case studies, we have longitudinal data over four years, from 2013 to 2016, there are numerous methods to predict the number of electric vehicles in the future and how will they influence existing charging infrastructure, as shown in Figure 4.7. This is not the key component for the functionality of the EVCI framework, moreover, if the prediction is made far into the future, it may considerably influence the accuracy of the utilisation prediction model, i.e., the error in the prediction of the number of electric vehicles in the future can introduce significant error into the prediction of charging station utilisation on which the EVCI framework is based upon.

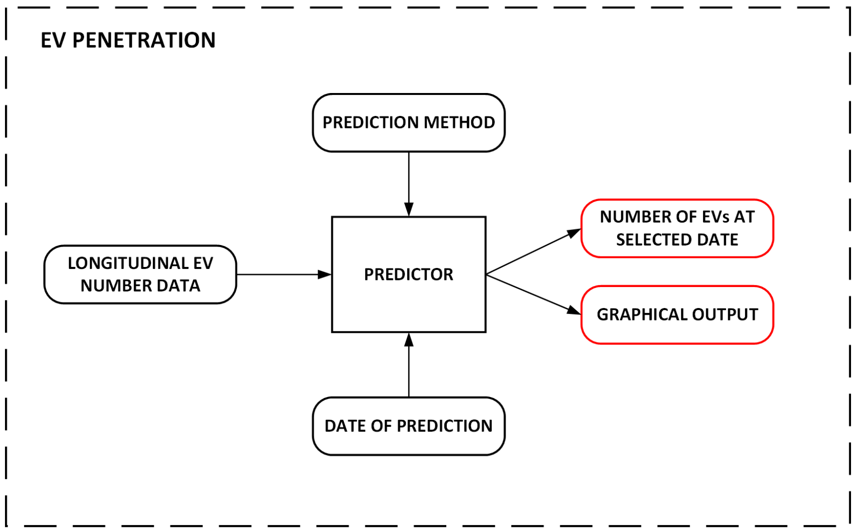


Figure 4.7: EV penetration model

The chosen time series models for this application are ARIMA [122] and ETS [123] models. It is important to notice how this two models predict different types of data. ETS is better option if there is specific trend or seasonality in the dataset, e.g., the number of EVs is increasing every spring. On the other hand, if there is certain auto-correlation in the data, i.e., the observed past indicates the future, ARIMA is better choice. Both models are implemented to ensure certain level of abstract for the developed framework.

This module, as shown in Figure 4.8 enables prediction of the number of EVs in the future for the purpose of better infrastructure planning, i.e., EVCI framework takes as an input the time span for which the growth of the number of EVs should be plotted, as well as the date for which the number of EVs should be calculated. and can be included in the charging station utilisation prediction in order to choose an optimal location for the new charging station.

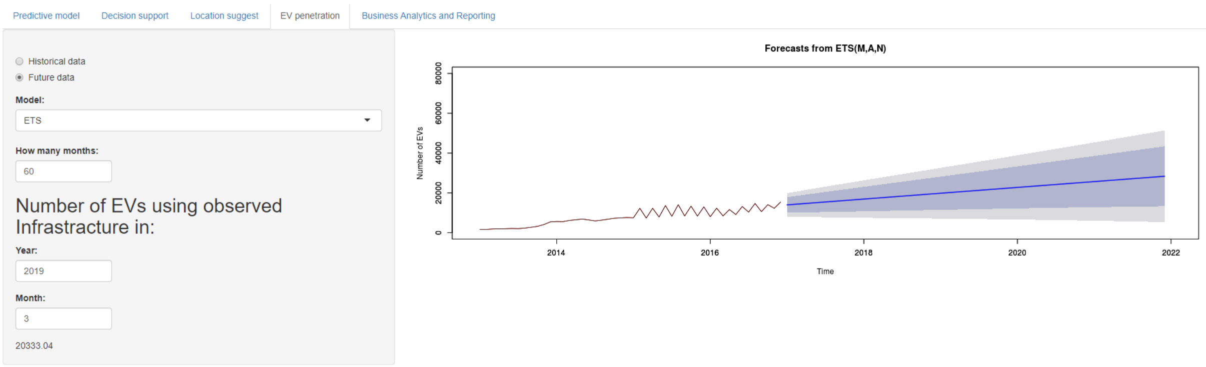


Figure 4.8: Example of EV penetration component

4.4 Prediction of the charging station utilisation

Arguably, accurately predicting the charging utilisation is one of the most important steps towards optimally placing new charging stations. In the scope of this thesis, two different machine learning algorithms are applied in the EVCI framework. First, to understand how each variable affects charging utilisation, a *multiple linear regression* (MLR) model is trained. When it comes to the predictive model itself, the *XGBoost* algorithm is used due to its versatility in handling non-linear relationships between variables, which often results in higher accuracy. XGBoost is a variation of gradient boosted decision tree with emphasis on speed and performance. Prediction element as shown in Figure 4.9 takes three input parameters and has dual output.

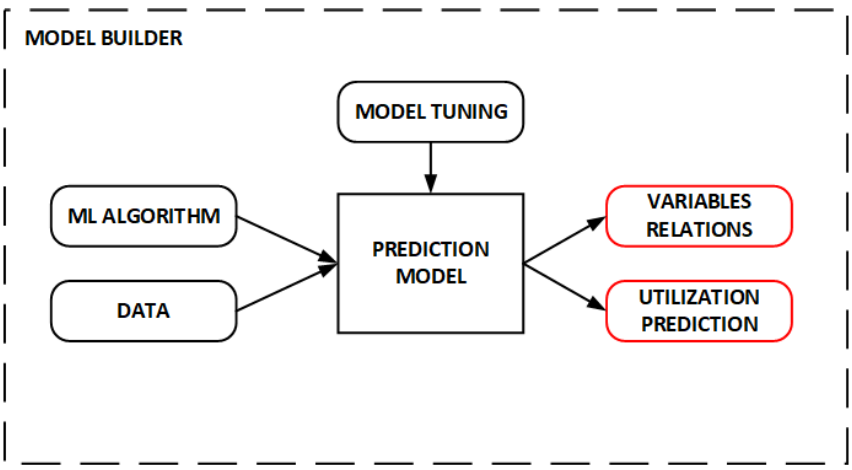


Figure 4.9: Model Builder EVCI component

MLR models were built considering the EVCI dataset under the following time resolutions:

- Day of the year (e.g., every day in a year);
- Day of the week (e.g., every Monday of a year);
- Hour of the day of the week (e.g., 8 AM for every Monday in a year);
- Hour of the day (e.g., 8 AM for each day through a year);
- Category of the day (i.e., morning, afternoon, evening, and night) of the week in a month

of a year.

Main goal when building all these models was to observe how each variable influences charging utilisation depending on the selected time interval. All scenarios have 17 common variables, i.e., 13+1 PoI categories, charging zone ID, the number of different EV owners' cards, and the number of charging plugs in the zone. Clearly, the scenarios have different variables for specifying the time interval. After testing PoI categories for correlation, it was discovered that they highly correlate with each other, e.g., the PoI category community has a coefficient of correlation not less than 0.75 with every other PoI category. Solving this problem was accomplished by summing all PoI categories (except for the variable about competitors' chargers) into one variable: *sumPoi*. After this summation of variables, there were 5 variables shared across all models, namely the number of competing charging stations, charging zone IDs, the number of different EV owners' cards, the total number of PoIs, and the number of chargers in the charging zone. Charging zone ID is a categorical variable and one-hot-encoding technique was used to extend that variable into a vector of variables. The same is true for the variables describing the time intervals.

The results of the multiple linear regression model for the most complex time interval (i.e., hour of the weekend and weekdays for each month) are provided in Table 4.2. As can be seen from the p-values, all variables are relevant, which is understandable after a careful inspection of the dataset. Table 4.2 also shows the accuracy of the MLR algorithm. This algorithm explains around 30% of the variance in the dependent variable, which is not good enough to make dependable predictions of charging utilisation. The influence of a single variable on utilisation can be derived from the estimated coefficients. For example, the variable that describes the number of plugs in a certain area has a negative influence on utilisation, i.e., for each new added charger, if nothing else changes, the utilisation will decrease in expectation by $1.16 * 10^{-3}$. Contrary to the number of plugs, the variable that represents the total number of PoIs in an area has a positive impact on the charging utilisation, i.e., if another PoI is added to a specific area without changes to other variables, then the utilisation is expected to increase by $5.47 * 10^{-6}$.

To predict the charging utilisation, the XGBoost algorithm was used since it is currently one of the most used algorithms due to it's accuracy [124] and it is well adjusted to the type of the dataset used throughout this research. This algorithm is based on building decision trees and it allows for a great fine-tuning through its parameters. To validate and calculate the accuracy of the XGBoost algorithm without inducing bias, the dataset was split into three parts: *training dataset*, *validation dataset*, and *test dataset* in a *60:30:10* ratio. The predictive model was built using the hour of the weekday/weekend timespan and was validated on the validation dataset until satisfactory accuracy was achieved. After achieving a high accuracy on the validation set, the test dataset was used to calculate the final model's error.

The XGBoost model is compared against a *baseline model*. The baseline model is the

Table 4.2: Result of Multiple Linear Regression prediction algorithm

formula = hourly actual charging time $\sim$ hour day + is weekend + month + number of cards + number of chargers + zone + competitor chargers	
Variable	p-value
hour day i, i $\in$ [1,23]	*** (hour day 18, **)
month j, j $\in$ [1,11]	*** (month 1 and 2, *)
zone k, k $\in$ [1,661]	***
is weekend	***
number of cards	***
number of chargers	***
competitor chargers	***
sumPoi	***
Significance codes 0 ’***’, 0.001 ’**’, 0.01 ’*’, 0.1 ’.’, 1 ”	
Residual standard error 0.06495	
Multiple R-squared 0.30650	

statistical model that returns the historical average value of utilisation for a specific cluster at a specific hour of the weekday/weekend. The aforementioned predictive model is natural in this scenario because many of the patterns in charging utilisation are defined in terms of the time when the charging session occurred. In Table 4.3, a comparison between the prediction errors for the XGBoost algorithm and the baseline algorithm is provided. As it can be seen in that table, the XGBoost has a low error of only 5% (respectively, 3%) for the root mean square error (respectively, the mean absolute error), thus beating the baseline model in the terms of accuracy. One can argue that the reason why the XGBoost model is more accurate is due to the same relying not only on variables from the core dataset (business data), but also on variables that originate from the other sources (e.g., POIs from geographical data). Figure 4.10 depicts the variable importance for the top 15 variables used in the XGBoost model. The variable importance is calculated based on the number of times the decision trees in the XGBoost model were split based on each specific variable. As expected, the number of plugs in a zone is the most influential variable in the model.

4.5 Range anxiety black-box model

Range anxiety, fear of running out of electricity before reaching another available charging station, as explained in Chapter 3.1 is measured with the optimal distance between two neigh-

Table 4.3: Comparison of error measures for the XGBoost algorithm and the baseline model

Measure	XGBoost	Baseline model
Mean absolute error	0.03184	0.04699
Root mean square error	0.05122	0.07057

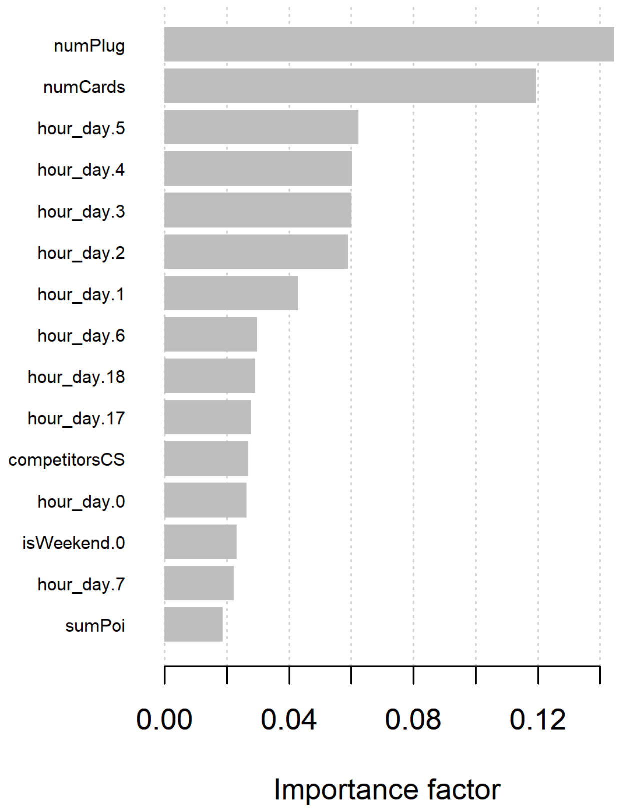


Figure 4.10: Variable importance for the built XGBoost algorithm.

bouring charging stations, perceived from both, the EV owners and potential EV owners. This distance is important parameter in the definition of charging zones, since it can potentially mitigate the range anxiety and motivate potential EV owners to purchase an EV.

One of the conclusions about the range anxiety is that, although it is 7 km on average, it significantly differs considering the settlement hierarchy the participant is from. Therefore, the framework, if the area is defined as one of the settlement hierarchy can cluster charging stations into charging zones based on the range anxiety manifested around that specific settlement hierarchy, e.g., 5 km for big cities or 10 km for villages.

The EVCI framework, as shown in Figure 4.11 takes as a parameter range anxiety measured as a preferred distance between two neighbouring charging stations, locations of charging stations, and the location settlement hierarchy. Based on those inputs, the distance for the definition of charging zones is defined as the input for the clustering component of the EVCI framework.

This is, same as the prediction of future EV numbers, optional parameter for the EVCI

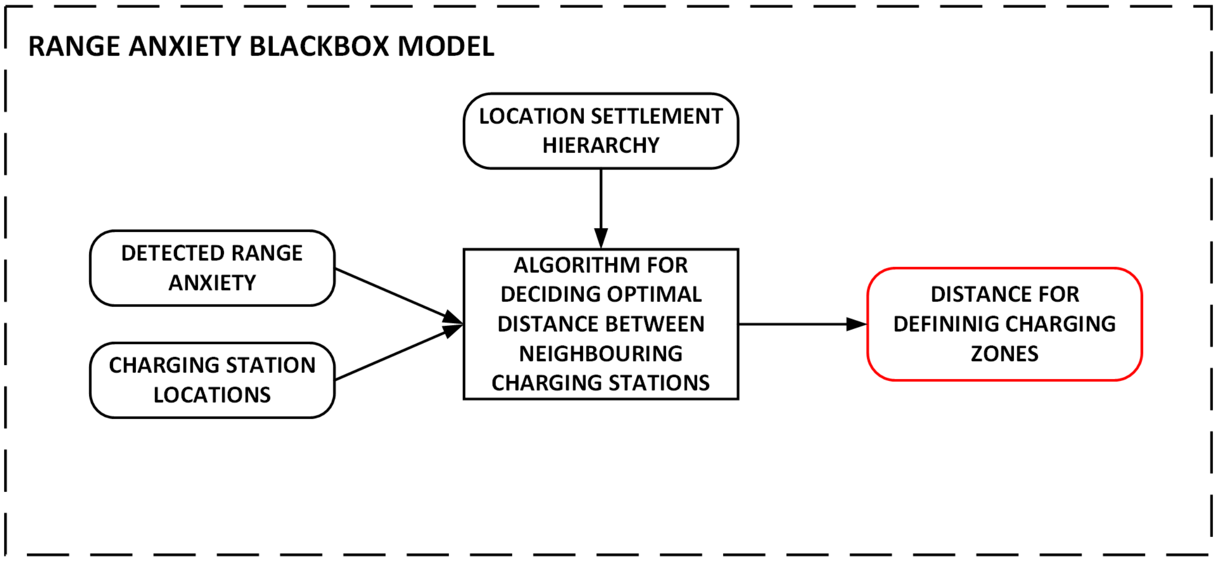


Figure 4.11: Range anxiety black-box component of the EVCI framework

framework, however, it is significant from the business decision perspective since it can significantly lower the cost of deploying new charging stations, e.g., longitudinal villages, typical for Croatia, do not demand the charging station being placed at every 7th km like it is the case with big cities. Scarce charging station infrastructure in those areas wont influence potential EV owners decision to purchase an EV.

4.6 Business analytics and reporting

Business analytics and reporting is one of the key components of the EVCI framework, even if it is not the key element for the charging station infrastructure extending functionality. Business analytics and reporting is implemented for both micro and macro development of the charging station infrastructure, as explained in the following Chapters, together with examples.

This component, as depicted in Figure 4.12 visualise the state of the charging station infrastructure as it is, and with all changes that could be implemented, i.e., it provides analysis of *what-if* scenarios.

4.6.1 Utilisation of charging stations

Utilisation of the charging station is the core information in the EVCI framework. It is important to provide sufficient analysis of the utilisation to better understand how the current charging station infrastructure is utilised. For the purpose of this analysis, the dataset is processed to show utilisation in different time intervals, i.e., day of the week, hour of the day of the week, hour of the day, and day of the year.

For each time interval, one can see how charging station from the dataset are utilised, how

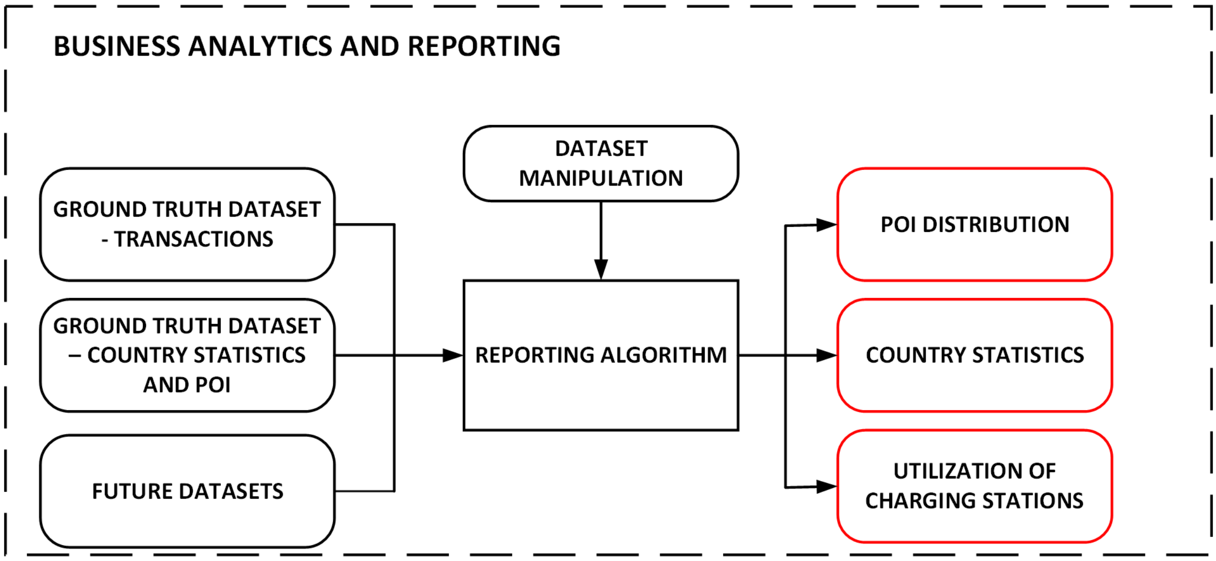


Figure 4.12: Business analytics and reporting module

the parking spaces associated with those charging stations are utilised, and the comparison between the aforementioned. The framework also enables analysis of specific charging stations from the dataset, ones that are utilised the most, as well as the utilisation per certain time interval, e.g., for the winter or summer time.

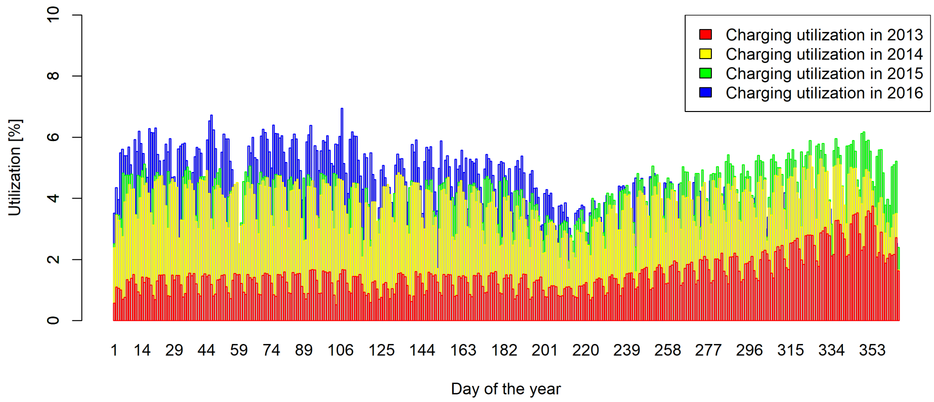
The EVCI framework, also enables the cumulative analysis, or the longitudinal analysis for each year in the dataset.

Descriptive statistic of the transactions EVCI dataset

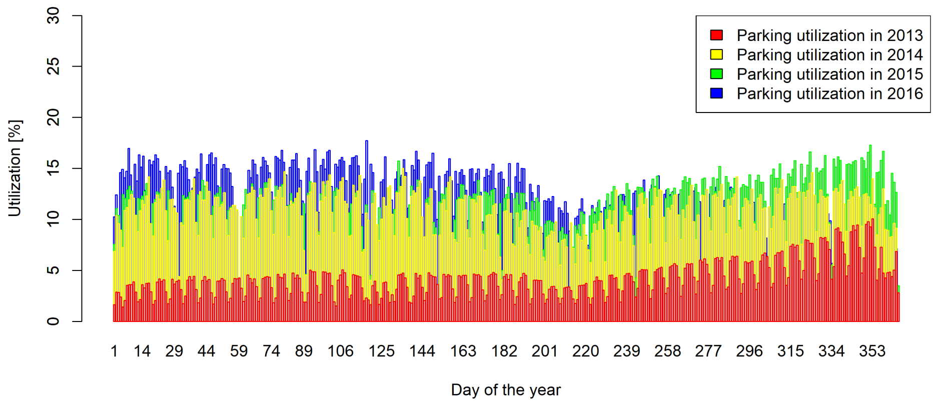
Understanding the dataset is an important step towards effectively using proper machine learning algorithms. For this reason, a descriptive statistical analysis of the dataset is performed, which led to interesting conclusions about the utilisation of charging stations and parking spaces.

The transaction based EVCI dataset consists of charging transaction data concerning four consecutive years (i.e., from 2013 to 2016). Figure 4.13 describes the yearly utilisation of charging stations and parking spaces. It can be observed that the utilisation of both charging stations and parking spaces increase over the years, which is expected as a result of technological advancements and increased consumer knowledge about and adoption of electric vehicles.

In Figure 4.13, a consistent drop in utilisation is noticeable around July and August. One can argue that such a drop in utilisation corresponds to the period of the year when individuals usually go on vacation. Also, Figure 4.13 shows that both utilisation are lower in the last quarter of the year 2016 than during the same time in 2015. This might be because of the expansion of the charging station infrastructure of the competitors of the charging station owner from the EVCI dataset. At the end of 2016, EVCI charging station owner had around 15% of the EV charging infrastructure in the Netherlands. This share is unknown for previous years.



(a)



(b)

Figure 4.13: Comparison of (a) charging and (b) parking average utilisation over the years 2013-2016.

Figure 4.14 illustrates the utilisation for both charging stations and parking spots for each hour of the day for the year of 2016. It can be observed that the charging utilisation has two peaks during a day, mainly around 8 AM and 5 PM. These correspond to times when drivers usually arrive at workplaces and at home coming from work. With this information, charging stations can be classified as charge-near-work and charge-near-home, depending on the time the charging station utilisation reaches its peak. For the sake of illustration, Figure 4.15 depicts the average utilisation of charging stations near home. Figure 4.14 also compares the utilisation of charging stations and parking spots. The utilisation of parking spots is approximately two times greater than the utilisation of charging stations. Also, the utilisation of parking spots has two noticeable drops right before peaks in charging utilisation. One can argue that this phenomenon corresponds to the time when drivers are driving to work from home and to home coming from work, thus leaving parking spaces unoccupied.

Another interesting fact is that hourly utilisation greatly differs between weekday and week-

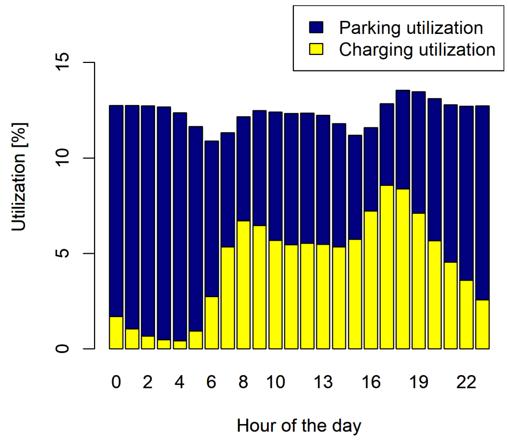


Figure 4.14: Average charging and parking utilisation per hour of the day for the year of 2016.

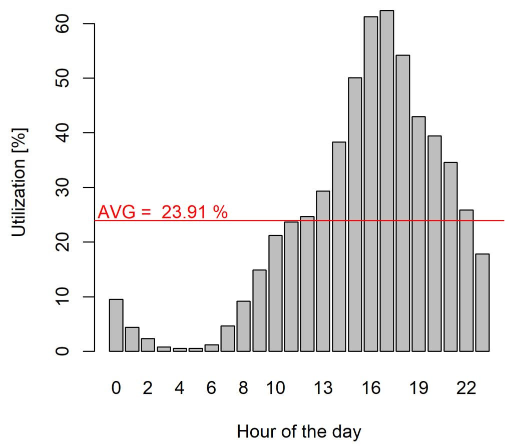


Figure 4.15: Average hourly charging utilisation of charging stations located near home for the year of 2016.

end, which can potentially be explained by the assumption that cars are used more often during working days, e.g., for the sake of commuting to work. Figure 4.16 depicts the utilisation of charging stations per hour of the day on weekends. It can be observed that there is only one peak in the utilisation around 3 PM. For the weekday utilisation, the pattern is the same as in Figure 4.14.

Yet another interesting observation about EV owners' charging behaviour can be observed in Figure 4.17, which shows that drivers are more likely to charge their EVs during weekdays than weekends. The utilisation reaches its peak around mid-week and then starts falling almost linearly.

Charging stations utilisation, as can be seen in Figure 4.13, varies considerably depending

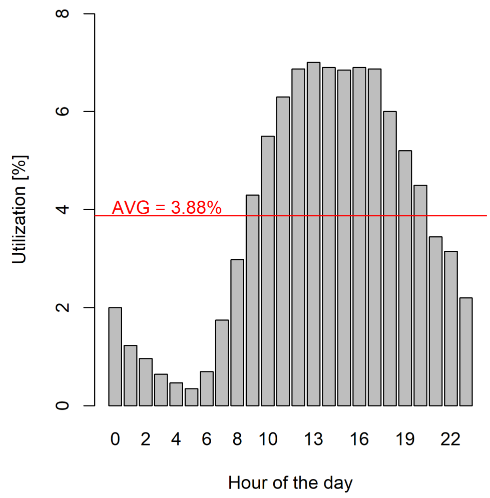


Figure 4.16: Average hourly charging utilisation on weekends for the year of 2016.

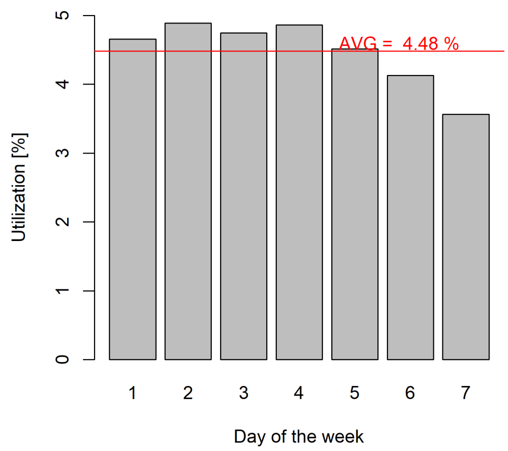
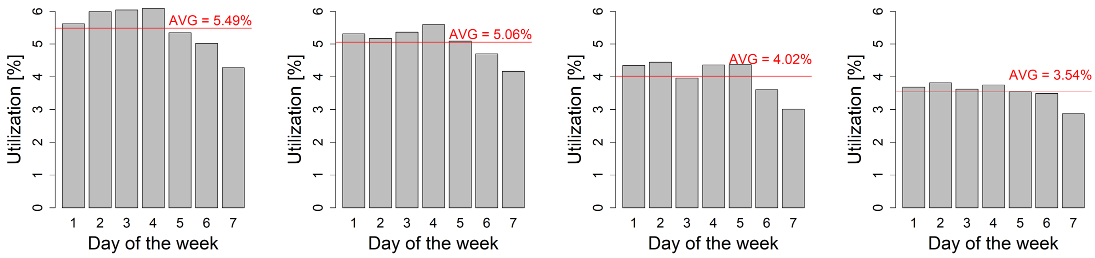


Figure 4.17: Average daily charging utilisation for the year of 2016.

on the weather season. Figure 4.18 depicts daily utilisation for each quarter of the year of 2016. The utilisation of charging stations is the highest in the first quarter (average of 5.49%), while the utilisation is the lowest in the last quarter of the year (3.54%).

The transaction based EVCI dataset for the year 2016 of includes 1,765 charging stations, some of them having more than one charging plug (CP). The total number of charging plugs in the dataset for the year of 2016 is 2,922. The top 500 CPs (which make around 17% of the dataset) are involved in 65% of all the charging transactions throughout the year. The rest of the CPs have a negative impact on the overall average utilisation of CPs in the Netherlands. That can be seen in the histogram in Figure 4.19.

Figure 4.20 compares the average utilisation of the top 10, 100, 200, 400, 500, 1,000, and all CPs. As the number of charging plugs increases, the charging utilisation becomes lower as



(a) Q1 (b) Q2 (c) Q3 (d) Q4

Figure 4.18: Comparison of average charging utilisation for each quarter of the year of 2016.

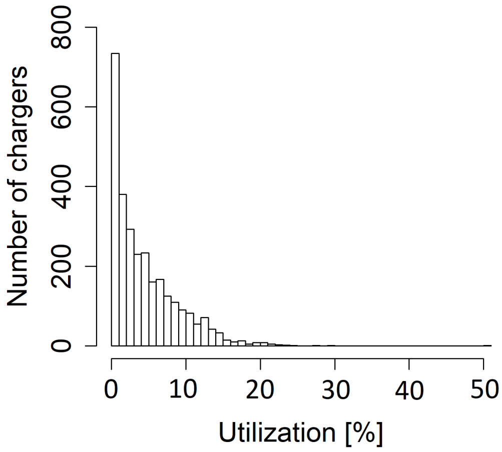


Figure 4.19: Distribution of chargers per utilisation level for the year of 2016.

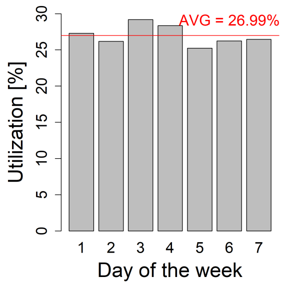
expected from the previously described fact about charging plugs. The top 10 charging plugs have an average utilisation around 27%, while the parking spots associated with them have parking utilisation over 50%. The most utilised chargers are located near big cities.

4.6.2 Geospatial business analytics and reporting

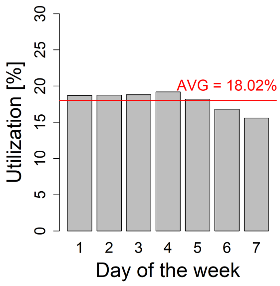
Geospatial reporting revolves around the *places of interest* their share for specific area and location regarding charging stations. To understand current situation with charging station infrastructure development, it is important to put the analysis of one specific area in context with others, as shown in the Appendices 7.1 Figure 7.6, 7.7, and 7.8.

Business analytics and reporting was performed for each country in Europe and consist of following reports:

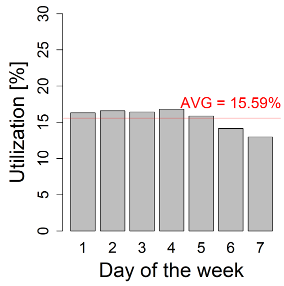
- Share of places of interest;
- How the proximity of specific PoI category influence the number of charging stations;
- Number and distribution of charging stations; and
- Number and distribution of charging zones.



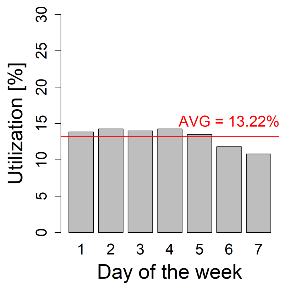
(a) Top 10



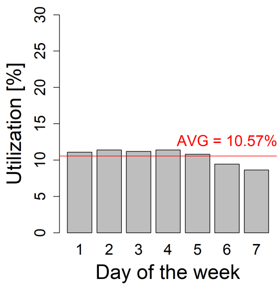
(b) Top 100



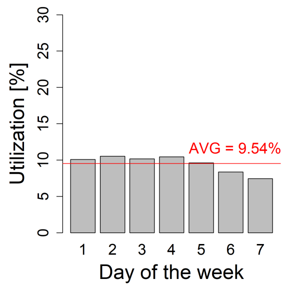
(c) Top 200



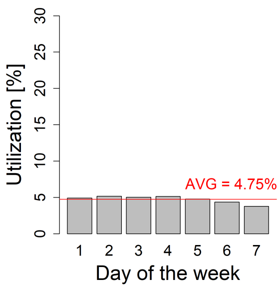
(d) Top 400



(e) Top 500



(f) Top 1,000



(g) All charging plugs

Figure 4.20: Comparison of average utilisation of top charging plugs for the year of 2016.

Following paragraphs provide examples and explanation for the analysis performed on the geospatial data in order to enable the macro development functionality of the EVCI framework.

Descriptive statistic of the geospatial based EVCI dataset

During the analysis of the descriptive statistic of the geospatial EVCI dataset, one of the major conclusions is that the charging station infrastructure is globally underdeveloped, as can be seen in the Figure 4.21, majority of European countries have less than 200 charging stations, with mean around the 1,190. The mean number of charging stations is heavily influenced by top three countries with more than 5,000 charging stations.

The aforementioned difference is best depicted in Figure 4.22 on the example of Romania and Netherlands. On this Figure it is clear how the commuting between the biggest cities in Romania is virtually impossible in Romania, i.e., due to underdeveloped charging station infrastructure, charging stations are too far apart for EV to cover the distance between them

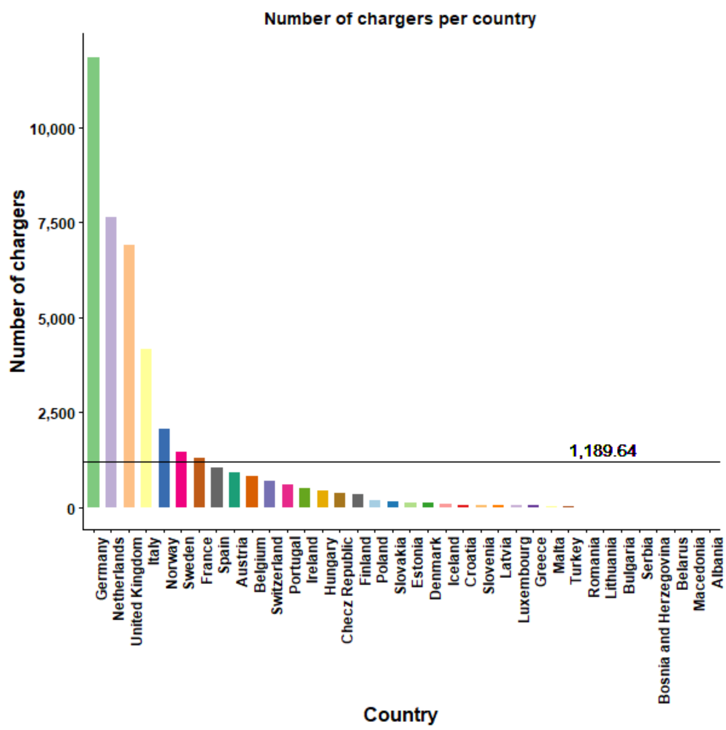


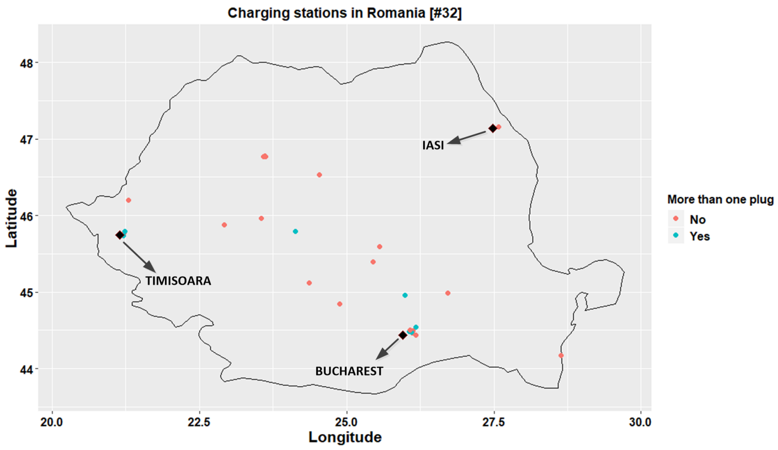
Figure 4.21: Number of chargers per each European country.

without loosing energy, while in the Netherlands, there is next to non range anxiety since it has developed charging infrastructure. One of the reasons behind this phenomenon lies in the fact that Netherlands has significantly larger number of early EV adopters, and higher life standards than Romania.

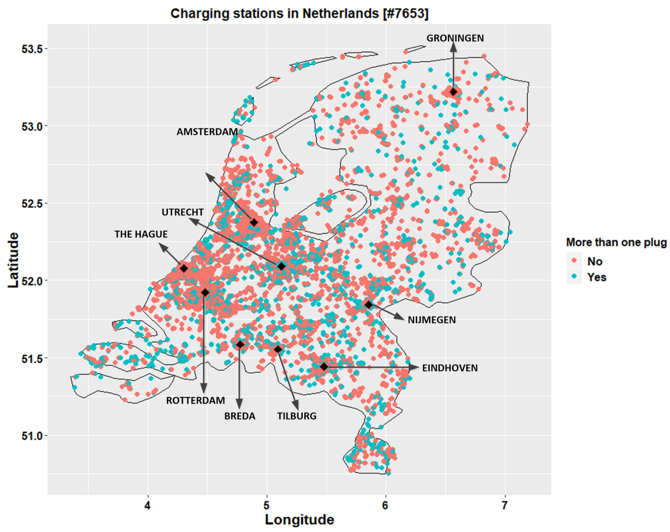
As defined in Chapter 3.2, number of clusters in contrast to the number of charging stations depicts the connection of the charging infrastructure regarding the *range anxiety*. If country is significantly populated with charging stations, while having small number of charging zones, the country is well connected and each charging zone is either very large, or has large number of charging stations. Example of well and poorly connected country is best depicted on a same case of Romania and Netherlands, as shown in Figure 4.23.

Another important segment of this analysis is the distribution of PoI categories for each country, firstly it was depicted using the standard pie chart. However, this was not an optimal method since when there are more categories, pie charts can be vast and hard to read. Therefore, the share of each PoI category is represented using treemaps. Comparison of pie chart and tree map for the PoI category share is depicted in Figure 4.24.

As can be seen in Figure 4.24b *transportation* category has the major share between PoIs, this is not only the case for the UK, this is the case for every analysed country. Reason behind this fact is that the *transportation* category includes all public commute stations, as well as garages, parking lots, fuel stations, and toll booths, since those are locations where EV owners may leave their EVs to charge.



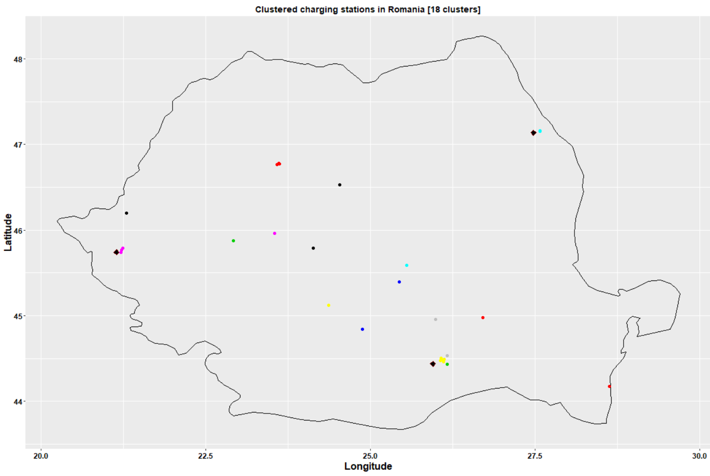
(a) Number of charging station in Romania



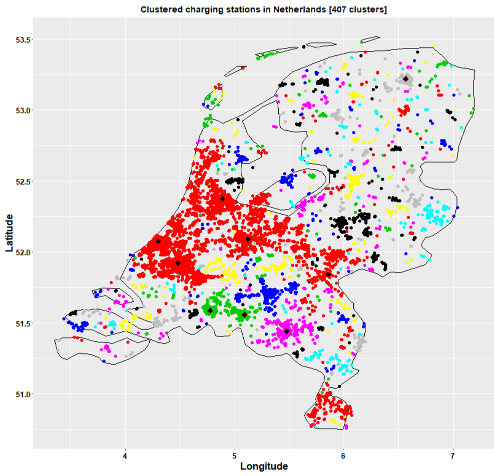
(b) Number of charging stations in Netherlands

Figure 4.22: Comparison of the number of charging station in charging station infrastructure developed country vs underdeveloped.

Finally, the analysis of influence of PoIs on the number of charging station in immediate proximity is performed, more specifically, how certain PoI category influence the number of charging stations in their proximity. As can be seen in Figure 4.25, top 3 most influential categories are transportation, shops, and places to eat with almost linear growth. Top three least influential categories are offices, religion buildings and tourism related buildings. This is common appearance for all countries with developed charging station infrastructure. For the countries with underdeveloped charging infrastructure, conclusion based on descriptive statistic can not be drown, since the charging station infrastructure is scarce and the number of PoIs around those chargers are not representative.



(a) Number of charging zones in Romania

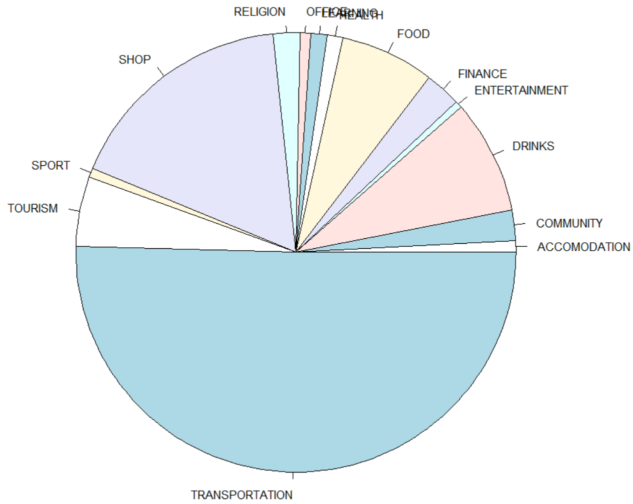


(b) Number of charging zones in Netherlands

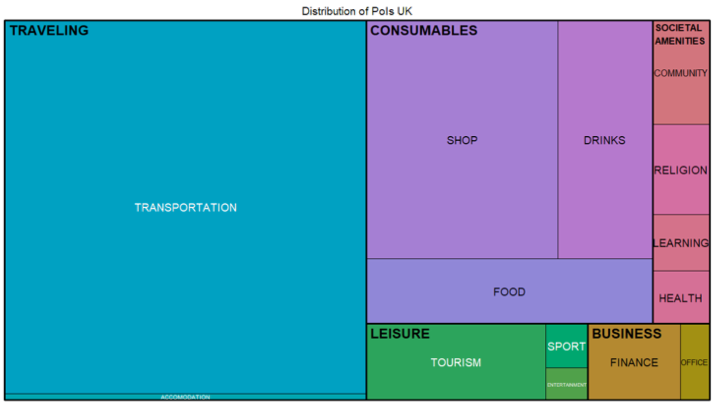
Figure 4.23: Comparison of the number of charging zones in developed country vs underdeveloped.

4.7 Decision support system for developing charging station infrastructure

EVCI framework, as explained before, serves as a macro and micro charging station infrastructure deployment decision support system. Since the EVCI framework has two decision making modes, the decision making process is in its nature dual: based on the charging transactions and based on the geographical locations. The micro development of the charging station infrastructure is dependant on the historical charging transactions in each defined charging zone, while the macro development is dependant on the geographical locations of charging stations and places of interest. Following two subsections will explain the decision making process in details.



(a) PoI share in UK as a pie chart



(b) PoI share in UK as a treemap

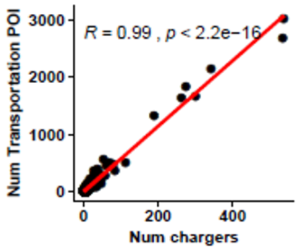
Figure 4.24: Comparison of PoI visualisation using pie chart and treemap

4.7.1 Historical transactions based decision

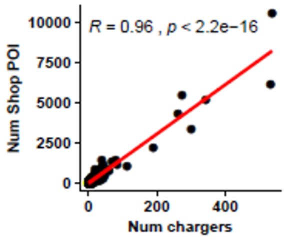
Part of the EVCI framework that takes into consideration historical transactions heavily relies on the machine learning algorithms for the utilisation of charging station prediction and on the mathematical model that defines how the utilisation is calculated. This Subsection formalise how charging zones are represented, how utilisation is calculated, and how the objective functions for charging station deployment are defined.

Let Z be the total number of zones. For any given zone z, for $z \in \{1,\ldots,Z\}$, N_z and N_{tot} denotes, respectively, the number of charging plugs in that charging zone and the total number of charging plugs.

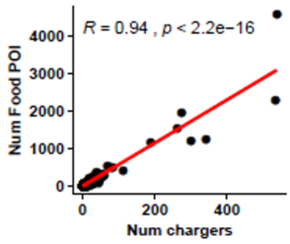
$$\sum_{z=1}^{Z} N_z = N_{tot} \tag{4.2}$$



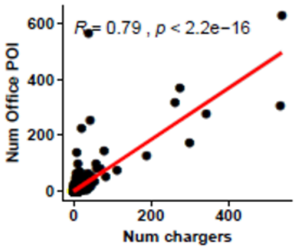
(a) Transportation PoI



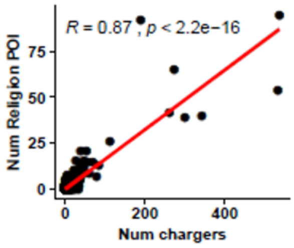
(b) Shop PoI



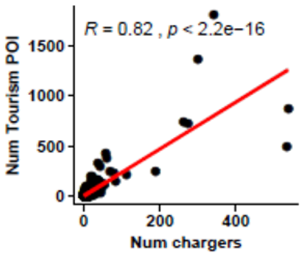
(c) Food PoI



(d) Office PoI



(e) Religion PoI



(f) Tourism PoI

Figure 4.25: Comparison of influence of PoIs on the number of charging stations in their proximity.

The '*charging utilisation*' at zone z with a total number of N_z charging plugs is defined as the likelihood that, at any time, a car is being charged by one of the charging plugs in that charging zone. Formally:

$$U_{ch}(z,N_z) = \frac{\sum_{n=1}^{N_z} \sum_{t=1}^{T} I_{ch}(n,z,t)}{N_z T} \tag{4.3}$$

where T is the length of the time horizon under study, and $I_{ch}(n,z,t)$ is the charging indicator function, which equals to 1 if an EV is charging at charging plug n, zone z, during time t, and 0 otherwise. In other words, $U_{ch}(z,N_z)$ is the likelihood that any charging plug is used in a certain zone over the entire time horizon (T).

After building a predictive model, one must next determine how such a model will be used to address the question of the optimal placement of new charging stations. This choice is captured via defining optimisation problems. Suppose that the original setting has N_{tot} charging plugs in total. A potential investment will increase the number of charging plugs to $N_{tot} + M_{tot}$. We can split the new M_{tot} chargers among different charging zones in many different ways or permutations. Let $M_z \geq 0$ be the number of new charging plugs in zone z. Then, any feasible vector of values $(M_1, M_2, \ldots, M_Z)$ must satisfy:

$$\sum_{z=1}^{Z} M_z = M_{tot} \tag{4.4}$$

Note that after the installation of new chargers, the total number of charging plugs in any zone z will be $N_z + M_z$. Define $\mathscr{M}$ to be the set of all feasible tuples $(M_1, M_2, \ldots, M_Z)$ of additional charging plugs in all zones, i.e.:

$$\mathscr{M} = \left\{ (M_1, M_2, \ldots, M_Z) \middle| \sum_{z=1}^{Z} M_z = M_{tot} \right\}. \tag{4.5}$$

In other words, $\mathscr{M}$ includes all possible ways the additional M_{tot} charging plugs can be split among all zones. This raises the question: what is the best permutation or tuple among all feasible permutations? or what is the optimal tuple among all feasible tuples in $\mathscr{M}$? Mathematically speaking, this is equivalent to finding an optimal tuple $(M_1, M_2, \ldots, M_Z) \in \mathscr{M}$, denoted by $\mathscr{M}^{opt}$. Clearly, this depends on the underlying optimisation problems. Here, three important optimisation problems are defined as follows:

P1: (Utilisation Maximisation): Find the optimal zones to place the new charging plugs so that the new setting has the maximum total utilisation. Mathematically:

$$\mathscr{M}^{opt} = \underset{(M_1, M_2, \ldots, M_Z) \in \mathscr{M}}{\operatorname{argmax}} \left(f_1(M_1, M_2, \ldots, M_Z) \right) \tag{4.6}$$

where

$$f_1(M_1, M_2, \ldots, M_Z) = \frac{\sum_{z=1}^{Z} U(z, N_z + M_z)}{\sum_{z=1}^{Z} U(z, N_z)}, \tag{4.7}$$

and U represents the charging utilisation U_{ch} defined in Equation (4.3). The numerator of f_1 is the total utilisation after adding the new charging stations to the system, and the denominator is the original utilisation before the upgrading. Clearly, $f_1 \leq 1$, because adding new charging stations decreases the utilisation of the charging stations in their vicinity and, hence, the overall utilisation of the fleet when its averaged out over all charging stations.

Adding charging stations in such a way is certainly desirable from a charging station owner's point of view since this leads to profit maximisation due to having charging stations in places where they will likely be mostly utilised.

P2: (Underpopulated Area First): Another way to formulate the optimisation problem is to consider the EV owners' and local governments' points of view. Their primary interest is in the number of available charging stations. One way to capture this view is by defining an optimisation problem that tries to increase the number of charging stations in unpopulated area. Formally:

$$\mathscr{M}^{opt} = \underset{(M_1, M_2, \ldots, M_Z) \in \mathscr{M}}{\operatorname{argmax}} \left(f_2(M_1, M_2, \ldots, M_Z) \right) \tag{4.8}$$

$$f_2(M_1, M_2, \ldots, M_Z) = \frac{\min_{z \in \{1, \ldots, Z\}} (N_z + M_z)}{\overline{N}} \tag{4.9}$$

where $\overline{N} = \frac{\sum_{z=1}^{Z}(N_z+M_z)}{Z}$ is the average number of charging stations in each cluster after adding the new installations. Clearly, $f_2 \leq 1$, because the minimum of a set is always less than or equal to its average. This objective function ensures that the new charging plugs are installed in areas with the least number of existing charging plugs, hence giving prioritising unpopulated areas.

P3: (Hybrid solution): Since the first optimisation problem generally favours charging station owners and the second optimisation problem favours EV owners and local governments, the third approach aims at combining those two potentially conflicting objectives, thus keeping a fair balance between the two stakeholders. Mathematically:

$$\mathscr{M}^{opt} = \underset{(M_1,M_2,\ldots,M_Z)\in\mathscr{M}}{\text{argmax}} \quad (\alpha f_1 + \beta f_2) \tag{4.10}$$

where α and β are weights that define the importance of the objective functions f_1 and f_2.

4.7.2 Places of interest based decision

After the analysis for specific area is conducted, as explained in Chapter 3.2, charging station within that area are clustered into charging zones based on the distance derived from the *range anxiety* model. When clusters are available, together with the location of big cities and PoIs within certain area, there are couple objective functions that this decision model takes into a consideration: *(i)* connect two largest clusters or cities and *(ii)* connect two closest clusters.

The main idea behind the first approach is to mitigate the range anxiety by connecting big cities or clusters and enabling inter-city commute. This would connect two existing clusters and potentially other smaller clusters on the way. The algorithm, firstly, finds two charging stations on the border of the two biggest charging zones that are closest to each other, next, using GraphHopper ** fastest route between those two charging stations is calculated and charging station deployed at each **X** km, where **X** is derived from the *range anxiety* research. This is the *simple* approach. Final step is to include PoIs into the calculation, more precise, PoIs that are close to the route calculated by the GraphHopper are added into the calculation. The reason behind this is the fact that there is no need for charging stations to be placed at every **X** km, it is rather good business decision how many charging stations along the calculated route should be grouped around certain PoI category, or around certain amount of nearby PoIs. This algorithm, without business decision implemented, assumes that the PoIs are evenly distributed along the calculated route when the charging stations are evenly distributed. Since that is not the case, charging stations are distributed along the route to match the distribution of PoIs.

The second approach is to connect two closest charging zones. The main idea behind this approach is to reduce the charging station density, as explained in Chapter 3.2, while deploying

** www.graphhopper.com/

the lowest amount of charging stations. It takes the less amount of charging stations to connect two charging zones that are closest, making them one charging zone. The following steps to decide on the optimal location for the new charging station are the same as in the first approach.

The flow diagram depicted in Figure 4.26 shows all steps necessary in order to make a decision on a charging station placement based on a geospatial analysis. As can be seen from the Figure 4.26, information about places of interest is used only if the decision branch is to *deploy charging stations with regards to PoIs*, which leads to a conclusion that PoI location is not necessary for this functionality of the EVCI framework, however, it adds the smart business component to the decision making process. It can be detected which PoI category is significant to the amount of time EV owners would spend charging, than the charging stations can be grouped around that PoI category, or charging stations can be evenly distributed around PoIs, rather than be deployed along the route.

After the functionality of the EVCI framework was introduced in this Chapter, together with detailed description of each major component of the framework, next chapter serves to demonstrate the functionality on a real world scenarios. More specifically, on a case of Netherlands, based on a real world charging transaction data and on the case of Croatia and Germany, based on a geospatial analysis.

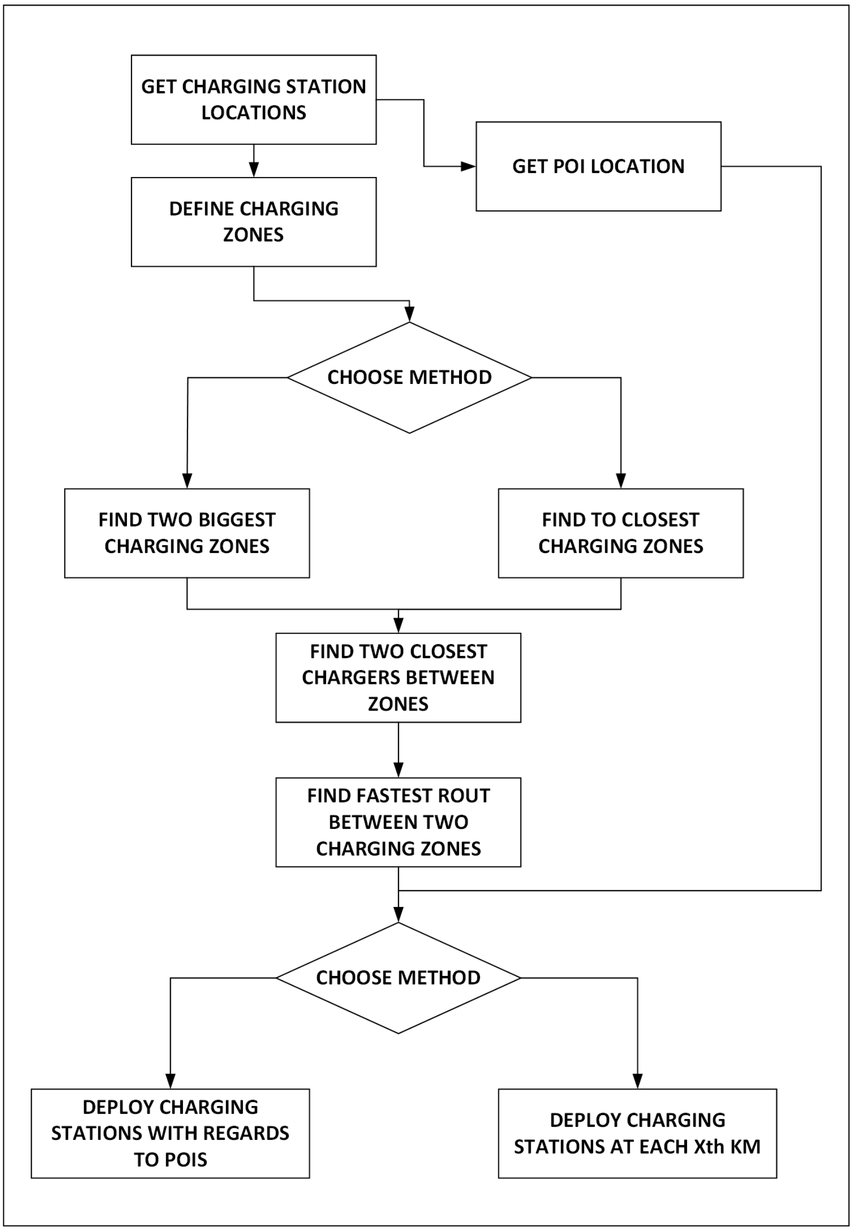


Figure 4.26: Geospatial analysis method of charging station deployment flow.

Chapter 5

Techno-economic analysis based on real world case studies

This Chapter will provide illustrative example of the EVCI framework functionality, as a decision support system, from the historical data and geospatial analysis point of view.

The first case study scenario will present the macro development of charging station infrastructure in Croatia and Germany, as a showcase of developed and underdeveloped charging infrastructure. The second case study is related to the charging station infrastructure in Netherlands, since that is the charging station operator presented in the EVCI dataset.

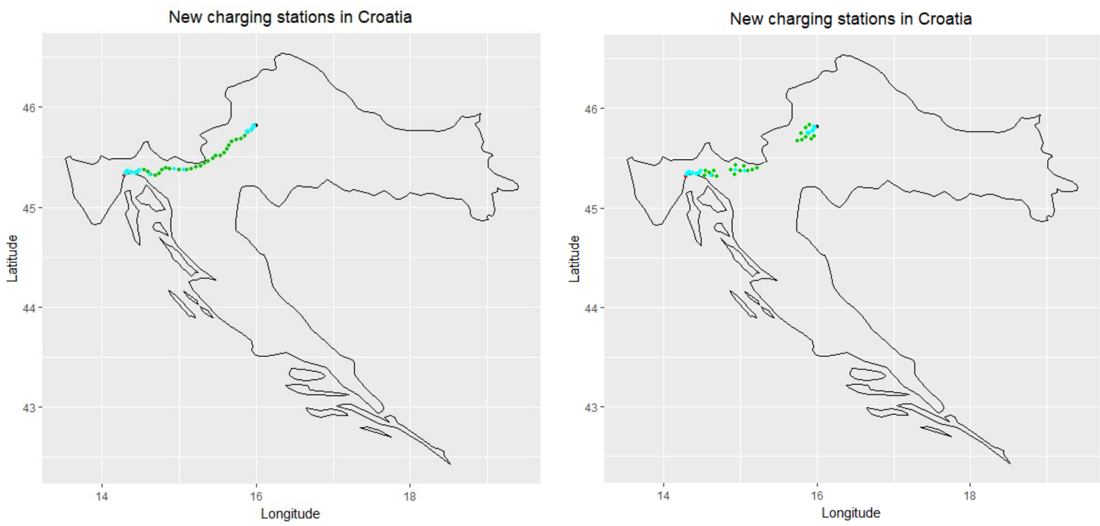
5.1 Decision based on geospatial analysis and current charging station development: Case studies of Croatia and Germany

When the data about the charging transactions is not present in the dataset, or when the decision on a deployment of new charging stations needs to be made on a macro level, as explained in Chapter 4, this part of the EVCI framework is able to provide a decision support.

This case study is oriented towards two European countries, Croatia and Germany, since they depict the differences in developed and underdeveloped countries regarding the charging station infrastructure.

From the perspective of the first objective function, defined in Chapter 4.7.2, to connect two biggest charging zones, results are as follows. In Croatia, it is not unusual that the two biggest charging zones are located in two of the biggest cities in Croatia, Zagreb and Rijeka. With those two connected with charging stations, commute between them would be without the emphasised range anxiety. The EVCI framework is depicted in Figure 5.1.

As can be seen in Figure 5.1a, charging stations are deployed at each 7th km disregarding

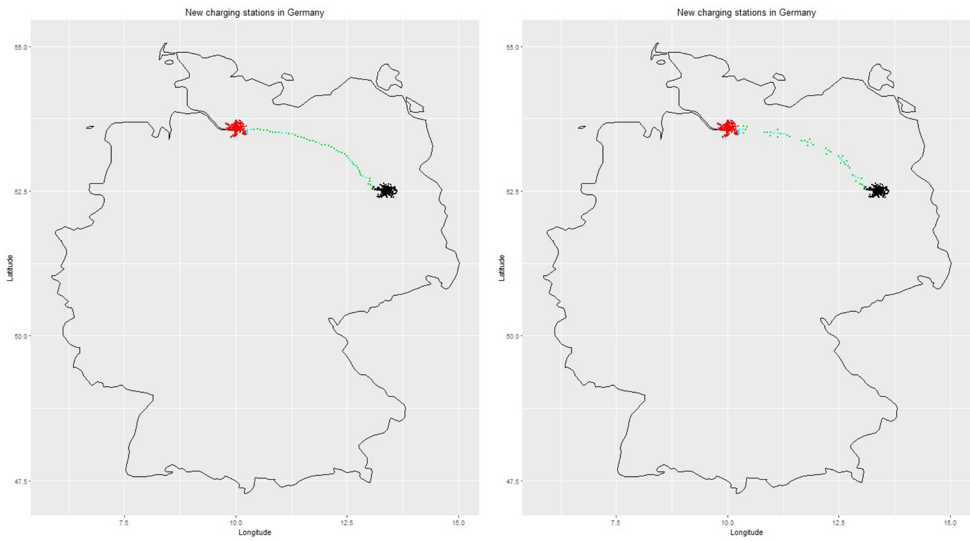


(a) Charging station deployment, basic (b) Charging station deployment, PoI

Figure 5.1: Charging station deployment with and without PoI information

the PoI information. In the Figure 5.1b charging stations are grouped around the PoIs, assuming all PoI categories have the same importance.

For the case of the Germany, situation is depicted in Figure 5.2. However, this is unnecessary, since Germany has developed charging station infrastructure and this area is most likely covered with charging stations, as can be seen in Chapter 3.2, Figure 3.13.

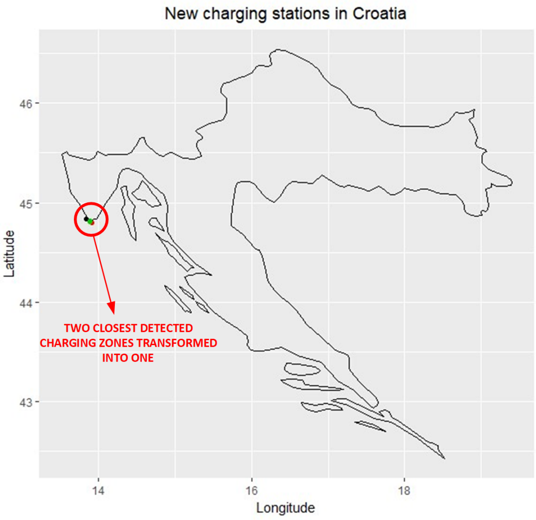


(a) Charging station deployment, basic (b) Charging station deployment, PoI

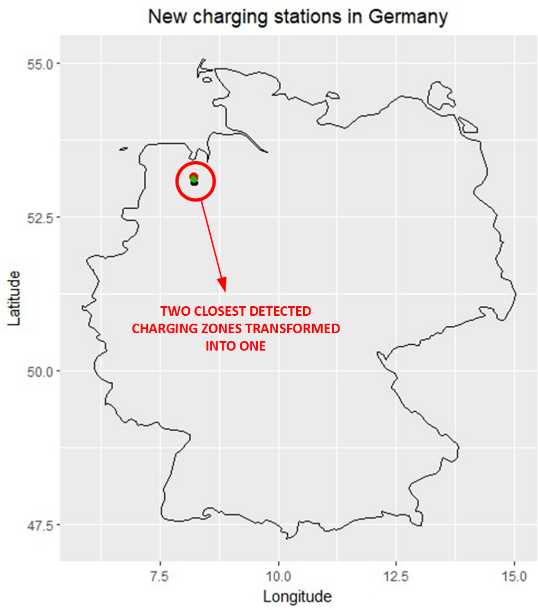
Figure 5.2: Charging station deployment with and without PoI information

Two biggest charging zones in Germany, naturally, are in cities of Hamburg and Berlin. Algorithm, as explained in Chapter 4 takes into a consideration shortest and fastest path between those two charging zones, and in this case it is a highway. In comparison with the Croatia case study, Germany has more PoIs along the way, thus creating more smaller clusters if the approach depicted in Figure 5.2b is taken.

Second objective function of this algorithm takes two closest charging zones and deploys smallest possible number of charging stations between them in order to make a connection and transform them into a single charging zone. This approach often does not need to take into a consideration PoIs since as depicted in Figure 5.3, two closest clusters are generally very close to each other and in the same city.



(a) Charging station deployment, case Croatia



(b) Charging station deployment, case Germany

Figure 5.3: Charging station deployment based on connecting closest clusters

For the case of Croatia, depicted in Figure 5.3a, only one charging station is needed to connect two charging zones located at the town Pula. For the case of Germany (Figure 5.3b), also only one charging station is needed located around the Oldenburg. In both cases, only one charging station is needed to lower the charging station infrastructure scarcity, as defined in Chapter 3.2.

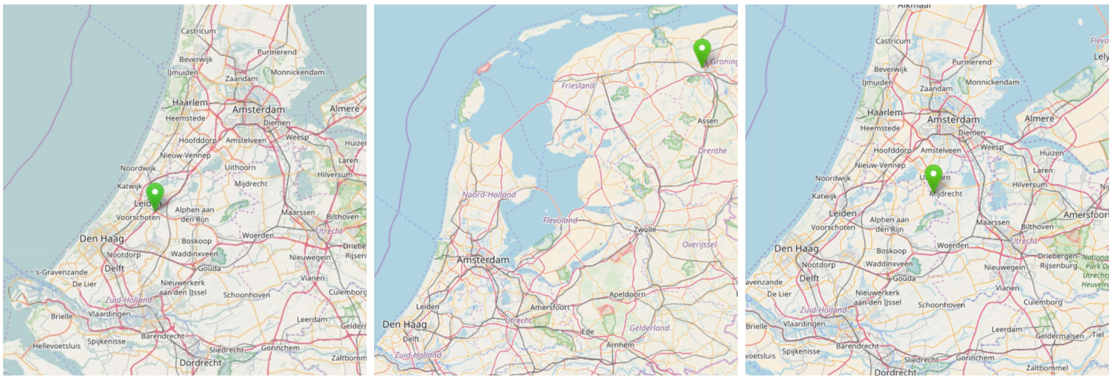
As can be seen from the example of Germany (if compared to the Chapter 3.2), the first objective function of this methodology is not the best option for countries with significantly developed charging station infrastructure. However, the second objective function can always be used successfully to lower the charging station scarcity.

5.2 Decision making based on historical transactions for developing charging infrastructure: Case study of Netherlands

Since the core dataset (business data) in our case study was provided by one of the leading charging infrastructure owner in Netherlands, this case study provides illustrative usage of the EVCI framework to prescribe a zone to add a new charger in Netherlands, i.e., where to deploy a new charging station with one charging plug in the infrastructure from the EVCI dataset. This Chapter will showcase the approach with three different scenarios: prescribing the optimal location based on the *(i)* maximisation of utilisation; *(ii)* increase of charging stations in unpopulated areas; and *(iii)* a hybrid approach between the first two approaches. These are the optimisation problems defined in Chapter 4.7.1.

The first scenario is based on the optimisation problem in Equation (4.6) and the goal of maximising the total utilisation of the EV charging infrastructure operated by one of the leading charging station owners in Netherlands. Specifically, for each zone in the dataset, we run our predictive model to estimate charging utilisation after adding one more charger to that zone. Figure 5.4a reveals that, for this scenario, a new charger should be deployed to the *"Zone 525"*, i.e., in a 7 km radius from the place marked on the map. This is located in a fairly populated part of the Netherlands, being close to three big cities: Rotterdam, The Hague, and Amsterdam. This region currently has only four charging plugs operated by the owner from the EVCI dataset, thus having a great potential for the addition of new chargers. Besides charging station owned from the operator in the EVCI dataset, there are also 9 charging stations from other EV charging station infrastructure providers in the *"Zone 525"*. If another charging station is deployed as a part of the infrastructure owned by the EVCI dataset infrastructure owner, the average utilisation of charging infrastructure in the *"Zone 525"* will have a decrease of only 0.000125%, which is not an unusual result since, under the reasonable assumption that the number of charging cards correspond to the number of EVs, that charging zone has around 90 EVs. This relatively high number of EVs, together with a small number of chargers, results in high charging demand, which means that adding another charger will have a low negative impact on the average utilisation per charger in the same zone, while having a positive impact on the aggregate utilisation for all chargers in the same zone.

After illustrating how a charging infrastructure provider can be informed on where to place a charging station so as to maximise the total charging utilisation, second objective function investigate a different point of view where one wants to place a new charging station in an area that has few stations. In this second scenario, which is defined by Equation (4.8), the utilisation of charging stations in a zone is completely ignored. This scenario can also be presented via



(a) (b) (c)

Figure 5.4: Recommended location for the new charging station based on a) maximising the overall utilisation, b) populating charger unpopulated areas, and c) hybrid approach between first two approaches

the hybrid function defined in Equation (4.10) by using the values $\alpha = 0$ and $\beta = 1$. The optimal solution in this scenario is to place the charger in a location in the northern part of the Netherlands (*"Zone 633"*), in a 7 km radius from the location marked on the map depicted in Figure 5.4b. That area, close to Groningen, will have a decrease of 4% in the average utilisation after the deployment of a new charging station, which is a significant decrease in comparison to the first scenario. This result, however, is not surprising since there are only 5 different EV owners' cards in that area, which we assume to be the number of EVs. Currently, this location has only one charging station owned by the EVCI dataset owner, as one competing charging station.

The first two scenarios have potentially conflicting objectives. One way to address this problem is to use the hybrid objective function, defined in Equation (4.10), which assigns certain weights to each of the two previously mentioned objectives (i.e., utilisation maximisation and finding the zone with the lowest number of charging stations). Determining the exact values for the parameters α and β is a complex challenge that must involve multiple stakeholders, e.g., charging infrastructure providers, EV owners, and local governments. For example, a decision maker who is more interested in making the charging infrastructure more utilised will define the value of α grater than β, whereas a decision maker who wants to promote EVs by adding chargers in areas with low number of charging stations will do the opposite. The precise estimation of the values of α and β is beyond the scope of this thesis. Instead, the third scenario is presented where the first and the second objective functions are equally important, i.e., $\alpha = 0.5$ and $\beta = 0.5$. In practice, this may represent a case where there is a fair trade-off between having a well-utilised charging system and deploying charging stations in areas that have the lowest number of charging stations. Based on predictions from our predictive model, the prescribed location for a new charging station is village De Hoef (*"Zone 391"*),i.e., 7 km radius from the place marked on the map depicted in Figure 5.4c. This area has two charging plugs maintained by the owner from the EVCI dataset and a drop in average utilisation of

0.002% when a new charger is added. Besides the EVCI dataset charging infrastructure owner charging stations, there is only one competing station. This can be explained by the fact that this village has only 8 different charging cards. Moreover, the same is not positioned around a major highway, which results in a lack of investments in charging stations in that location. Based on the conducted research regarding the charging station deployment, when the EVCI user is CPO, the α should be emphasised more than the β weight, e.g., $\alpha = 0.8, \beta = 0.2$ while when the user is government it should be the other way around.

Chapter 6

Conclusions and future work

Due to the recent environmental concerns, from the climate changes due to the air pollution to the climate-related illnesses, the electrification of the private transportation has begun. More and more people are deciding to purchase an electric vehicle as their personal car for one of the following reasons: environmental concerns, lower cost of recharging, i.e., alternative to the refuelling of traditional ICE vehicles, and increased comfort due to the common implementation of new technologies inside the EVs. That being said, there are still numerous obstacles for wide usage of EVs, especially in countries without the significant number of early EV adopters.

One of the major obstacles for EVs to reach their full market potential is underdeveloped charging station infrastructure in countries that are generally underdeveloped, or without the significant number of early adopters, i.e., many early adopters influenced the development of the charging infrastructure. Underdeveloped charging infrastructure is a negative influence within the potential EV owners in their decision to purchase an EV due to the phenomenon known as *range anxiety*. One of the possible solutions to this challenge is a smart development, i.e., deploying, reallocating, and removing, of charging stations within the infrastructure. In the scope of this thesis, model for the smart development of the charging station infrastructure, as well as the framework (EVCI framework) implementing this model is developed with the goal to partially mitigate the aforementioned range anxiety.

The EVCI framework is aimed towards three stakeholders: *(i)* EV owners, as well as potential EV owners, *(ii)* governments, and *(iii)* charging point operators (CPOs). In order to mitigate the *range anxiety*, firstly, it has to be defined. This thesis defines the range anxiety as a maximal acceptable distance between two neighbouring charging stations, and as explained in Chapter 4 this measurement is further used for managing the charging station infrastructure within the EVCI framework. With the objective to mitigate the range anxiety, EV owners and potential EV owners benefit with the increased insurance that their EV will not run out of electricity before reaching another available charging station. As for the governments, the EVCI framework can be used as a tool for global charging station deployment, based only on contextual information from the real world the plan for charging station deployment can be developed, even in countries without charging infrastructure. Finally, the CPOs benefit from the developed model with the increased profit, provided that the charging stations are deployed with the objective function to maximise the overall utilisation in the CPOs infrastructure.

Using real-world data, the developed methodology is able to recommend the optimal location for a new charging station with respect to, for example, the minimal average charging utilisation drop in a charging zone, which is the same as to say that it maximises the overall aggregate utilisation in a charging zone once the new charger is deployed. Besides proposing the location for a new charging station, this methodology also sheds light on the utilisation patterns of charging stations as well as EV owners' charging behaviour. Hence, the proposed methodology for extending the EV charging infrastructure can be used by EV charging infrastructure providers as a decision support tool that prescribes the optimal area to place a new charging station. As a definition of a charging zone, the proposed model employs the grouping of the charging stations based on the *range anxiety*, and therefore takes into a consideration EV owners' preferences and requirements.

The EVCI framework also serves as a versatile decision support system with a method for EV charging infrastructure development that is based on a real-world contextual information collected from the heterogeneous sources. Since the sources are heterogeneous, the framework has multiple modes with developed models for scenarios with or without certain type of data. If the data from the CPO, i.e., data about the charging transactions, is available EVCI framework can work in micro development mode. Micro development mode has specifically developed model that takes as an input charging transactions and based on the utilisation prediction decides on the placement of a new charging station with the charging zone as a resolution. This is very flexible model since as an input for the prediction it can take variable number of parameters, depending on he available data. On the other hand, if the data from the CPO is not available, or does not provide sufficient information, i.e., that is the case in countries with underdeveloped charging infrastructure, the EVCI framework is intended to be used in the macro development mode. In the macro development mode only publicly available data is needed, i.e., public charging station locations, PoI locations, and significant cities locations. Based on the provided data, and optionally business decision input, EVCI framework can provide a decision support regarding the location for a new charging station.

Finally, EVCI framework is a techno-economic framework that enables technology road mapping and scenario analysis for EV charging infrastructure development. Analysis of what-if scenarios was performed on multiple real-world scenarios. The micro development model implemented in the EVCI framework is showcased on he case of Netherlands, due to available transaction data. Since micro development provides decision support based on one out of three objective functions, these are the results: for the objective function to maximise overall utilisation, new charging station should be placed between three big cities in Netherlands, Rotterdam, The Hague, and Amsterdam, thus in Netherlands, the utilisation will decrease by only 0.000125%. Based on the second objective function, to populate charging station unpopulated area, new charging station should be placed close to Groningen. This will increase the number of charging stations in that specific zone, while in turn lower the utilisation by 4%. The macro development model is showcased on the example of the Croatia and Germany, thus representing the functionality on two countries with opposite state of the charging station infrastructure development. The macro development model of the framework connects two closest or two biggest charging zones. For the case of Croatia, two biggest charging zones are located in Zagreb and Rijeka. To connect those charging zones, 24 charging stations is needed and they can be grouped around 4 clusters of PoIs. For the case of Germany, two biggest charging zones are located near Berlin and Hamburg. To connect those two charging zones, 42 charging stations are needed and can be grouped around 7 PoI clusters. The second mode takes into a consideration two closest charging zones. For both cases, Croatia and Germany, only 1 charging station is needed to connect the closest charging zones.

Ultimately, the information provided by the proposed framework would be of great value when it comes to the three pillars of sustainability: (i) *people* will have lower range anxiety because the EV charging station infrastructure is optimally deployed; (ii) *profit* can be achieved by EV charging infrastructure providers by optimising their investment strategies; and (iii) *planet* would implicitly benefit as well through an increase of EV sales due to the likely reduction in CO_2 emissions.

The future work of this thesis can be inferred through the observed limitations. One of the major limitations of this research is the methodology for calculating the range anxiety. Therefore, plan is to customise the survey based on the feedback that was received from the EV owners, e.g., it is important to know whether someone owns a private charger since then there is no need for the access to the public charging infrastructure. This piece of information can greatly influence their responses considering the preferred distances, as well as their perception of the key EV parameters. Another interesting aspect for understanding the range anxiety phenomenon that was identified in this research is the influence of settlement type a (potential) EV owner is living in. In the future, plan is to focus on this aspect of the research by targeting a sufficient number of respondents in each of the settlement hierarchy type. Finally, plan for the future research is to mitigate some of the identified limitations regarding the distribution of the extended survey among respondents form a more geographically balanced base, i.e., have a more even distribution of participants from more countries, instead of primarily from Croatia, the United Kingdom, and the United States, as well as use more complex statistical approaches for interpreting the collected data in order to achieve more statistically significant results.

Besides the range anxiety, the EVCI framework has another major limitations regarding the charging stations specifications, more specifically, for the EVCI framework all charging stations are the same, which is not the case in the real-world. Charging stations can be divided into categories based on the charging speed: rapid, standard, and slow. This is feature is currently non existent in the EVCI framework due to the focus on real-world data. The information about the charger type was not presented in the CPO data, while from the open data it can not be deducted due to the inconsistency. The plan for the future research is to either obtain the data regarding the charger type or to simulate different charging types in order to include the information about the charging speed into the decision for a charging station placement, i.e., it makes more sense to place fast charger along a highway than a standard one. Another interesting aspect of deploying charging stations that is not implemented in the scope of this thesis is energy grid. Charging stations can not be deployed anywhere, only where the infrastructure can support the demand. Currently EVCI framework tackles this challenge by providing an area, rather than a specific point for a charging station placement. In the next iterations of this research, plan is to include the data about the energy grid on the observed area, as well as making it one of the key parameters in the decision making process. Aforementioned process would enable the EVCI framework to propose more specific location for a new charging station.

Lastly, the macro development mode of the EVCI framework is intended to make a decision about the charging station placement based on the two objective functions, connect two closest charging zones, and connect two biggest charging zones. Plan is to implement the third approach using heuristic methods. This approach would focus on lowering the scarcity of charging infrastructure, i.e., lowering the amount of smaller clusters, using the available number of charging stations.

Appendices

7.1 Appendix 1: EVCI framework showcase

A working example of micro development component of the EVCI framework. Functionality of specific elements is described in the Chapter 4.

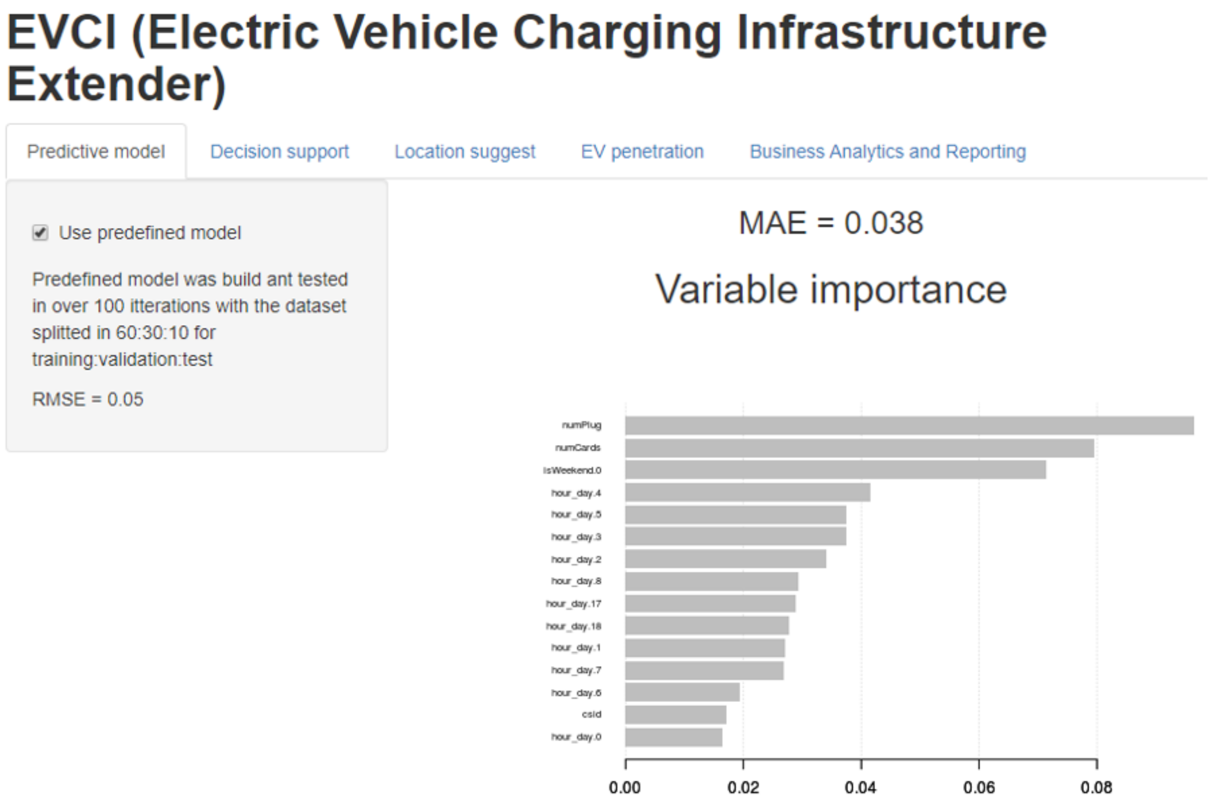


Figure 7.1: User of the EVCI framework can use the predefined model, providing that all the data, mandatory and optional, is available for further analysis. Predefined model is built into the EVCI framework in order to showcase basic functionalities without the need for custom model creation.

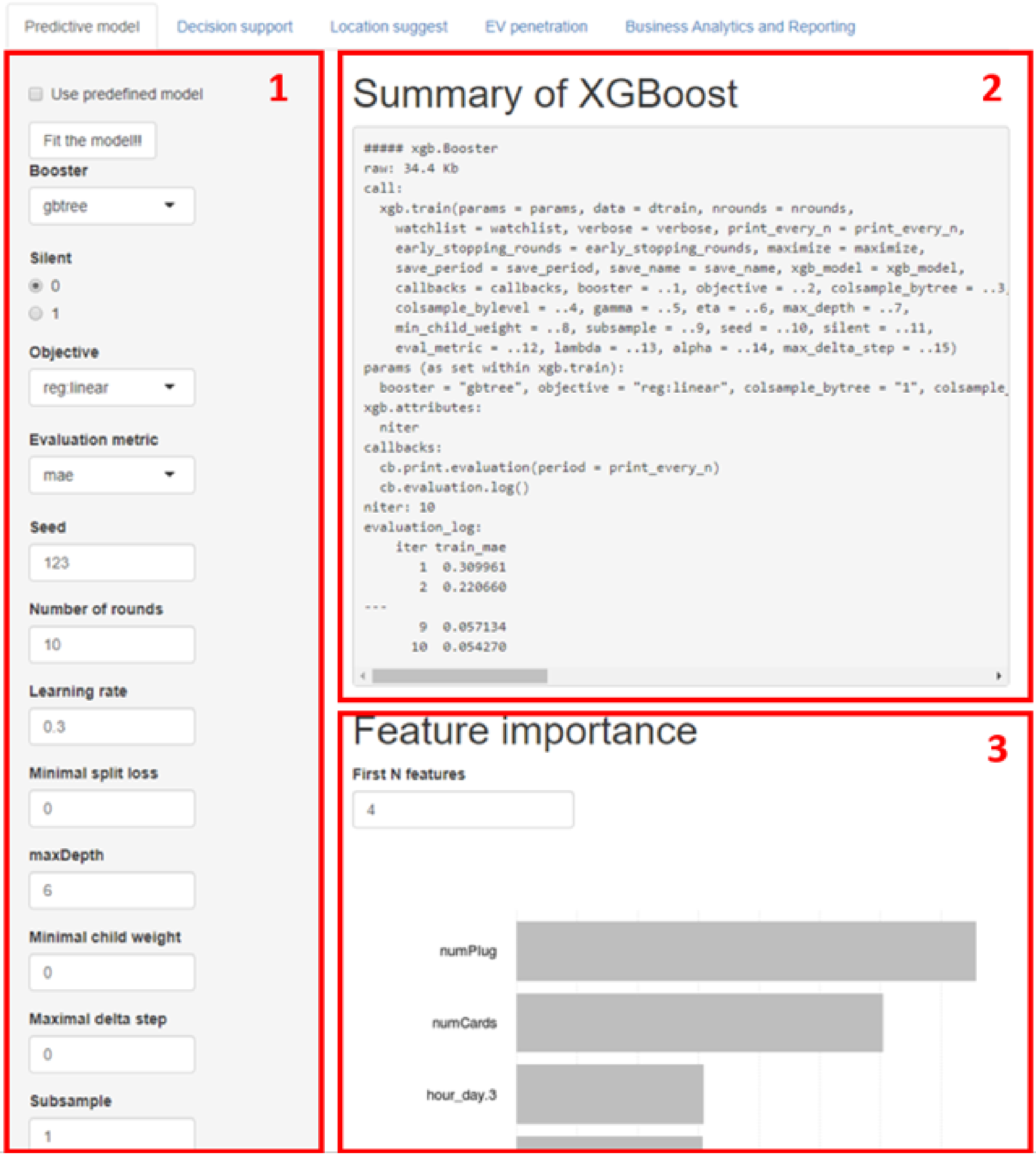


Figure 7.2: In case that user wants to customise the model, weather due to the insufficient data or due to unsatisfactory error measure. In the part of the application marked with "1" user can fine tune the model, all model parameters have descriptions that are triggered with mouse hoover. Part of the application marked with "2" is used to monitor the output of the model, from parameters to error measurement. Finally, part of the application marked as "3" is used to detect N most important model features, i.e., variables.

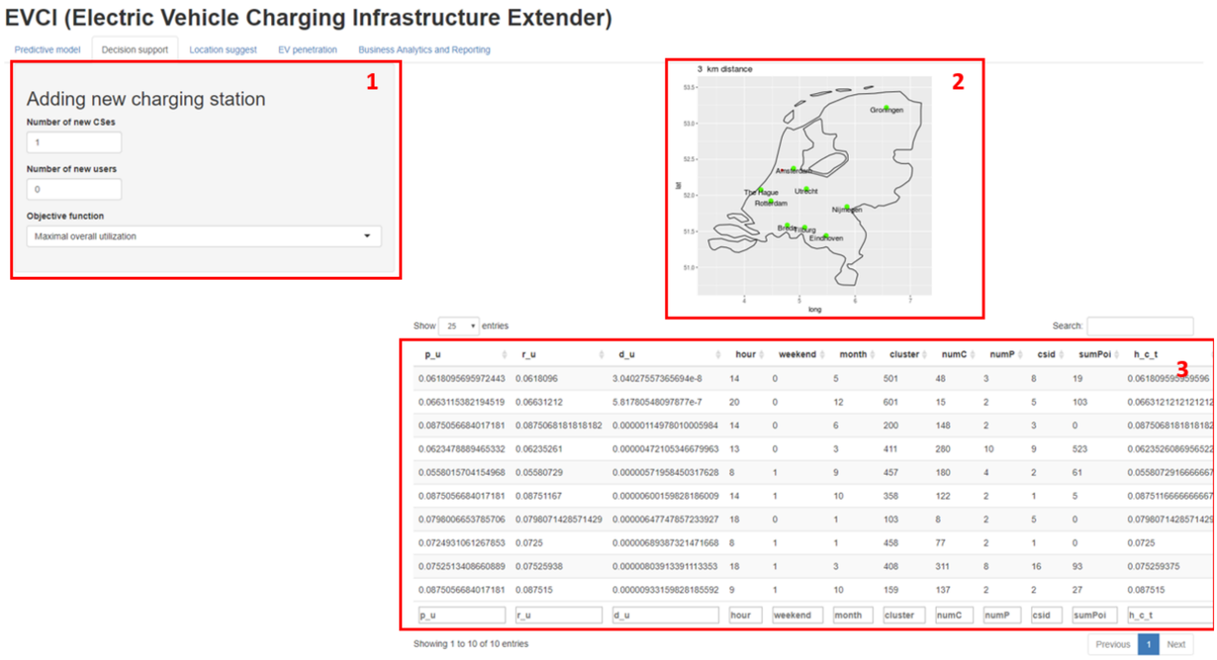


Figure 7.3: This part of the EVCI framework is for the support in the decision about the placement of a new charging stations. The part marked with "1" is used to input the number of newly available charging stations, number of new EVs (optional), as well as one of the objective functions described in 4. Part of the application marked with number "2" is used for the visualisation of the proposed location, while the table marked with "3" is detailed comparison of charging station utilisation per charging zone after new chargers are added to the infrastructure.

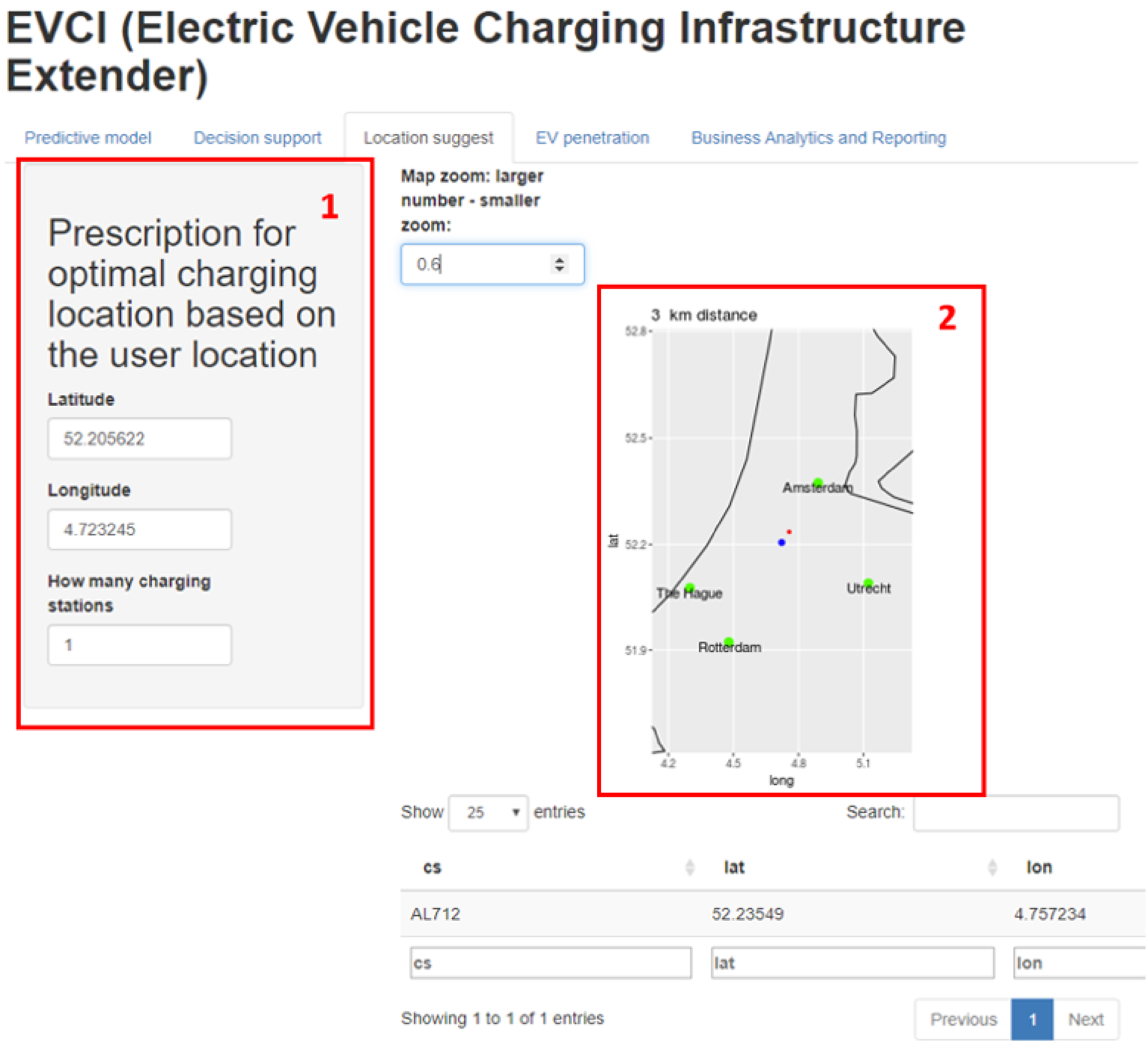


Figure 7.4: Location suggest module based on the location of the user (marked with "1") suggest closest charging station that is based on the historical data most likely unoccupied. The result is presented on the map around the location of the user (marked with "2").

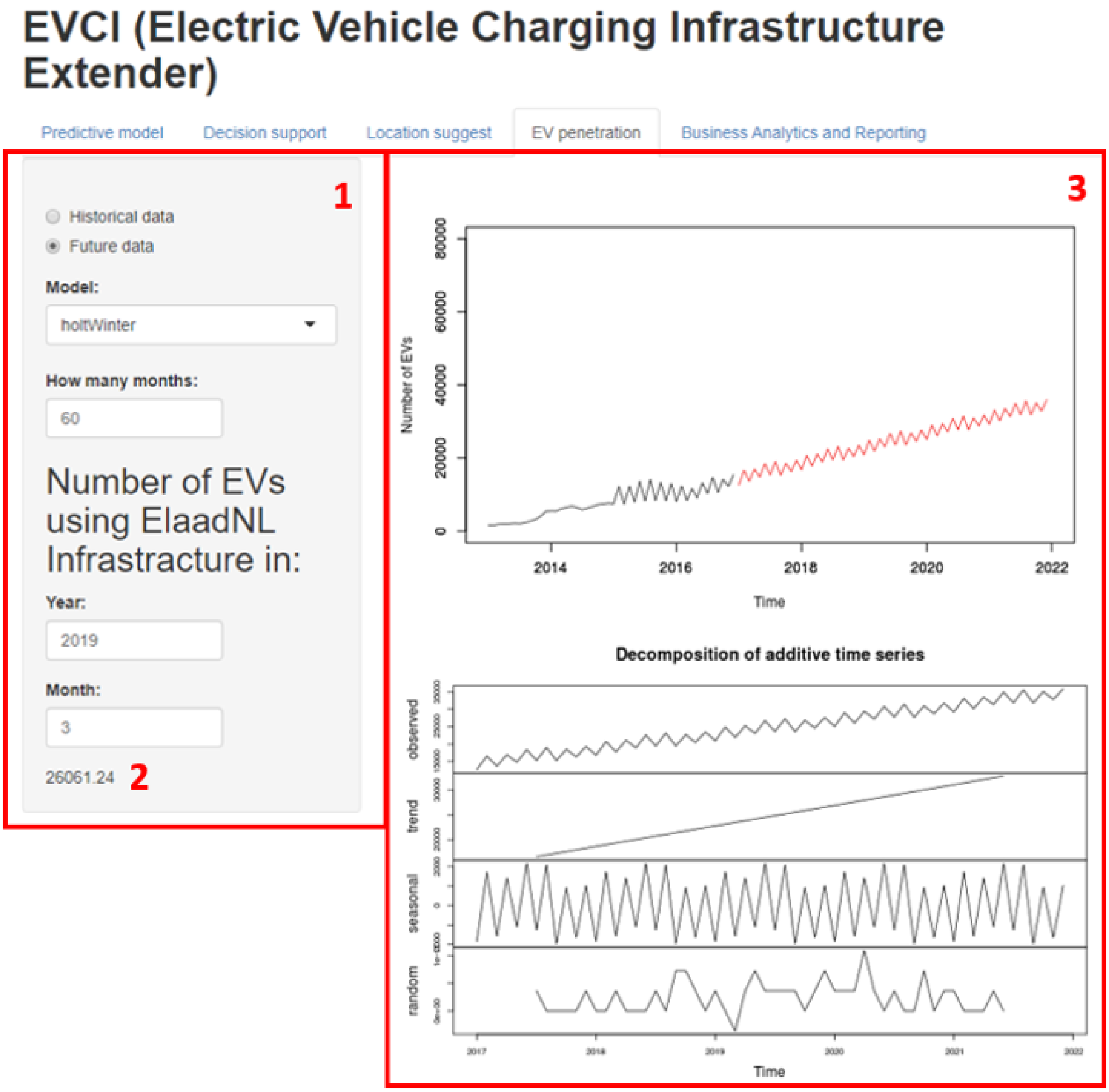


Figure 7.5: EV penetration module is used to calculate the number of EVs in the future based on the historical time series data, i.e., number of EVs. The left panel ("1") enables the user to select the method for prediction, as well as the date. Result is shown on the bottom of the panel, and can be used in the context of Figure 7.3. On the right ("2") is depicted predicted growth of EVs through the time.

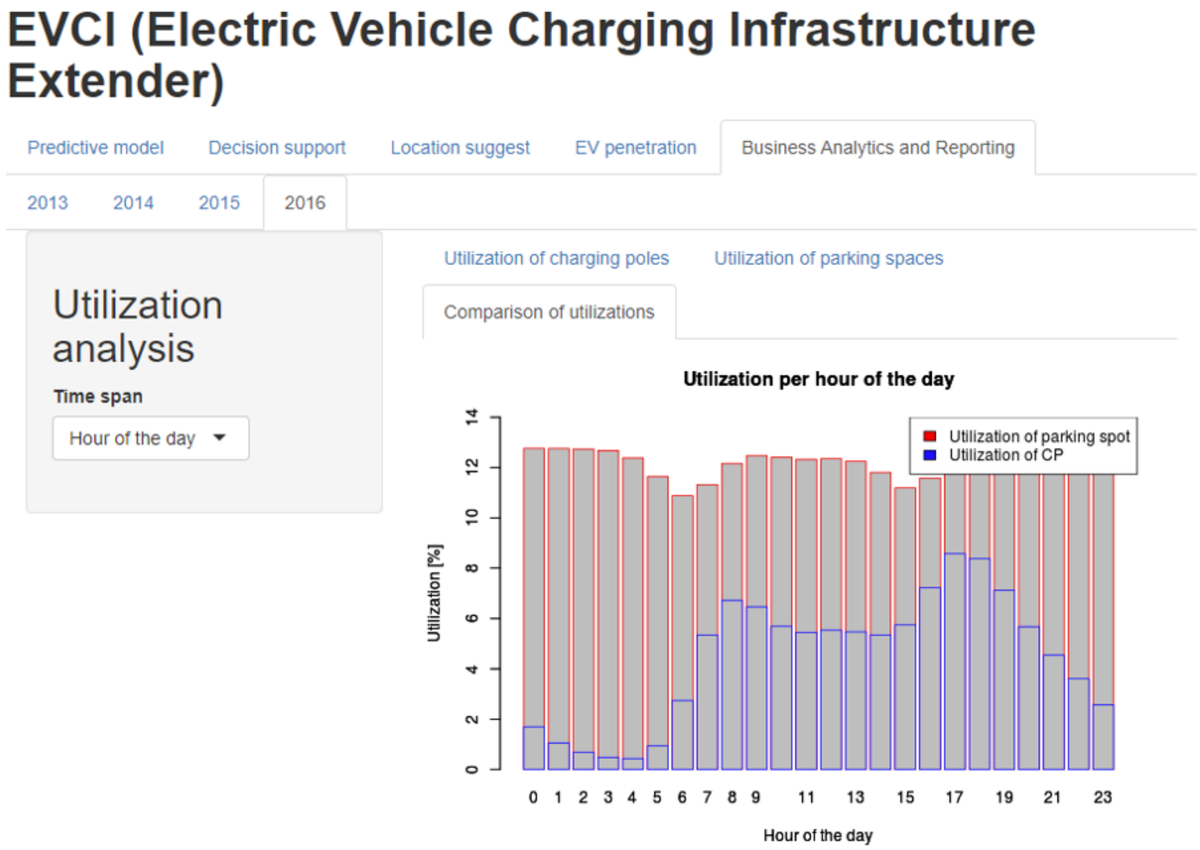


Figure 7.6: Business analytics and reporting module is used to analyse historical and future state of the charging station infrastructure, namely, charging station utilisation over different time resolutions.

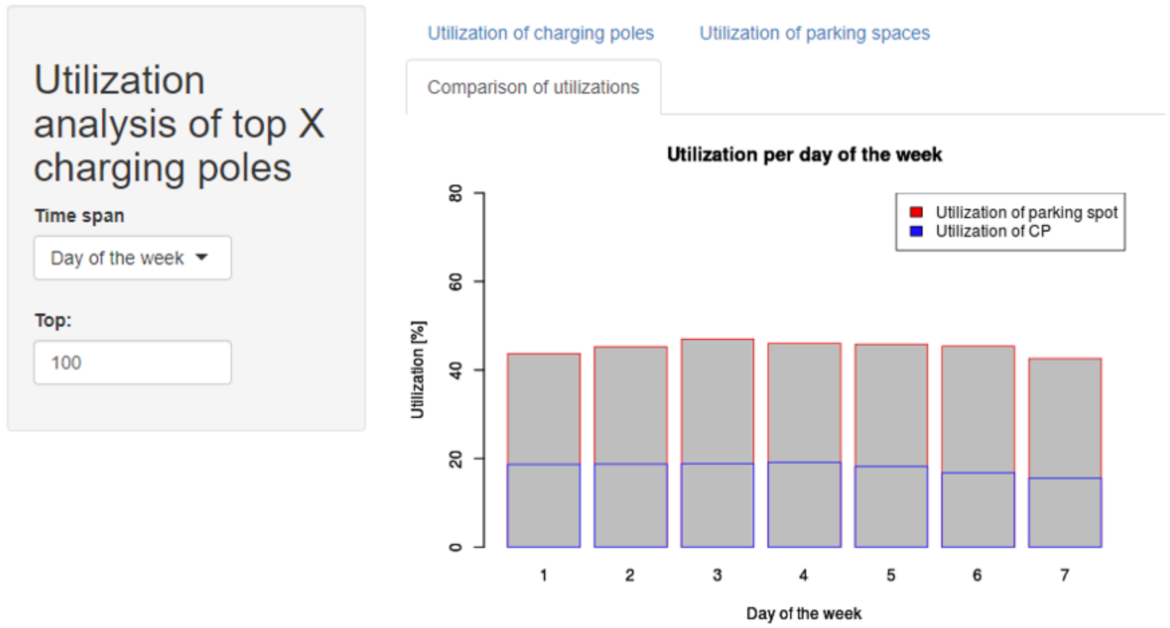


Figure 7.7: Besides the average utilisation in the whole charging station infrastructure, EVCI framework enables utilisation analysis over the top N charging stations.

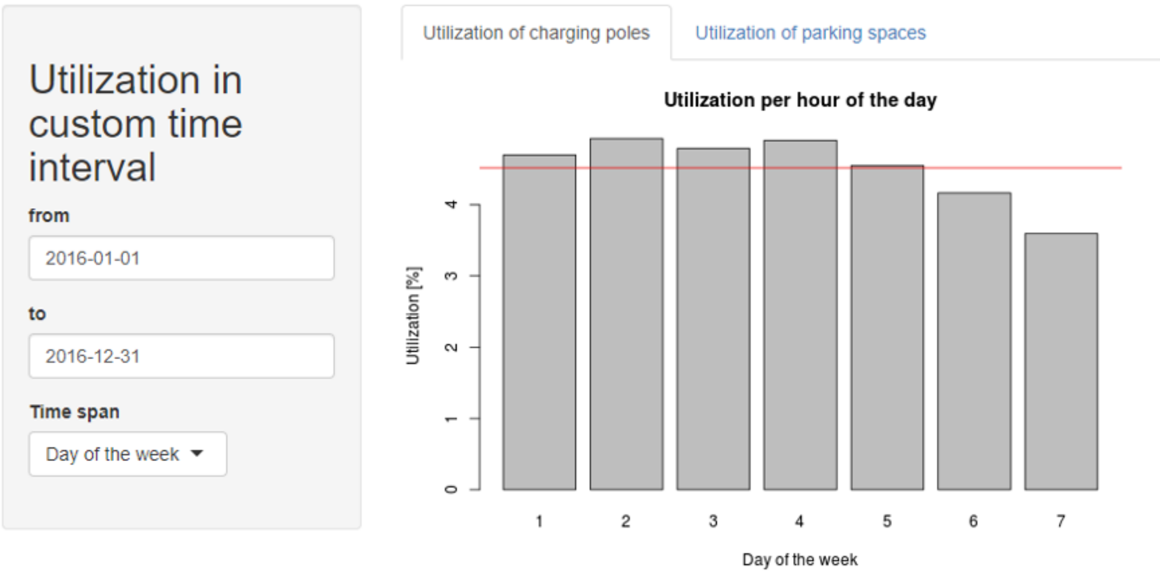
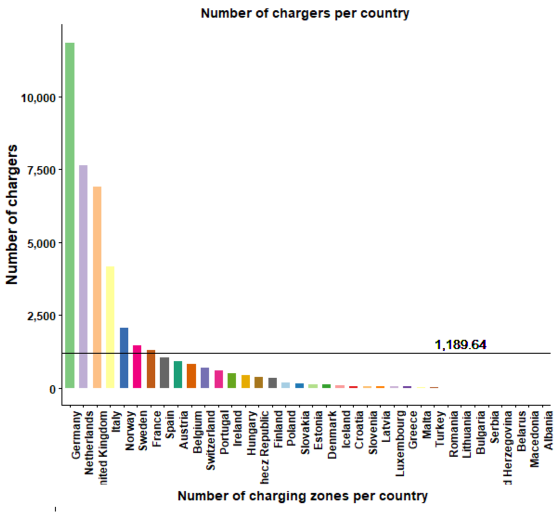


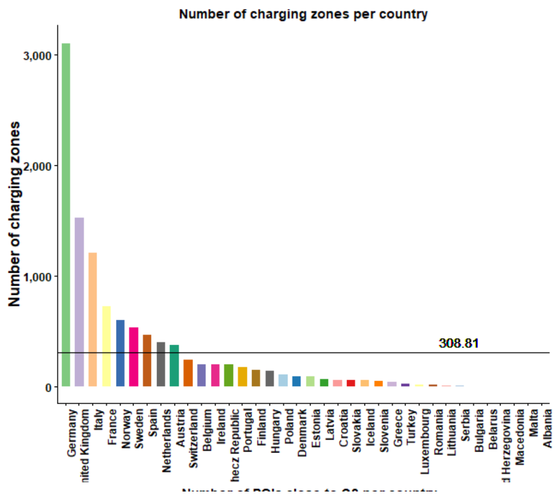
Figure 7.8: Aside from the overall utilisation analysis, and utilisation analysis on the top N charging stations, EVCI framework enables the analysis of utilisation over the custom time period, i.e., analysis of seasonality of charging station utilisation.

7.2 Appendix 2: EU countries charging station infrastructure scorecard

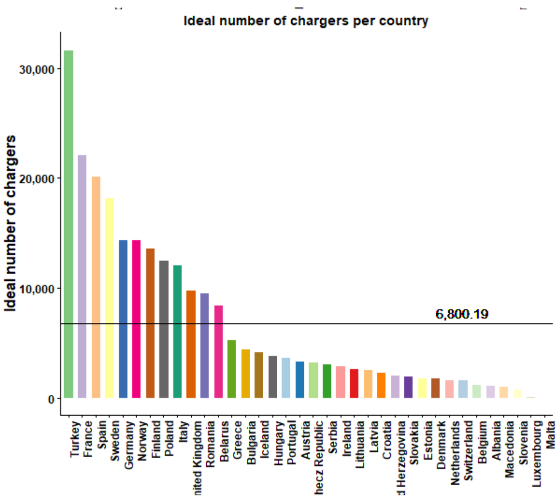
Results of the PoI and publicly available data on charging stations is depicted here for all of the countries in the Europe. Results are shown per country, as well as in the context with all the countries.



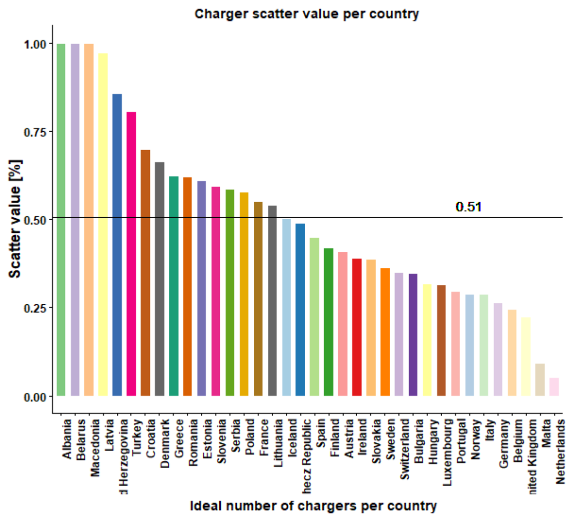
(a) Charging stations per European country



(b) Charging zones per European country



(c) Ideal number of charging stations per European country



(d) Scatter value for charging zones per European country

Figure 7.9: Each European country in context with others, regarding the number of charging stations, number of charging zones, ideal number of charging zones, and scatter value for the charging zones

Table 7.1: Based on the calculated and detected KPIs, each country can be ranked in context with other countries. The score is calculated by the country rank. Therefore, the country with the smallest score has potentially the most developed charging infrastructure.

COUNTRY	NUMBER OF CSes	NUMBER OF CZs	NUMBER OF POIS	SCATTER VALUE	IDEAL NUMBER OF CSes	TOTAL SCORE	RANK
Germany	1	1	1	5	3	11	1
United Kingdom	3	2	2	3	4	14	2
Netherlands	2	8	3	4	1	18	3
Italy	4	3	4	7	8	26	4
Norway	5	5	7	6	12	35	5
Belgium	10	11	11	4	5	41	6
Switzerland	11	10	10	12	7	50	7
Sweden	6	6	8	13	18	51	8
Austria	9	9	9	16	9	52	9
Portugal	12	14	12	8	11	57	10
France	7	4	5	22	20	58	11
Spain	8	7	6	18	21	60	12
Ireland	13	12	15	15	10	65	13
Hungary	14	16	13	10	14	67	14
Checz Republic	15	13	16	19	13	76	15
Finland	16	15	14	17	25	87	16
Slovakia	18	22	18	14	17	89	17
Malta	27	35	26	2	2	92	18

Luxembourg	25	27	25	9	6	92	19
Poland	17	17	17	23	26	100	20
Estonia	19	19	22	26	16	102	21
Denmark	20	18	20	29	19	106	22
Iceland	21	23	24	20	24	112	23
Slovenia	22	24	27	25	15	113	24
Croatia	23	21	21	30	22	117	25
Greece	26	25	19	28	27	125	26
Bulgaria	31	31	23	11	31	127	27
Latvia	24	20	28	33	23	128	28
Lithuania	30	29	30	21	28	138	29
Romania	29	28	29	27	33	146	30
Serbia	32	30	31	24	30	147	31
Turkey	28	26	32	31	35	152	32
Bosnia and Herzegovina	33	33	33	32	32	163	33
Macedonia	35	34	34	34	29	166	34
Belarus	34	32	35	35	36	172	35
Albania	36	36	36	36	34	178	36

European Country Charger Statistics: Albania

Country specific | Context | Explanation of certain variables

Choose a country:

Albania

Area

28,748 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

2,870,324 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

2 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

10,189 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

80 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

1,150 — 31,343

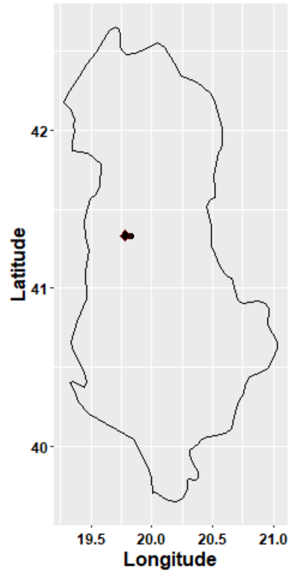
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

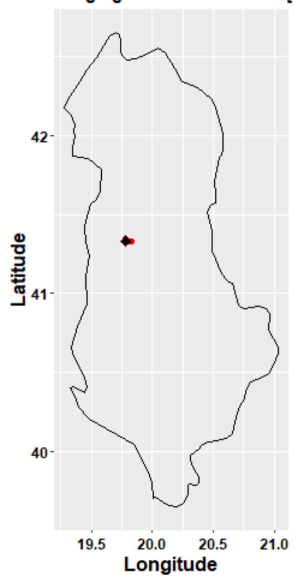
0.17 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38

Charging stations in Albania [#2]



Clustered charging stations in Albania [2 clusters]



European Country Charger Statistics: Austria

Country specific | Context | Explanation of certain variables

Choose a country:

Austria

Area

316 — 83,858 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

8,857,960 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 — 51.7 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

2 — 928 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

5,084 — 188,710 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

80 — 24,561 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 — 379 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.41 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

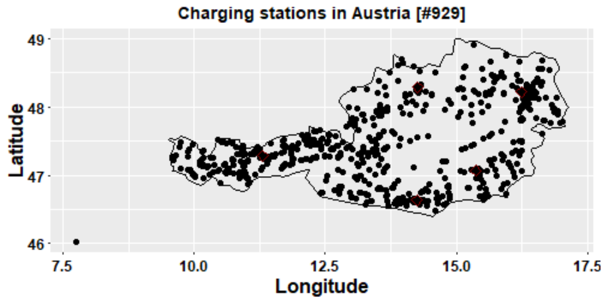
13 — 3,355 — 31,343

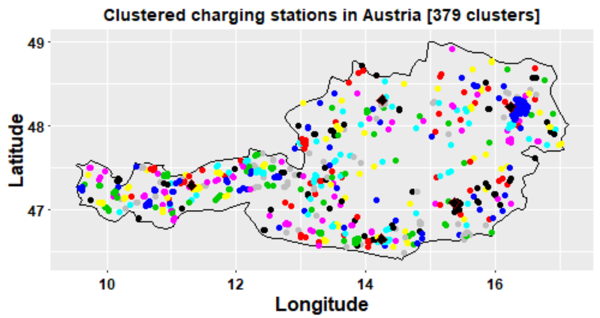
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

27.66 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Belarus

Country specific | Context | Explanation of certain variables

Choose a country:

Belarus

Area

316 207,600 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

355,620 9,477,100 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

6 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

7 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

75,518 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

91 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

7 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

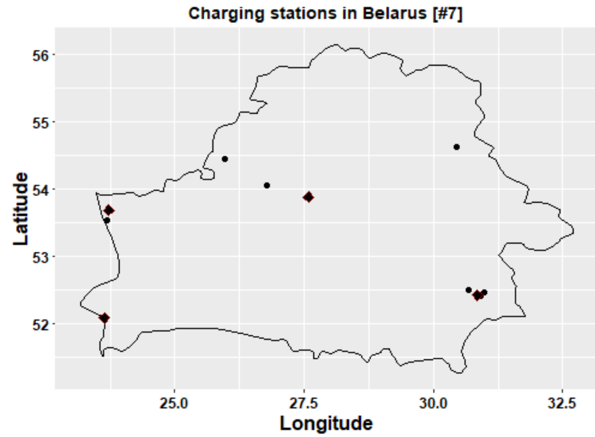
13 8,304 31,343

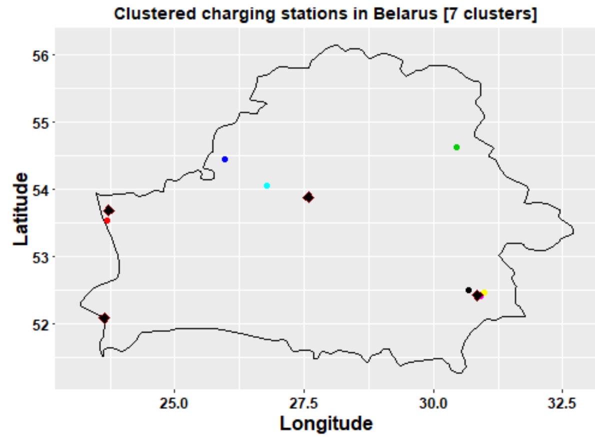
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

0.08 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Belgium

Country specific | Context | Explanation of certain variables

Choose a country:

Belgium

Area

30,510 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

355,620 11,449,656 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 47 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

2 846 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

5,084 141,086 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

80 20,231 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 208 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 0.25 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

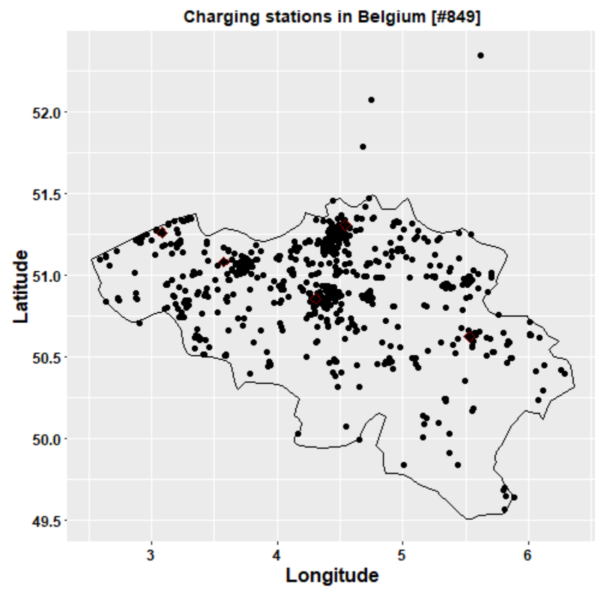
1,221 31,343

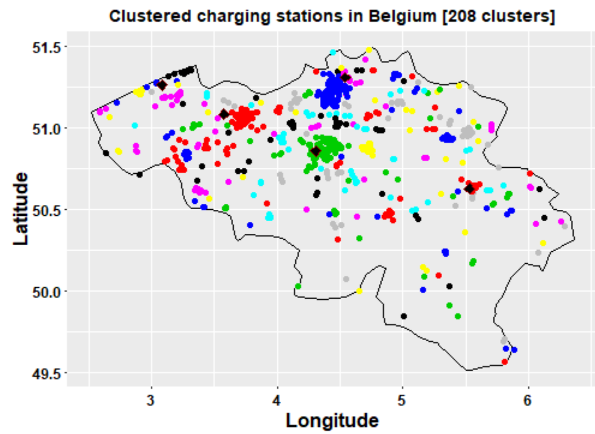
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

0.08 69.29 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Bosnia and Herzegovina

Country specific | Context | Explanation of certain variables

Choose a country:

Bosnia and Herzegovina

Area

316 51,129 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

3,511,372 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.7 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

8 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

13,887 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

348 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

6 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 0.86 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

13 2,046 31,343

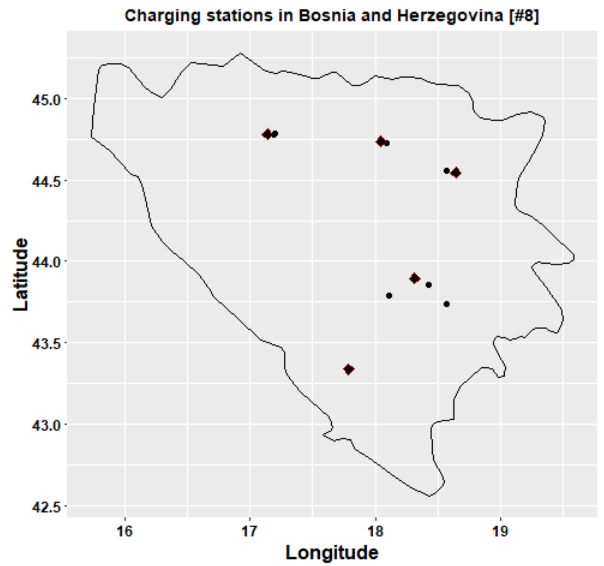
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

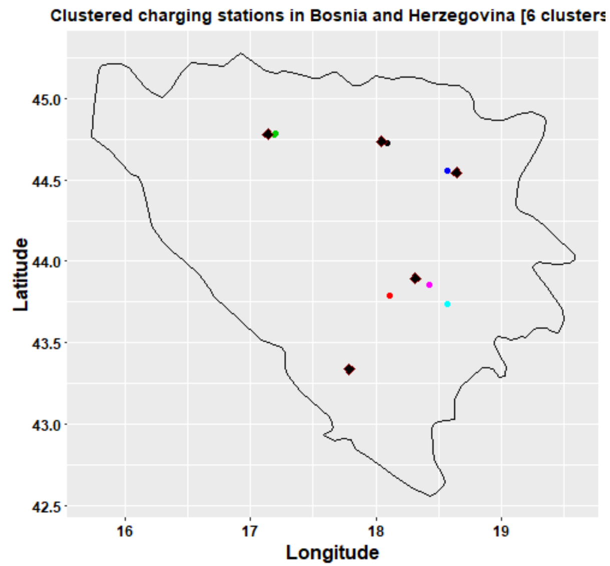
Real CS number:Ideal CS number

0.39 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38

29. 04. 2020. European Country Charger Statistics: Bosnia and Herzegovina





European Country Charger Statistics: Bulgaria

Country specific | Context | Explanation of certain variables

Choose a country:

Bulgaria

Area

316 — 110,994 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

7,050,034 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

9.1 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

23 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

35,266 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

2,641 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

8 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.35 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

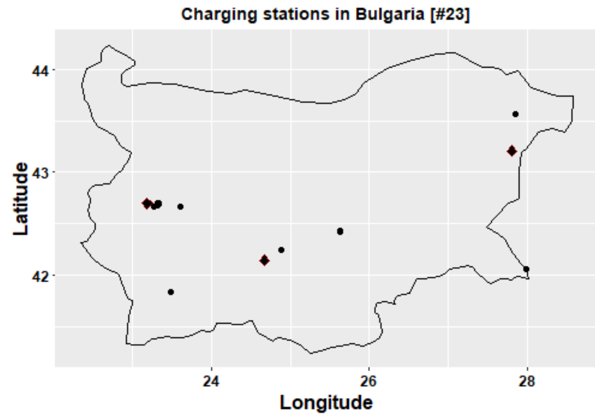
13 — 4,440 — 31,343

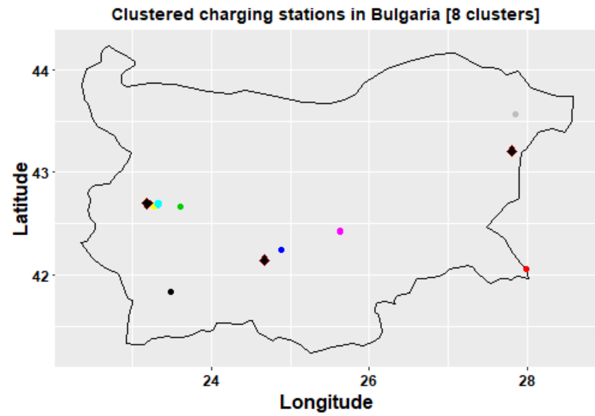
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

0.52 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Croatia

Country specific | Context | Explanation of certain variables

Choose a country:

Croatia

Area

316 56,594 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

4,105,493 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 14.6 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

94 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

40,835 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

3,037 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

65 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 0.7 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

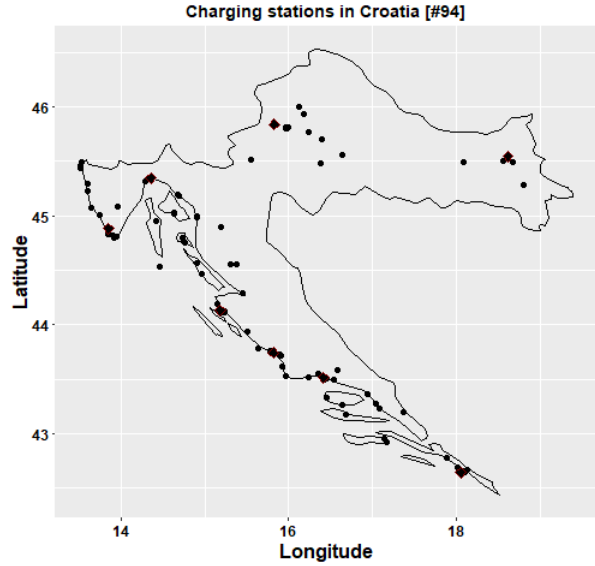
13 2,264 31,343

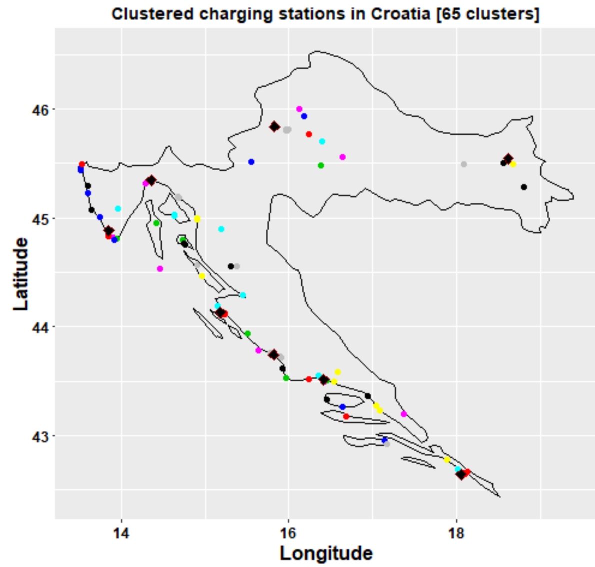
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

4.15 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Czech Republic

Country specific | Context | Explanation of certain variables

Choose a country:

Czech Republic

Area

316 78,866 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

355,620 10,627,794 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 23.1 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

2 414 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

5,084 146,318 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

10,548 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 201 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 0.49 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

13 3,155 31,343

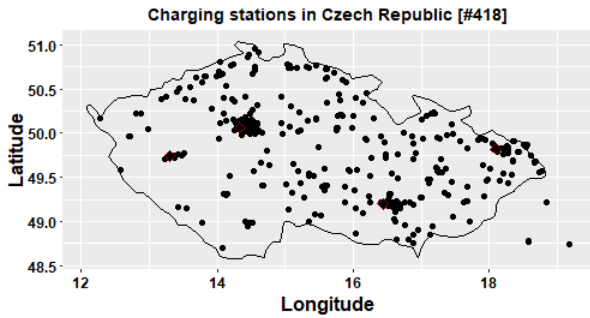
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

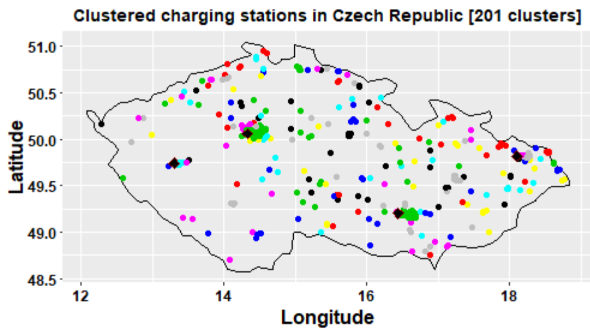
Real CS number:Ideal CS number

13.12 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38

29. 04. 2020. European Country Charger Statistics: Czech Republic





European Country Charger Statistics: Denmark

Country specific | Context | Explanation of certain variables

Choose a country:

Denmark

Area

44,493 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

5,806,015 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 — 61.2 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

143 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

52,500 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

3,485 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 — 95 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.66 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

13 — 1,780 — 31,343

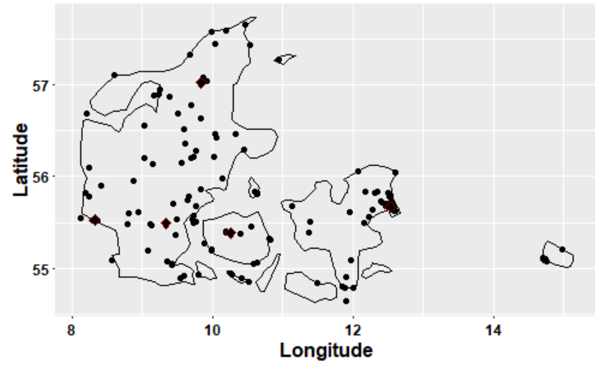
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

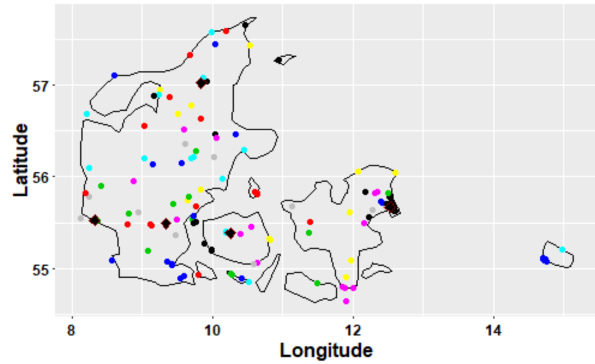
8.03 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38

Charging stations in Denmark [#143]



Clustered charging stations in Denmark [95 clusters]



European Country Charger Statistics: Estonia

Country specific | Context | Explanation of certain variables

Choose a country:

Estonia

Area

45,339 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

1,319,133 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 22.4 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

154 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

25,083 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

2,848 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 94 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 0.61 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

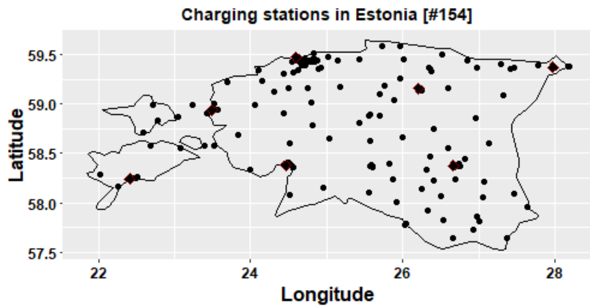
13 1,814 31,343

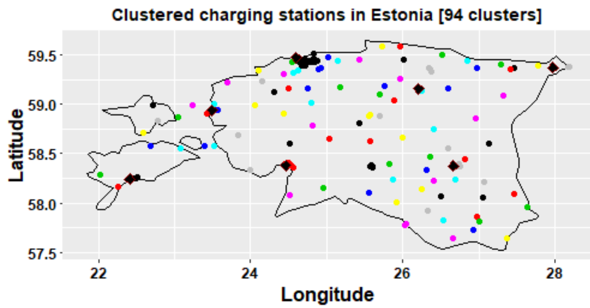
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

8.49 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Finland

Country specific | Context | Explanation of certain variables

Choose a country:

Finland

Area

316 — 338,145 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

5,522,015 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 — 50.1 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

2 — 365 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

5,084 — 141,562 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

12,278 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 — 153 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.42 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

13 — 13,526 — 31,343

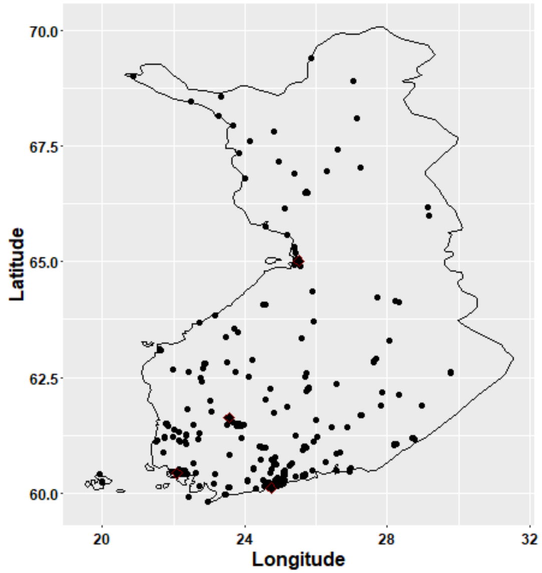
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

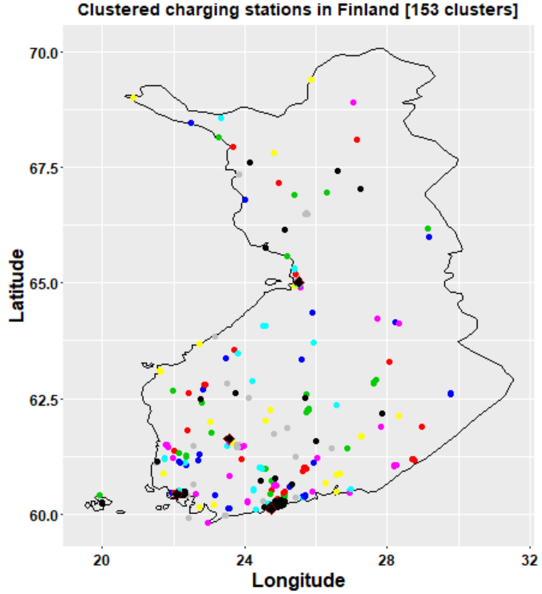
2.7 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38

Charging stations in Finland [#365]



Clustered charging stations in Finland [153 clusters]



European Country Charger Statistics: France

Country specific | Context | Explanation of certain variables

Choose a country:

France

Area

316 — 551,695 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

355,620 — 67,372,000 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 — 42.9 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

2 — 1,323 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

5,084 — 677,792 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

80 — 54,080 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 — 730 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.55 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

13 — 22,068 — 31,343

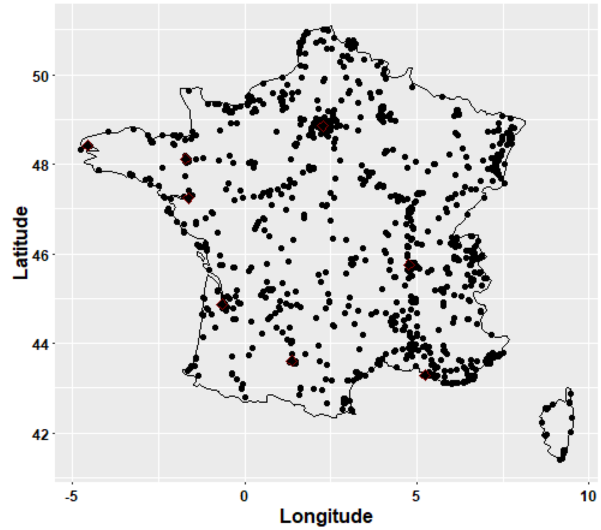
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

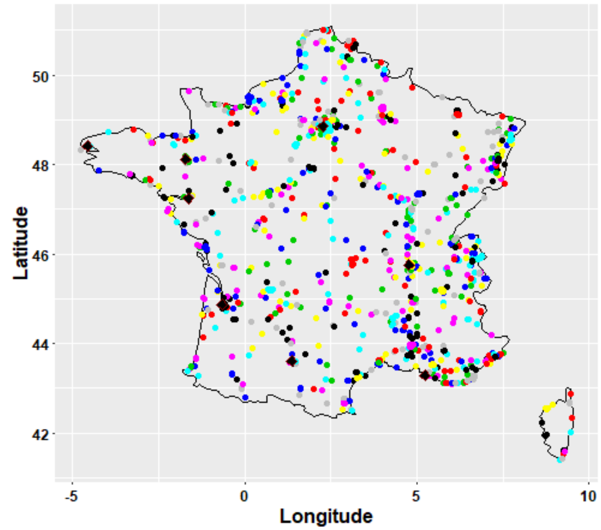
6 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38

Charging stations in France [#1323]



Clustered charging stations in France [730 clusters]



European Country Charger Statistics: Germany

Country specific | Context | Explanation of certain variables

Choose a country:

Germany

Area

316 — 357,386 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

355,620 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 — 48.7 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

2 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

5,084 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

80 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.26 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

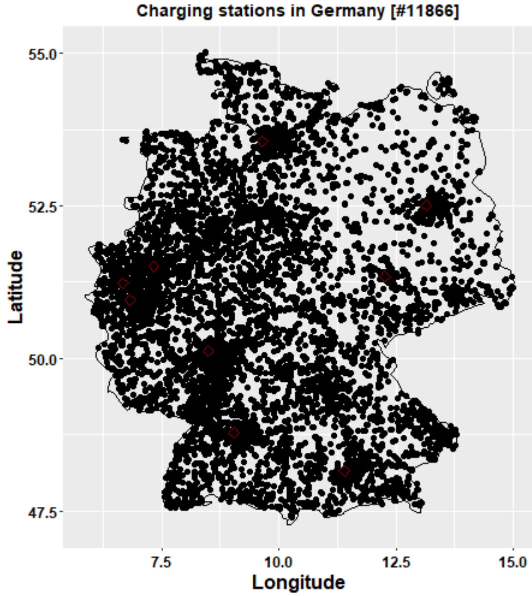
13 — 14,296 — 31,343

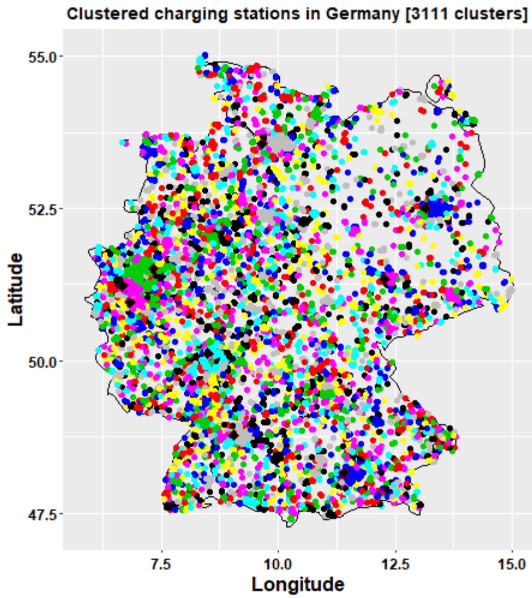
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

0.08 — 83 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Greece

Country specific | Context | Explanation of certain variables

Choose a country:

Greece

Area

316 — 131,940 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

355,620 — 10,768,193 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 — 20.3 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

69 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

91,568 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

3,531 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

43 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.62 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

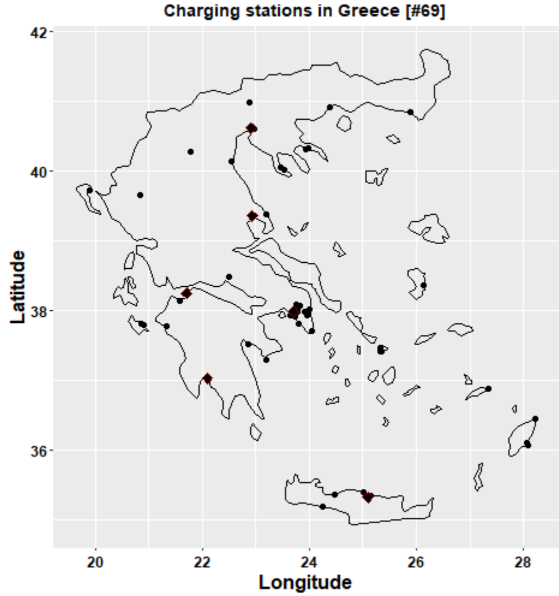
13 — 5,278 — 31,343

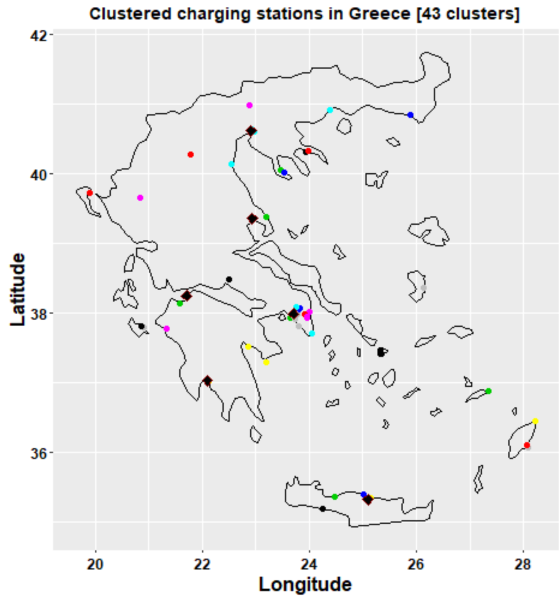
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

1.31 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Hungary

Country specific | Context | Explanation of certain variables

Choose a country:

Hungary

Area

316 93,030 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

355,620 9,771,000 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 16 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

2 449 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

110,239 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

16,020 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 143 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 0.32 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

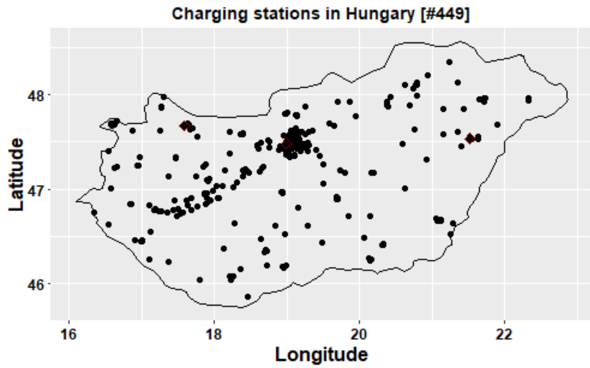
13 3,722 31,343

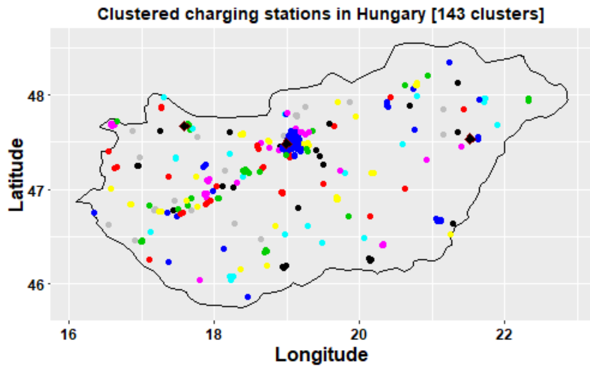
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

12.06 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Iceland

Country specific | Context | Explanation of certain variables

Choose a country:

Iceland

Area

316   102,775   783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

355,620   82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26   75.7   113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

121   11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

6,250   1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

1,848   339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

61   3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053   0.5   1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

13   4,111   31,343

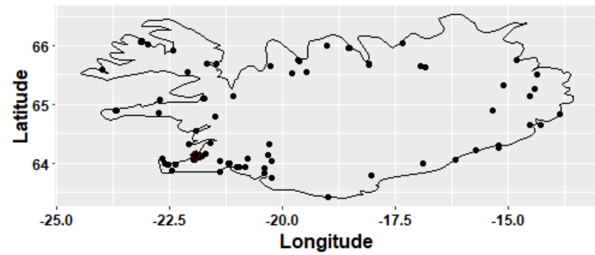
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

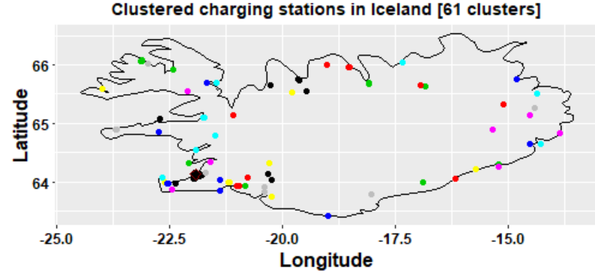
2.94   464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38

Charging stations in Iceland [#121]



Clustered charging stations in Iceland [61 clusters]



European Country Charger Statistics: Ireland

Country specific | Context | Explanation of certain variables

Choose a country:

Ireland

Area

316 — 70,273 — 783,562

316 | 78,716 | 157,116 | 235,516 | 313,916 | 392,316 | 470,716 | 549,116 | 627,516 | 705,916 | 783,562

Population

4,857,000 — 82,887,000

355,620 | 8,609,620 | 16,863,620 | 25,117,620 | 33,371,620 | 41,625,620 | 49,879,620 | 58,133,620 | 66,387,620 | 74,641,620 | 82,887,000

GDP

5.26 — 75.2 — 113.95

5.26 | 16.2 | 27.1 | 38 | 48.9 | 59.8 | 70.7 | 81.6 | 92.5 | 103.4 | 113.95

Number of charging stations

2 — 529 — 11,866

2 | 1,189 | 2,376 | 3,563 | 4,750 | 5,937 | 7,124 | 8,311 | 9,498 | 10,685 | 11,866

Number of PoIs

44,789 — 1,339,230

5,084 | 138,584 | 272,084 | 405,584 | 539,084 | 672,584 | 806,084 | 939,584 | 1,073,084 | 1,206,584 | 1,339,230

Number of PoIs in proximity to chargers

12,253 — 339,030

80 | 33,980 | 67,880 | 101,780 | 135,680 | 169,580 | 203,480 | 237,380 | 271,280 | 305,180 | 339,030

Number of clusters

2 — 206 — 3,111

2 | 313 | 624 | 935 | 1,246 | 1,557 | 1,868 | 2,179 | 2,490 | 2,801 | 3,111

Scatter Value

0.053 — 0.39 — 1

0.053 | 0.15 | 0.25 | 0.35 | 0.45 | 0.55 | 0.65 | 0.75 | 0.85 | 0.95 | 1

Ideal number of chargers

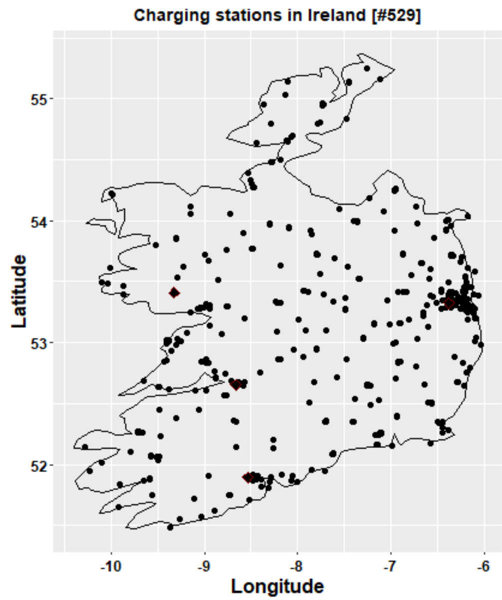
13 — 2,811 — 31,343

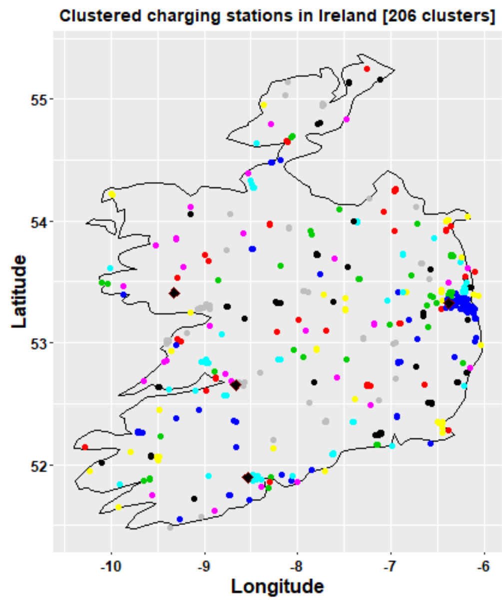
13 | 3,146 | 6,279 | 9,412 | 12,545 | 15,678 | 18,811 | 21,944 | 25,077 | 28,210 | 31,343

Real CS number:Ideal CS number

18.82 — 464.38

0.08 | 46.51 | 92.94 | 139.37 | 185.8 | 232.23 | 278.66 | 325.09 | 371.52 | 417.95 | 464.38





European Country Charger Statistics: Latvia

Country specific | Context | Explanation of certain variables

Choose a country:

Latvia

Area

316 64,589 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

1,921,300 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 17.6 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

75 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

22,783 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

959 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

73 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 0.97

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

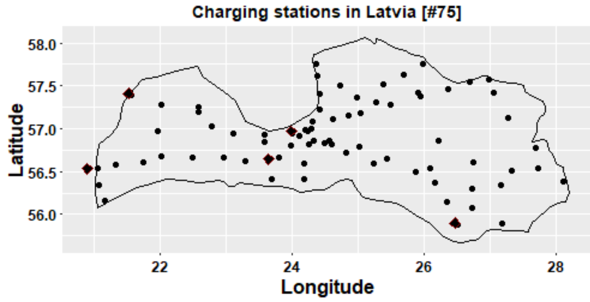
13 2,584 31,343

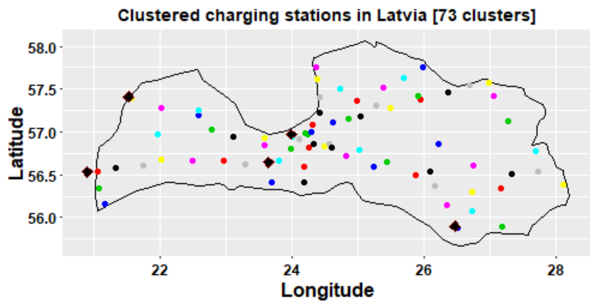
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

2.9 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Lithuania

Country specific | Context | Explanation of certain variables

Choose a country:

Lithuania

Area

316 65,300 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

2,793,986 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 18.9 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

25 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

30,206 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

785 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

13 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 0.54 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

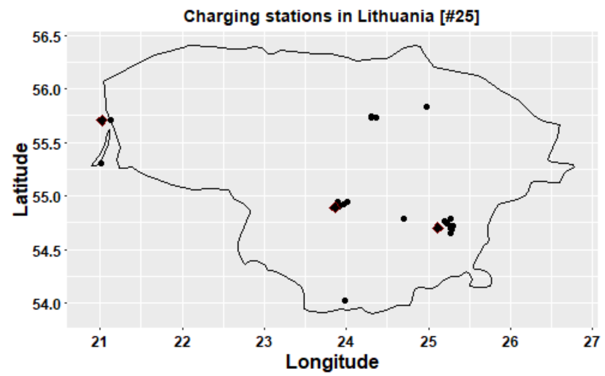
13 2,612 31,343

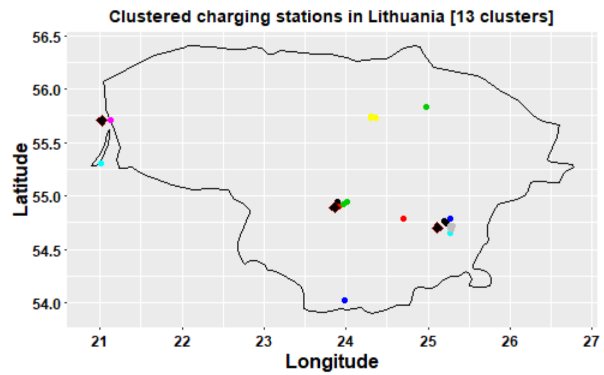
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

0.96 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Luxemburg

Country specific | Context | Explanation of certain variables

Choose a country:

Luxemburg

Area

2,586 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

602,005 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

73 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

12,511 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

1,697 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

23 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.32 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

104 — 31,343

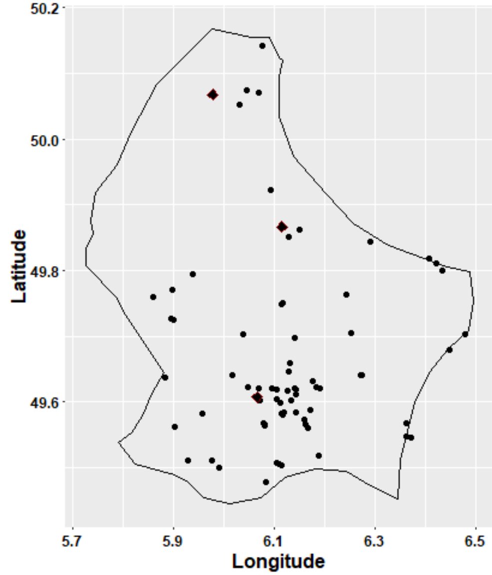
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

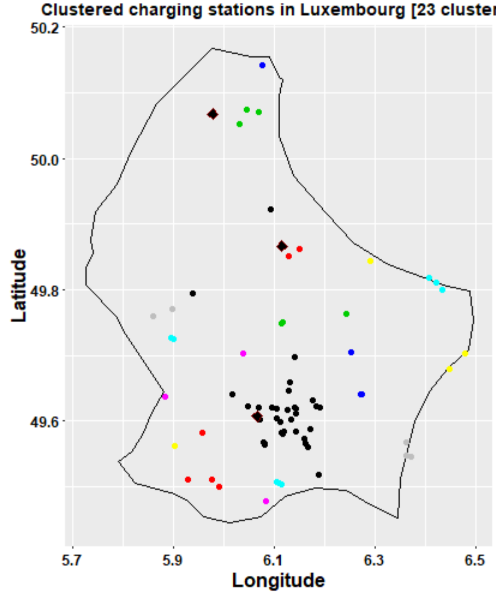
0.08 — 70.19 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38

Charging stations in Luxembourg [#73]



Clustered charging stations in Luxembourg [23 clusters]



European Country Charger Statistics: Macedonia

Country specific | Context | Explanation of certain variables

Choose a country:

Macedonia

Area

25,713 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

2,075,301 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

6 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

6 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

5,084 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

207 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

6 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

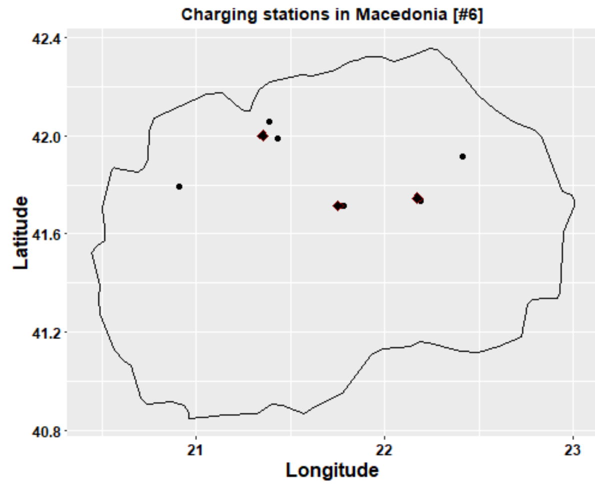
1,029 — 31,343

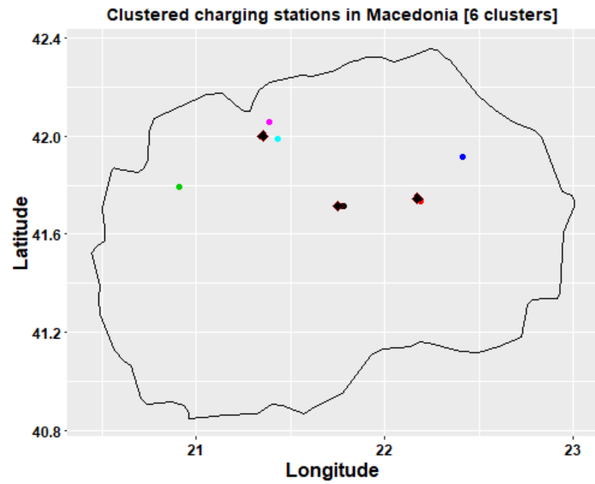
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

0.58 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Malta

Country specific | Context | Explanation of certain variables

Choose a country:

Malta

Area

316 – 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

475,701 – 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 – 30.5 – 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

54 – 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

5,357 – 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

1,645 – 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

5 – 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.09 – 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

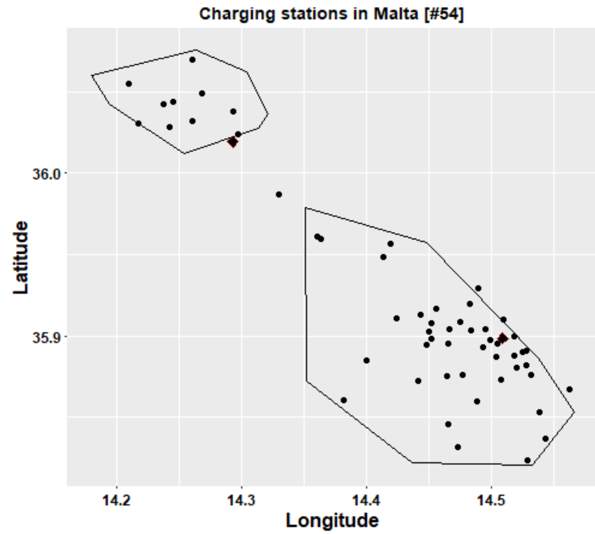
13 – 31,343

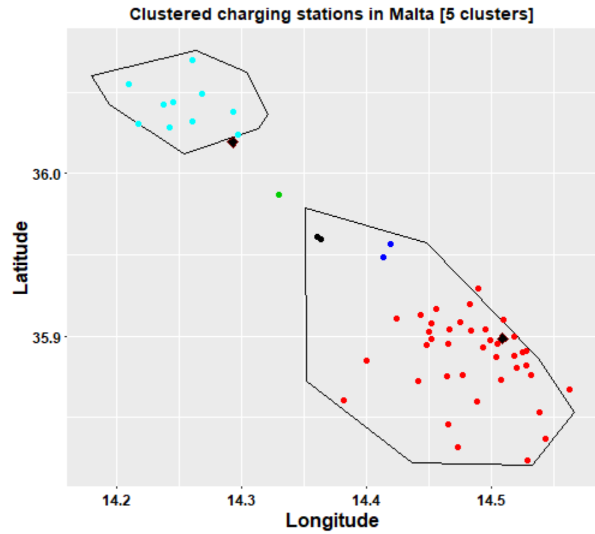
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

0.08 – 415.38 – 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Netherlands

Country specific | Context | Explanation of certain variables

Choose a country:

Netherlands

Area

41,198 (range 316 – 783,562)

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

17,305,660 (range 355,620 – 82,887,000)

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

52.9 (range 5.26 – 113.95)

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

7,653 (range 2 – 11,866)

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

173,983 (range 5,084 – 1,339,230)

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

95,073 (range 80 – 339,030)

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

407 (range 2 – 3,111)

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 (range 0.053 – 1)

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

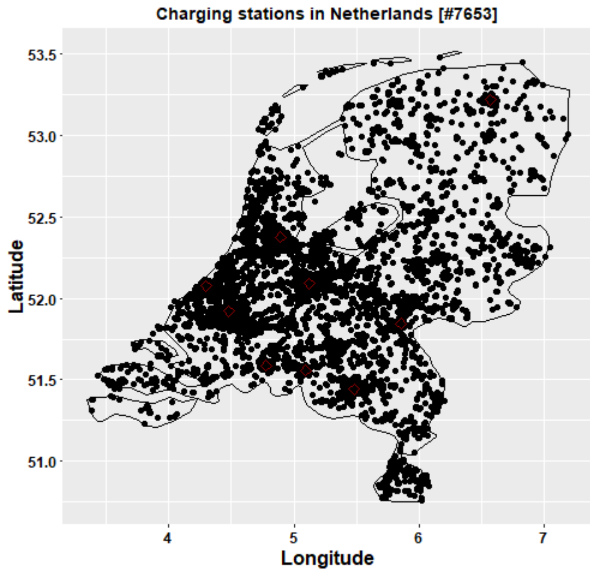
1,648 (range 13 – 31,343)

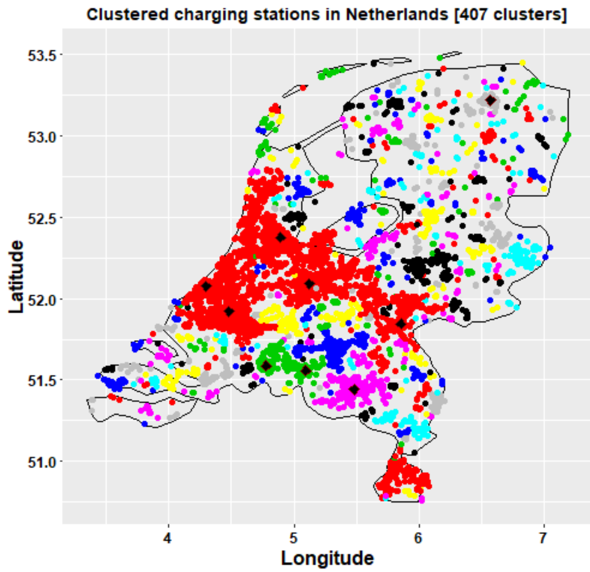
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

464.38 (range 0.08 – 464.38)

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Norway

Country specific | Context | Explanation of certain variables

Choose a country:

Norway

Area

316 — 358,178 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

5,323,933 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 — 82.4 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

2 — 2,097 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

5,084 — 140,416 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

80 — 29,694 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 — 606 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.29 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

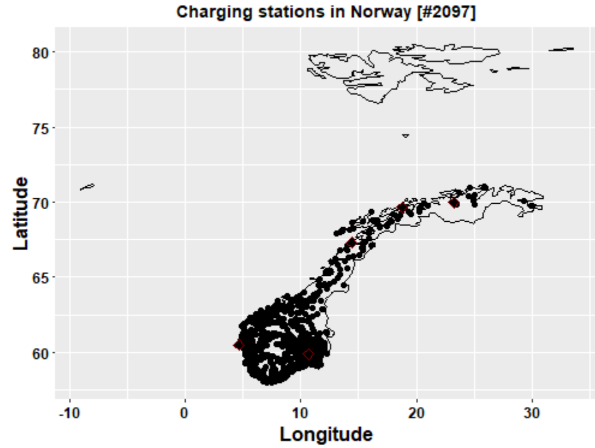
13 — 14,328 — 31,343

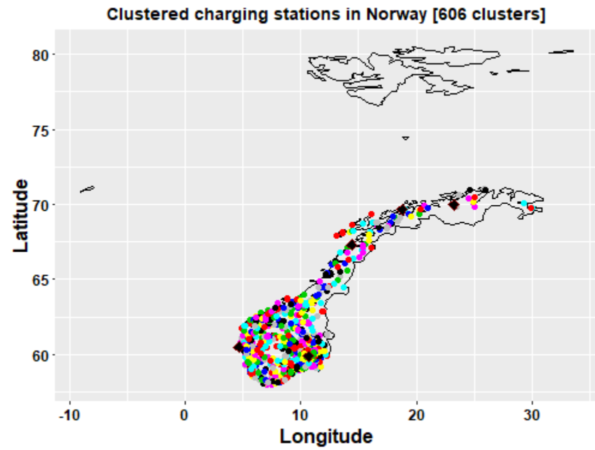
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

14.64 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Poland

Country specific | Context | Explanation of certain variables

Choose a country:

Poland

Area

316 — 312,685 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

355,620 — 38,433,600 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 — 14.5 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

193 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

5,084 — 290,748 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

9,154 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 — 112 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.58 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

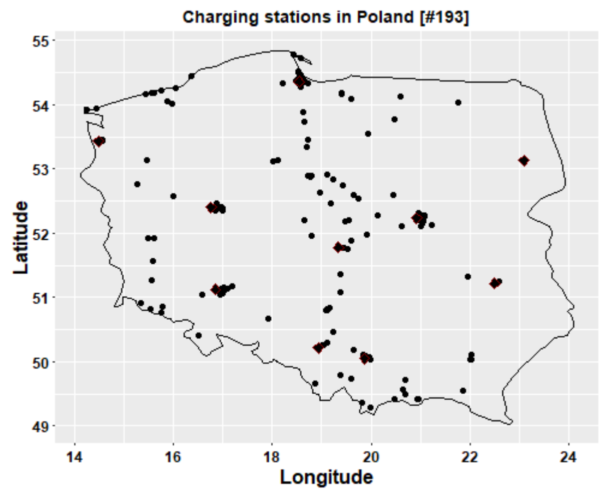
13 — 12,508 — 31,343

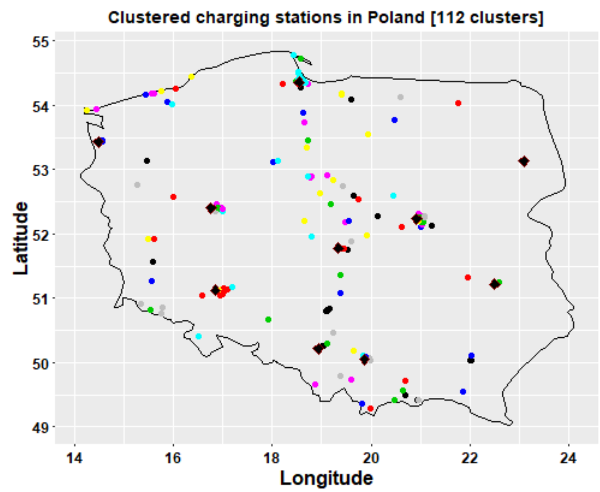
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

1.54 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Portugal

Country specific | Context | Explanation of certain variables

Choose a country:

Portugal

Area

316 — 91,568 — 783,562

316 | 78,716 | 157,116 | 235,516 | 313,916 | 392,316 | 470,716 | 549,116 | 627,516 | 705,916 | 783,562

Population

355,620 — 10,291,027 — 82,887,000

355,620 | 8,609,620 | 16,863,620 | 25,117,620 | 33,371,620 | 41,625,620 | 49,879,620 | 58,133,620 | 66,387,620 | 74,641,620 | 82,887,000

GDP

5.26 — 23.2 — 113.95

5.26 | 16.2 | 27.1 | 38 | 48.9 | 59.8 | 70.7 | 81.6 | 92.5 | 103.4 | 113.95

Number of charging stations

2 — 611 — 11,866

2 | 1,189 | 2,376 | 3,563 | 4,750 | 5,937 | 7,124 | 8,311 | 9,498 | 10,685 | 11,866

Number of PoIs

90,612 — 1,339,230

5,084 | 138,584 | 272,084 | 405,584 | 539,084 | 672,584 | 806,084 | 939,584 | 1,073,084 | 1,206,584 | 1,339,230

Number of PoIs in proximity to chargers

16,848 — 339,030

80 | 33,980 | 67,880 | 101,780 | 135,680 | 169,580 | 203,480 | 237,380 | 271,280 | 305,180 | 339,030

Number of clusters

2 — 182 — 3,111

2 | 313 | 624 | 935 | 1,246 | 1,557 | 1,868 | 2,179 | 2,490 | 2,801 | 3,111

Scatter Value

0.053 — 0.3 — 1

0.053 | 0.15 | 0.25 | 0.35 | 0.45 | 0.55 | 0.65 | 0.75 | 0.85 | 0.95 | 1

Ideal number of chargers

13 — 3,663 — 31,343

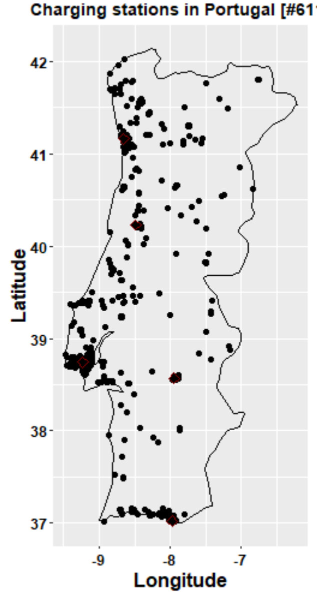
13 | 3,146 | 6,279 | 9,412 | 12,545 | 15,678 | 18,811 | 21,944 | 25,077 | 28,210 | 31,343

Real CS number:Ideal CS number

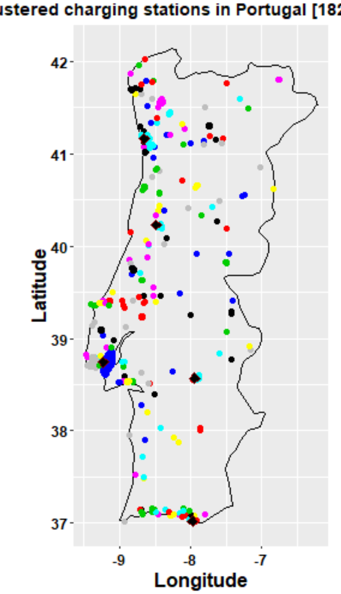
16.68 — 464.38

0.08 | 46.51 | 92.94 | 139.37 | 185.8 | 232.23 | 278.66 | 325.09 | 371.52 | 417.95 | 464.38

Charging stations in Portugal [#611]



Clustered charging stations in Portugal [182 clusters]



European Country Charger Statistics: Romania

Country specific | Context | Explanation of certain variables

Choose a country:

Romania

Area

316 — 238,397 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

355,620 — 19,523,621 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 — 12.2 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

32 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

65,378 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

911 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

18 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.62 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

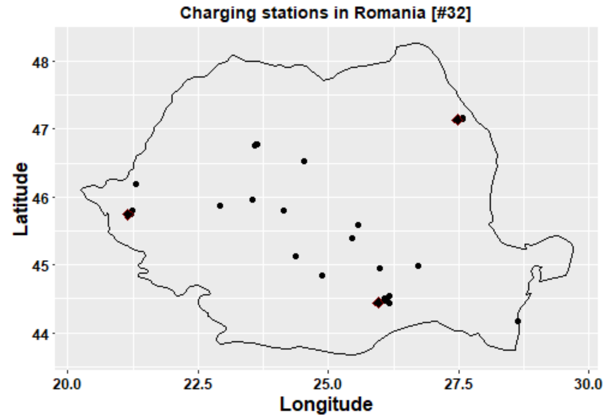
13 — 9,536 — 31,343

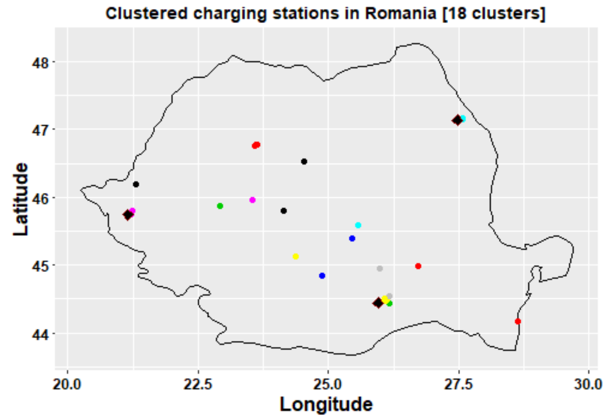
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

0.34 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Serbia

Country specific | Context | Explanation of certain variables

Choose a country:

Serbia

Area

316 — 77,453 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

7,001,444 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

6.8 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

17 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

18,473 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

610 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

10 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.59 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

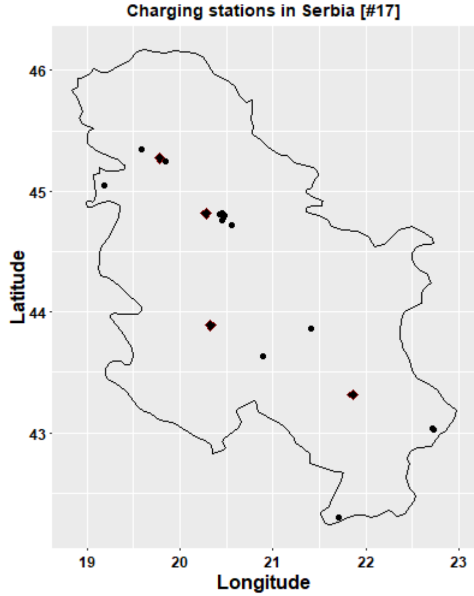
13 — 3,099 — 31,343

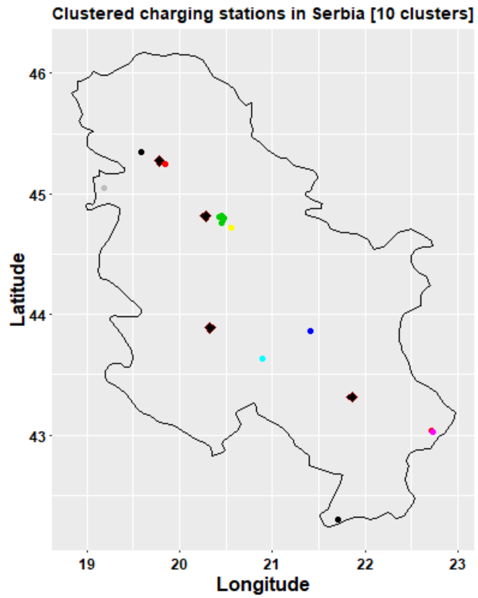
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

0.55 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Slovakia

Country specific | Context | Explanation of certain variables

Choose a country:

Slovakia

Area

316 49,036 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

5,445,087 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 19.6 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

165 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

78,196 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

7,482 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

64 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 0.39 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

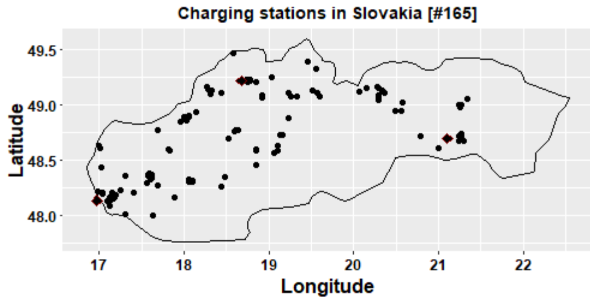
13 1,962 31,343

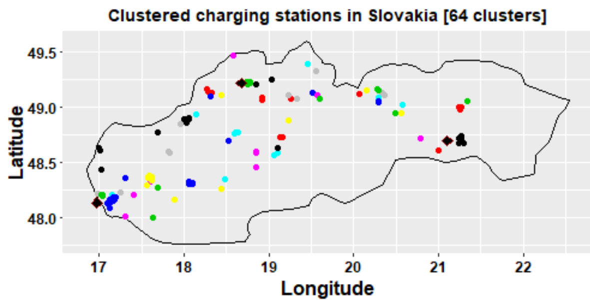
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

8.41 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Slovenia

Country specific | Context | Explanation of certain variables

Choose a country:

Slovenia

Area

20,273 | 783,562

316 | 78,716 | 157,116 | 235,516 | 313,916 | 392,316 | 470,716 | 549,116 | 627,516 | 705,916 | 783,562

Population

2,070,050 | 82,887,000

355,620 | 8,609,620 | 16,863,620 | 25,117,620 | 33,371,620 | 41,625,620 | 49,879,620 | 58,133,620 | 66,387,620 | 74,641,620 | 82,887,000

GDP

5.26 | 26.6 | 113.95

5.26 | 16.2 | 27.1 | 38 | 48.9 | 59.8 | 70.7 | 81.6 | 92.5 | 103.4 | 113.95

Number of charging stations

94 | 11,866

2 | 1,189 | 2,376 | 3,563 | 4,750 | 5,937 | 7,124 | 8,311 | 9,498 | 10,685 | 11,866

Number of PoIs

21,230 | 1,339,230

5,084 | 138,584 | 272,084 | 405,584 | 539,084 | 672,584 | 806,084 | 939,584 | 1,073,084 | 1,206,584 | 1,339,230

Number of PoIs in proximity to chargers

1,433 | 339,030

80 | 33,980 | 67,880 | 101,780 | 135,680 | 169,580 | 203,480 | 237,380 | 271,280 | 305,180 | 339,030

Number of clusters

56 | 3,111

2 | 313 | 624 | 935 | 1,246 | 1,557 | 1,868 | 2,179 | 2,490 | 2,801 | 3,111

Scatter Value

0.053 | 0.6 | 1

0.053 | 0.15 | 0.25 | 0.35 | 0.45 | 0.55 | 0.65 | 0.75 | 0.85 | 0.95 | 1

Ideal number of chargers

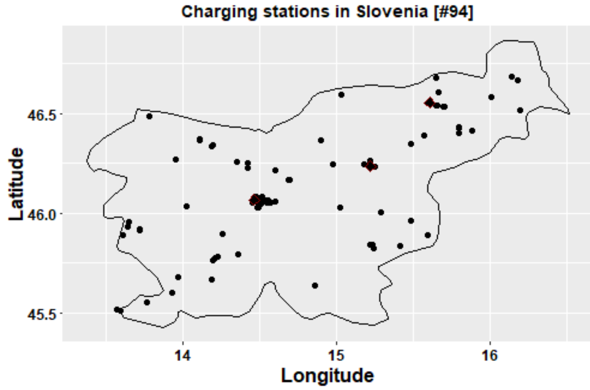
811 | 31,343

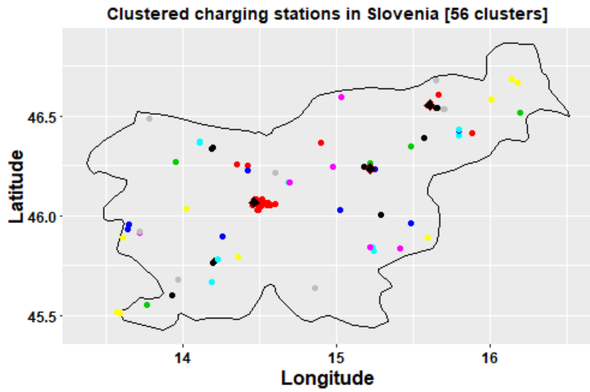
13 | 3,146 | 6,279 | 9,412 | 12,545 | 15,678 | 18,811 | 21,944 | 25,077 | 28,210 | 31,343

Real CS number:Ideal CS number

11.59 | 464.38

0.08 | 46.51 | 92.94 | 139.37 | 185.8 | 232.23 | 278.66 | 325.09 | 371.52 | 417.95 | 464.38





European Country Charger Statistics: Spain

Country specific | Context | Explanation of certain variables

Choose a country:

Spain

Area

316 — 498,468 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

355,620 — 46,733,038 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 — 31.1 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

2 — 1,064 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

5,084 — 347,401 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

80 — 39,951 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 — 470 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.45 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

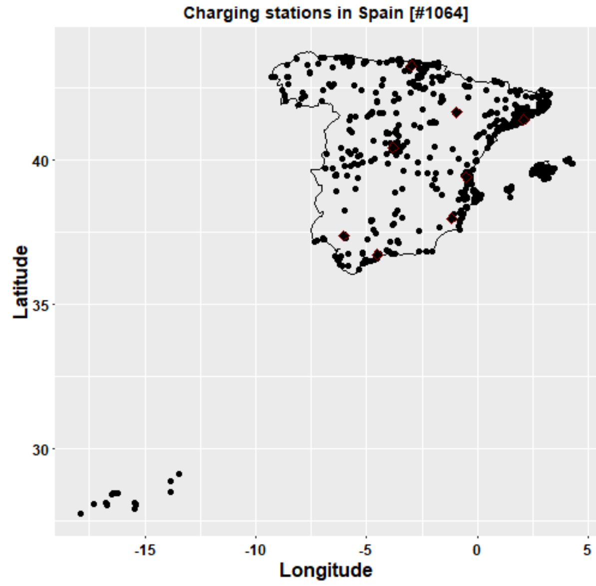
13 — 19,939 — 31,343

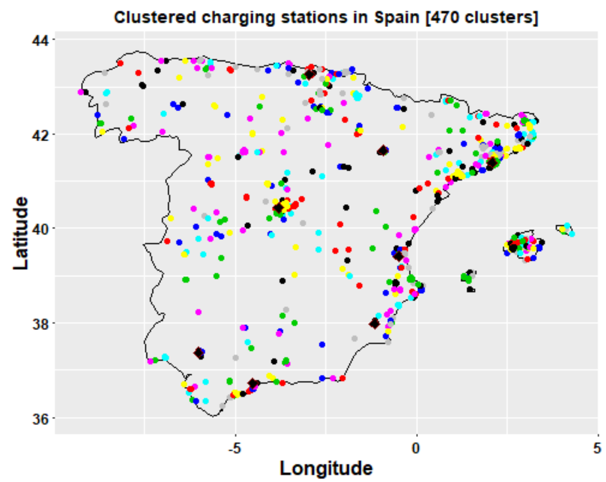
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

5.34 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Sweden

Country specific | Context | Explanation of certain variables

Choose a country:

Sweden

Area

316 — 450,295 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

355,620 — 10,215,250 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 — 53.9 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

2 — 1,470 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

5,084 — 118,902 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

80 — 25,246 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 — 535 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.36 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

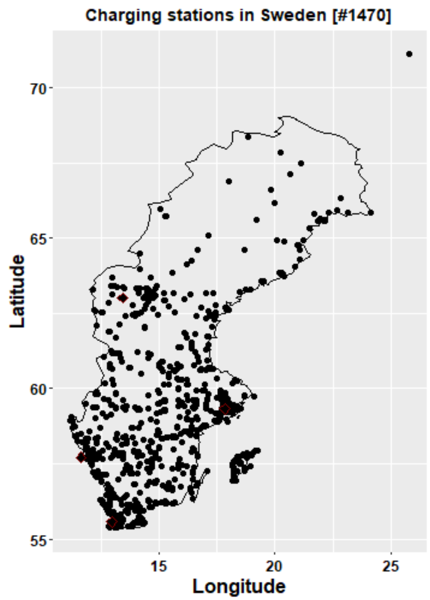
13 — 18,012 — 31,343

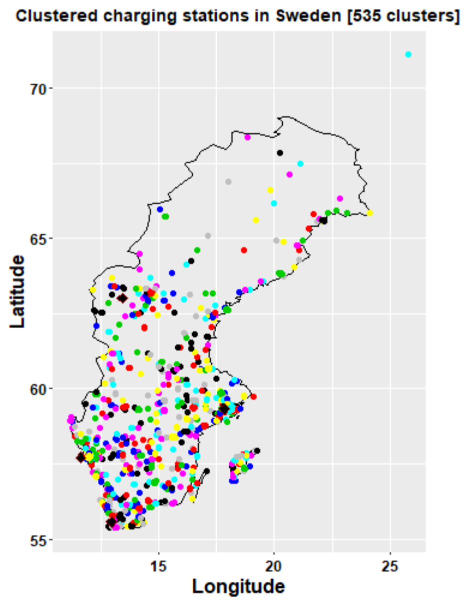
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

8.16 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Switzerland

Country specific | Context | Explanation of certain variables

Choose a country:

Switzerland

Area

41,290 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

8,526,932 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 83.6 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

2 708 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

5,084 149,198 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

80 22,046 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 247 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 0.35 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

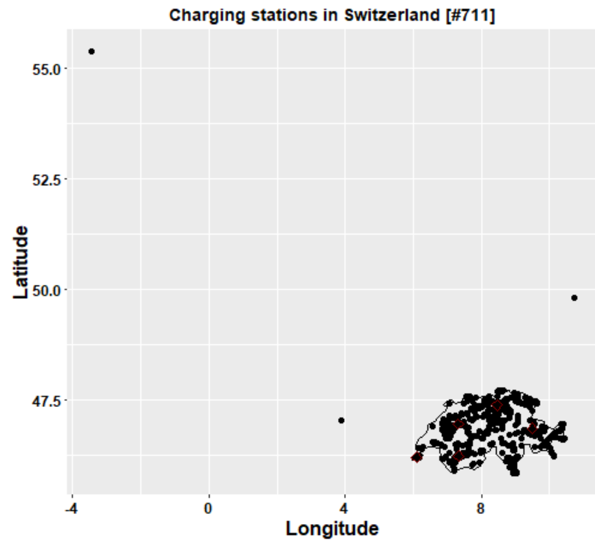
13 1,652 31,343

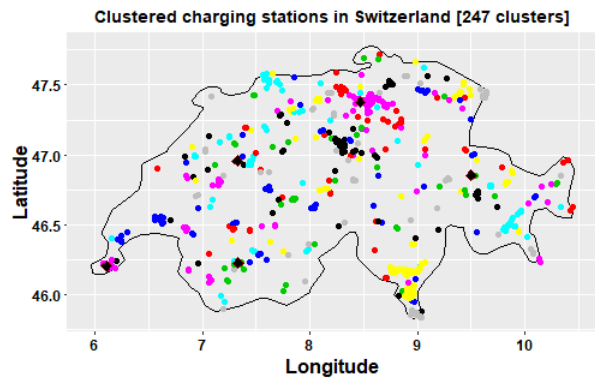
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

0.08 42.86 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: Turkey

Country specific | Context | Explanation of certain variables

Choose a country:

Turkey

Area

316 – 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

355,620 – 82,003,882

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

8.7 – 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

36 – 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

101,924 – 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

410 – 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

29 – 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 – 0.81 – 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

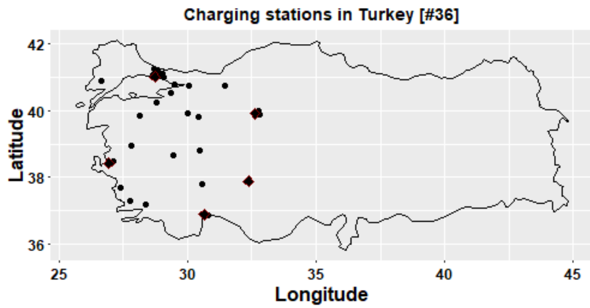
13 – 31,343

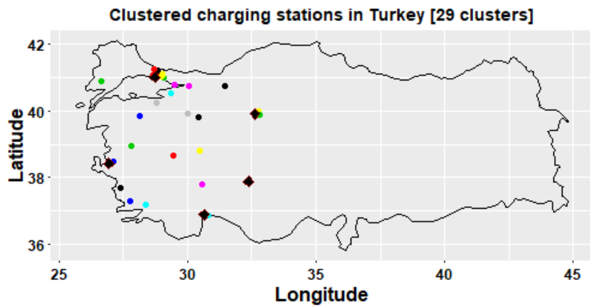
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

0.11 – 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38





European Country Charger Statistics: United Kingdom

Country specific | Context | Explanation of certain variables

Choose a country:

United Kingdom

Area

316 — 242,495 — 783,562

316 78,716 157,116 235,516 313,916 392,316 470,716 549,116 627,516 705,916 783,562

Population

355,620 — 66,040,229 — 82,887,000

355,620 8,609,620 16,863,620 25,117,620 33,371,620 41,625,620 49,879,620 58,133,620 66,387,620 74,641,620 82,887,000

GDP

5.26 — 42.3 — 113.95

5.26 16.2 27.1 38 48.9 59.8 70.7 81.6 92.5 103.4 113.95

Number of charging stations

2 — 6,919 — 11,866

2 1,189 2,376 3,563 4,750 5,937 7,124 8,311 9,498 10,685 11,866

Number of PoIs

5,084 — 529,217 — 1,339,230

5,084 138,584 272,084 405,584 539,084 672,584 806,084 939,584 1,073,084 1,206,584 1,339,230

Number of PoIs in proximity to chargers

80 — 123,568 — 339,030

80 33,980 67,880 101,780 135,680 169,580 203,480 237,380 271,280 305,180 339,030

Number of clusters

2 — 1,537 — 3,111

2 313 624 935 1,246 1,557 1,868 2,179 2,490 2,801 3,111

Scatter Value

0.053 — 0.22 — 1

0.053 0.15 0.25 0.35 0.45 0.55 0.65 0.75 0.85 0.95 1

Ideal number of chargers

13 — 9,700 — 31,343

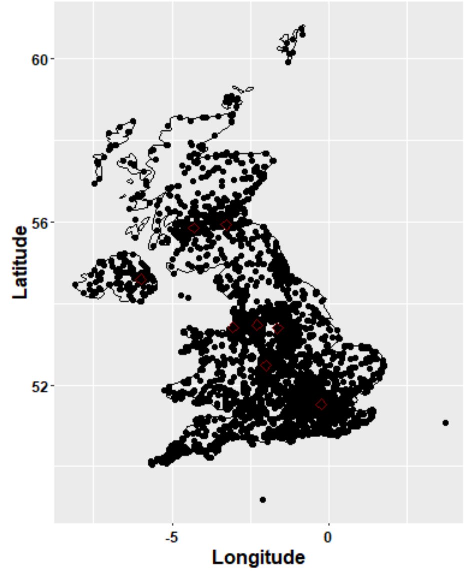
13 3,146 6,279 9,412 12,545 15,678 18,811 21,944 25,077 28,210 31,343

Real CS number:Ideal CS number

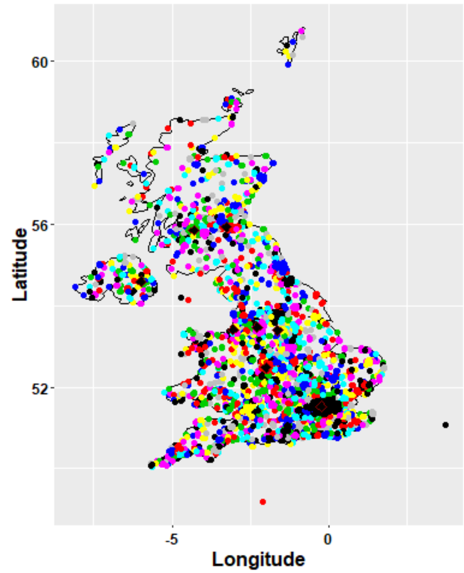
0.08 — 71.33 — 464.38

0.08 46.51 92.94 139.37 185.8 232.23 278.66 325.09 371.52 417.95 464.38

Charging stations in UK [#6919]



Clustered charging stations in UK [1537 clusters]



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Biography

Dario Pevec was born on June 5th, 1991 in Zagreb, Croatia. He received his M.Sc. Degree in the profile of Telecommunication and Informatics at the Faculty of Electrical Engineering and Computing, University of Zagreb (FER), 2016. Currently he is doctoral student at the same faculty, financed by Croatian Science Foundation. As a part of the doctoral study, a qualification doctoral exam was held successfully in 2017, as well as a public discussion in 2018 where the title of the dissertation was defined as: “Real-world data-driven decision support system for electric vehicle charging infrastructure development”. As a part of the work at the Faculty of Electrical Engineering and Computing, the University of Zagreb he conducts teaching activities on several courses.

He attended summer school at the Ericsson Nikola Tesla company (2015) where he worked on the project "Big Data Analysis in the field of networking". He continues to work with the Ericsson Nikola Tesla company as a student and through his master thesis which. Since 2016 he works at the Department of Telecommunications at FER as a member of the “Social Networking and Computing Laboratory (socialLAB)” where he worked on research problems under project "Managing Trust and Coordinating Interactions in Smart Networks of People, Machines and Organizations" which was funded by Croatian Science Foundation.

As a doctoral student, he participated in several international conferences, workshops, as well as PhD schools.

List of publications

Journal papers

1. Pevec, D., Babic, J., and Podobnik, V. (2019). Electric Vehicles: A Data Science Perspective Review. Electronics, 8(10), 1190.
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4. Orsolic, I., Pevec, D., Suznjevic, M., and Skorin-Kapov, L. (2017). A machine learning approach to classifying YouTube QoE based on encrypted network traffic. Multimedia Tools and Applications, 76(21), 22267-22301.

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1. Pevec, D., Vdovic, H., Gace, I., Sabolic, M., Babic, J., and Podobnik, V. (2019, July). Distributed Data Platform for Automotive Industry: A Robust Solution for Tackling Big Challenges of Big Data in Transportation Science. In 2019 15th International Conference on Telecommunications (ConTEL) (pp. 1-8). IEEE.
2. Pevec, D., Babic, J., Carvalho, A., Ghiassi-Farrokhfal, Y., Ketter, W., and Podobnik, V. (2019, June). Electric Vehicle Range Anxiety: An Obstacle for the Personal Transportation (R) evolution?. In 2019 4th International Conference on Smart and Sustainable Technologies (SpliTech) (pp. 1-8). IEEE.
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6. Pevec, D., and Podobnik, V. (2017, January). Decision Support System for Managing Electric Vehicle Charging Infrastructure. In The 14th International Conference on

Telecommunications–ConTEL 2017: PhD Forum.

7. Orsolic, I., Pevec, D., Suznjevic, M., and Skorin-Kapov, L. (2016, December). Youtube QoE estimation based on the analysis of encrypted network traffic using machine learning. In 2016 IEEE Globecom Workshops (GC Wkshps) (pp. 1-6). IEEE.

Životopis

Dario Pevec rođen je u Zagrebu 1991. godine. Diplomirao je na profilu Telekomunikacije i informatika na Sveučilištu u Zagrebu Fakultetu elektrotehnike i računarstva (FER), 2016. godine. Trenutno pohađa doktorski studij na istom fakultetu, uz financiranje Hrvatske zaklade za znanost. U sklopu doktorskog studija uspješno je održan kvalifikacijski doktorski ispit, 2017. godine, kao i javni razgovor 2018. godine na kojemu je definiran i naslov disertacije „Sustav za potporu odlučivanju o razvitku infrastrukture punionica za električna vozila zasnovan na podacima iz stvarnoga svijeta“. U sklopu rada na Fakultetu elektrotehnike i računarstva, Sveučilišta u Zagrebu provodi nastavne aktivnosti u sklopu nekoliko predmeta.

Pohađa ljetnu školu kompanije Ericsson Nikola Tesla (2015. godina) te radi na projektu "Analiza velike količine podataka u području mrežnog prometa". Nakon ljetne škole nastavlja suradnju s kompanijom Ericsson Nikola Tesla kroz diplomski rad. Od 2016. godine radi na Zavodu za telekomunikacije FER-a kao član „Laboratorija za društveno umrežavanje i društveno računarstvo (socialLAB)“ gdje obavlja istraživačke djelatnosti unutar istraživačkog projekta "Managing Trust and Coordinating Interactions in Smart Networks of People, Machines and Organizations" kojeg je financirala Hrvatska zaklada za znanost.

Kao doktorski student sudjeluje na nekoliko međunarodnih konferencija, radionica i doktorskih škola.