



# **Analysis and Optimization of the Charging Station Network in Germany**

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List of Symbols

$G$	—	Graph
$dist(u, v)$	m	Distance between node $u$ and $v$
$V$	—	Set of vertices
$E$	—	Set of edges
$N$	—	Number of vertices
$M$	—	Number of edges
$D(G)$	m	Diameter of graph $G$
$v_i$	—	Vertex with index $i$
$e_i$	—	Edge with index $i$
$L(G)$	m	Average distance of graph $G$

## List of Abbreviations

GA	Genetic Algorithm
EV	Electric Vehicles
RF	RandomForest
ML	Machine Learning
KNN	K-Nearest Neighbors
MAE	Mean Absolute Error
MSE	Mean Squared Error
EVCS	Electric Vehicle Charging Stations
FRLP	Flow Refueling Location Problem
MINLP	Mixed-Integer Non-Linear Programming
RVGA	Real-valued Genetic Algorithm
HGA	Hybrid Genetic Algorithm
PGA	Parallel Genetic Algorithm



# 1. Introduction

The transformation of the global automobile industry toward electric mobility is underway. Many factors may influence the EV market penetration:

**Anxiety of Range:** The phenomenon termed “range anxiety” is common among potential EV owners. Range anxiety refers to the worry that an EV has insufficient reach to get to its destination and would leave the driver stranded. It is one of the key barriers to EV adoption [1]. This fear can be mitigated by the availability of a comprehensive, convenient, and reliable charging network, thus directly linking EV market penetration to charging infrastructure [2].

**Infrastructure:** A critical factor influencing this trend is the availability and accessibility of Electric Vehicle (EV) charging infrastructure. It has been widely studied and proven that the prevalence of charging stations strongly influences the acceptance and adoption of EVs [3] [4] [5] [6]. In the U.S., a positive correlation between public infrastructure and EV uptake has been proven [6]. When charging infrastructure was more available and accessible, the likelihood of consumers purchasing an EV increased. Moreover, a study examined the influence of various factors on international electric vehicle policies and EV sales in 30 countries [7]. They found that charging infrastructure was among the most substantial determinants of national electric vehicle market share [8].

**Policies and Regulations:** Government policies also play a crucial role in the proliferation of charging stations and, consequently, the promotion of EV adoption. Incentives like grants, subsidies, and tax reductions have been applied in various countries to accelerate the deployment of EV charging stations [9]. Such policy measures have substantially impacted both the expansion of charging infrastructure and the adoption of electric vehicles.

**EV Prices, Battery Capacity:** While the charging infrastructure is a significant factor, other elements like EV prices, government subsidies, and battery capabilities are also key contributors to EV market penetration [9]. Reductions in battery prices and improvements in battery technology have increased the affordability and driving range of EVs, thereby supporting the growth of the EV market. Nevertheless, widespread EV adoption remains a challenge without an extensive and reliable charging network.

## 1.1 Factors Affecting Charging Station Location

The decision regarding the ideal placement of Electric Vehicle Charging Stations (EVCS) is a sophisticated process encompassing a plethora of considerations. Several interrelated quantitative and qualitative factors influence his decision, including but not limited to operator economics, driver satisfaction, vehicle power loss, traffic congestion, and power grid safety [10].

Falvo et al.'s work illustrates the role of reducing energy consumption by exploiting the capabilities of existing power plants. They draw attention to the interconnectivity of different transportation systems - EVs and subways - highlighting the potential for symbiotic relationships to optimize power usage. Their research sheds light on the strategic importance of aligning EVCS locations with the current power grid for energy efficiency, operational economics, and grid safety. It serves as a reminder that the placement of charging stations should be an integral part of broader urban energy planning [11].

Guo et al. present an alternative approach to the problem, employing a fuzzy TOPSIS method to assess potential locations. Their approach considers practical or economic factors and a broad array of environmental, economic, and social benchmarks. This underscores the importance of a holistic, multi-faceted evaluation process for locating EVCS. Beyond the fundamental requirements of power supply and accessibility, Guo et al. emphasize the need to assess potential locations' broader societal impact, environmental implications, and economic viability. These findings underscore that the decision-making process should not be limited to infrastructure and logistics alone but should strive to align with wider sustainable development goals [12].

Similarly, Asamer et al. propose a comprehensive, integrative approach to the placement of EVCS. They contend that several variables must be factored into the decision-making process, ranging from environmental conditions to the availability of power and legislative considerations. Significantly, they also highlight the importance of empirical data, employing taxi data as a proxy to assess charging demand. The utilization of real-world data, they suggest, can provide invaluable insights into patterns of use and potential demand hotspots, thus allowing for more targeted and effective placement of charging stations [13].

Building upon this foundation, Zhu et al. introduce an economic perspective into the analysis, evaluating how costs - both to the user and those associated with establishing and operating the charging stations - impact the final number and location of EVCS. This

underscores the need for a detailed cost-benefit analysis as part of the decision-making process. It also raises an important question of user satisfaction and accessibility, emphasizing that the locations need to be convenient for the end users to encourage uptake and continued use of EVs [14].

Complementing these perspectives, Sun et al. propose an innovative, user-centric approach. They consider residents' travel patterns, categorizing them as either short-distance or long-distance travelers. This differentiation aids in determining not only the optimal location for charging stations but also the appropriate number of stations needed. It serves as a reminder that the deployment of EVCS should not be a one-size-fits-all solution. Instead, it should be tailored to meet local residents' needs and ensuring maximum usability and efficacy [15].

In summary, the complex interplay of factors affecting the location of EVCS necessitates a multi-faceted and integrative approach. The studies mentioned above underline the need for strategies that balance technical requirements, economic feasibility, societal impact, and end-user needs. Through this careful balancing act, the optimal location for EVCS can be determined, thereby promoting widespread EV adoption and the resultant environmental benefits. The findings from these studies collectively demonstrate that the placement of EVCS is an intricate process, interweaving numerous factors and requiring comprehensive, multidimensional planning and assessment [10] - [15].

## **1.2 Optimization Models for EV Charging Station Distribution**

This section discusses various optimization models proposed by researchers for the distribution of EVCS. These models consider a broad spectrum of factors to help enhance the adoption of EVs and user satisfaction.

Frade et al. used a maximal covering model to identify potential demand areas and possible EVCS locations in Lisbon, aiming to maximize covered demands [16]. He et al. proposed a double-layer mathematical model considering vehicle driving distances and charging needs, underlining the importance of daily mobility patterns of EV users [17].

Shahraki et al. presented an optimization model maximizing vehicle mileage based on driving patterns, emphasizing the role of real-world data in location decisions [18]. Wu et al. designed a stochastic flow-capturing location model reflecting the randomness in EV users' traveling behavior [19].

Models by Tu et al. and Luo et al. included temporal and spatial constraints, making these models more realistic by considering variable parking availability, congestion levels, and EV owners' home and work locations [20] [21].

Battery characteristics have been factored into models by Liu et al. and Mehrjerdi et al., highlighting the need for different strategies for different charging applications, and the importance of power and capacity of charging facilities [22] [23].

He et al. and Davidov et al. incorporated economic aspects in their models, considering costs such as battery, charging station, and energy storage system expenses [24] [25].

Hosseini et al. integrated quantitative and qualitative aspects into their models, underlining the importance of subjective factors and user experience [26] [27].

Zeng et al. integrated human behavior into their station-level optimization framework, pointing out that station networks must accommodate user preferences [28].

Hodgson et al. further refined the models by considering EV charging during long trips and the limited range of EVs, which resulted in the Flow Refueling Location Problem (FRLP) [29] [30] [16].

The FRLP model has been extended to consider limited charging station capacity, alternative paths, different types of stations and vehicles, and congestion at stations [31] [32] [33] [34] [35] [36] [37]. Multi-period deterministic extensions of FRLP have been suggested, allowing for a dynamic opening of new stations and considering limited station capacity [38] [39].

Few studies have addressed uncertainties in EV charging infrastructure planning, such as unpredictable driving range or variability in recharging demand. Some recent works have introduced the concept of portable charging stations and advocated for robust optimization approaches [40] [41] [42] [43] [44].

These diverse models demonstrate the multi-faceted nature of EVCS placement and the need for comprehensive, flexible approaches incorporating demand characteristics, technical specifications, cost factors, and human behaviors to promote EV adoption and environmental benefits [16] - [28].

### **1.3 Algorithm for Optimal EV Charging Station Configuration**

This section discusses various optimization techniques used to determine optimal configurations of EVCS. The methods include optimization methods, genetic algorithms, decomposition algorithms, clustering methods, and combinations of these techniques.

Sadeghi-Barzani et al. used a mixed-integer non-linear programming (MINLP) optimization method and a genetic algorithm to find the optimal EVCS location and scale [45]. Arslan et al. utilized the Benders decomposition algorithm to optimize EVCS location, aiming to maximize mileage and minimize transportation costs [46].

Zhang et al. introduced a decentralized valley-filling charging strategy that used a cost-minimization pricing scheme, emphasizing the importance of pricing mechanisms [47]. Dong et al. applied the SNN clustering algorithm for optimizing EVCS placement on expressways [YYY].

Zhu et al. and Akbari et al. used genetic algorithms for optimizing EVCS locations, acknowledging the interplay between technical specifications, user charging demand, and spatial factors [48] [49]. Awasthi et al. combined a genetic algorithm with particle swarm optimization to determine optimal EVCS location and size [50].

Particle swarm optimization algorithms have been used by Li et al. and Chen et al. to determine EVCS deployment strategy and charging facility distribution [XXXX] [51]. Clustering methods like k-means cluster analysis were employed by Zhang et al. and Straka et al. to understand dynamic charging demand trends and user behavior [52] [53].

Wu et al. used approximate dynamic programming and an evolutionary algorithm to determine optimal charging start times for EVs, demonstrating the interest in smart charging strategies [54].

Despite these advancements, the article identifies gaps, including the lack of comprehensive analyses considering total social cost, underutilization of genetic algorithms, and limited case studies of specific charging station scenarios, like those in Ireland.

To address these gaps, the article proposes an optimal distribution model of EVCS based on total social cost, utilizing a genetic algorithm for iterative simulation. This model deviates from traditional reliance on Euclidean distance and includes a road bending coefficient. The article also incorporates a case study of Ireland, reflecting actual EV charging demand in five major cities. This approach provides a promising direction for future EVCS optimization research [45] - [54].

#### **1.4 Structure of this work and novelty**

This section aims to summarize the fundamental points of this work and the innovations compared to similar works. The first peculiarity is to approach the problem using graph

theory. Each charging station is considered a point (of which latitude and longitude are known) and is connected to every other point below a search distance. This distance is calculated as road distance (including one-way streets and dead ends) and therefore, represents a good approximation. Each edge of the graph is weighted with the distance between the two points that the branch connects. By doing so, a national graph is obtained from which it is possible to calculate parameters useful for optimization (e.g., diameter). Using these parameters ensures that positioning the charging stations not only follows the logic of demand-population (which creates large urban agglomerations as in the case of Berlin), but also improves the network by including peripheral areas and connecting points that, before, were divided. This way, clusters are not created in Munich and Berlin, but points are also inserted so that Munich and Berlin can be reached by car at a finite number of stations/stops.

A genetic algorithm was used to optimize the network as it is the most flexible to consider multiple parameters. Another novelty in the work is that predictive methods have been used within the algorithm to identify the optimal position for the initial population. This is done to obtain a more plausible provision and, indirectly, mimic the different economic and political positions of the various Lands on this issue. To accentuate the objective of extending the network to the suburbs, in addition to the parameters of the graph, the relationship between the area covered by the network and the territorial extension of Germany is also used.

## 2. Model and Analysis

### 2.1 Network Theory

#### 2.1.1 Diameter

The diameter of a graph is a fundamental concept in the field of graph theory, offering significant insights into the overall structural properties of the graph. In a formal sense, the diameter of a graph is defined as the greatest shortest path length between any pair of vertices within the graph. It signifies the longest of all the shortest paths which can be navigated from one vertex to any other vertex within the graph [55]. To express this mathematically, let's denote a graph as  $G = (V, E)$ , where  $V = \{v_1, v_2, v_3, \dots, v_N\}$  is the set of  $N$  vertices and  $E = \{e_1, e_2, e_3, \dots, e_M\}$  is the set of  $M$  edges present in the graph. For any pair of vertices,  $u$  and  $v$  in  $V$ , let  $dist(u, v)$  denote the shortest path distance between these vertices. Thus, the diameter  $D$  of  $G$  is represented by the Equation 2-1.

$$D(G) = \max_{u, v \in V} dist(u, v) \quad 2-1$$

Here, the diameter  $D$  is the maximum over all shortest path distances  $dist(u, v)$  for every pair of vertices  $u$  and  $v$  in the graph [56]. In the case of a disconnected graph, where there exist vertices that do not have a path between them, the diameter is often defined as infinity. For a graph containing only a single vertex, the diameter is defined as 0. The concept of the diameter of a graph is applied in numerous applications, such as in network design and analysis, devising algorithms for effective information routing in distributed systems, and in discerning the structure of social networks among others [57]. It's important to note that the process of calculating the diameter of a graph can be computationally expensive, particularly for large graphs. A number of algorithms have been developed to compute the diameter of a graph, which include but are not limited to, the Floyd-Warshall algorithm and Johnson's algorithm [56].

#### 2.1.2 Average Distance

The average distance in a graph, also known as the average path length or the characteristic path length, is another crucial concept in graph theory. This metric gives an indication of the overall navigability and connectivity of the graph. Formally, the average distance  $L(G)$  is the mean shortest path length between all pairs of vertices in the graph. That is, it represents the expected distance between two vertices chosen uniformly at random [57]. The average distance  $L$  of  $G$  can be given by the formula stated in Equation 2-2.

$$L(G) = \frac{1}{N(N-1)} \sum_{u,v \in V} dist(u,v) \quad 2-2$$

Here, the sum is over all pairs of distinct vertices, and  $n$  is the number of vertices in the graph. Essentially, we are summing up the shortest path distances between all pairs of vertices and then dividing by the total number of such pairs [56]. The average distance is a critical metric in understanding the properties of real-world networks, which often exhibit the small-world property. The small-world property describes networks where the average path length is relatively small, meaning that one can get from any given node to any other node in the network through a small number of steps [57]. It's important to note that the average distance only makes sense for connected graphs, where a path exists between every pair of vertices. If a graph is not connected, this metric can't be defined without modification.

### 2.1.3 Average Clustering

The average clustering coefficient is an essential measure in the field of graph theory, frequently used to evaluate the tendency of nodes in a network to cluster together. It provides insights into the overall clustering of the graph and the interconnectedness of its nodes. The clustering coefficient of a single node in a graph quantifies how close its neighbors are to being a complete graph. A complete graph is one where every pair of vertices is connected by a unique edge. The average clustering coefficient is simply the mean of the clustering coefficients of all the nodes in the graph [57]. To be more precise, let  $K_v$  denote the number of vertices that are neighbors of  $v$ , and let  $E_v$  denote the number of edges between the neighbors of  $v$ . The clustering coefficient  $C_v$  for the node  $v$  is given by:

$$C_v = 2E_v / K_v(K_v - 1)$$

The average clustering coefficient  $C$  of the graph is then calculated as:

$$C = \sum C_v / n$$

Here, the sum is over all vertices in the graph, and  $n$  is the total number of vertices [56]. The average clustering coefficient measures the degree to which nodes in a graph tend to



cluster together. It has found widespread application in the study of various types of networks, such as social networks, biological networks, and the World Wide Web, among others [57]. In calculating the average clustering coefficient, it is important to note that it is typically only defined for nodes with at least two neighbors, since the denominator of the formula for  $C_v$  would be zero for nodes with fewer than two neighbors. Computing the average clustering coefficient can be a computationally intensive task, especially for larger networks. Various algorithms have been developed to more efficiently calculate it, but the computational complexity is generally high due to the need to examine the local neighborhood of each node [56].

## 2.2 Genetic Algorithm<sup>1</sup>

Genetic Algorithms (GAs) are a family of search and optimization techniques inspired by the concept of natural selection [58]. Throughout time, GAs have been effectively used to resolve a vast variety of engineering challenges, covering function optimization, machine learning, and scheduling, as cited in reference [59]. This section provides a comprehensive overview of Genetic Algorithms, addressing their theoretical basis, elements, and variants. It also points out the positive and negative aspects of GAs.

The theoretical inspiration of GAs is based on the fundamental principles of biological evolution. According to Darwin's theory of evolution, the most physically fit people are chosen for reproduction, passing on their qualities to the next generation. Over a period of time, this phenomenon results in the acclimatization of species to their surroundings, thereby enhancing their likelihood of survival.

In GAs, a population consists of a set of potential solutions, each referred to as an individual. Genetic operators such as selection, crossover, and mutation are applied to this population. These operators simulate an evolutionary process that occurs over multiple generations [58]. The iterative nature of GAs enables efficient search space exploration and convergence to optimal or near-optimal solutions [60].

### 2.2.1 Process

**Representation** is an essential component of Genetic Algorithms, as it defines how potential solutions are encoded for the manipulation within the algorithm. The format that is used the most often is the binary string, where each possible answer is represented as a

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<sup>1</sup> This section is a slightly modified version of the Section 4.2. "Genetic algorithm" of the thesis "Automation of Design Synthesis for Electric Vehicle Transmission" published by the same author of this thesis and has been reproduced here with the permission of the copyright holder [77]

series of binary digits (0s and 1s) [58]. According to the nature of the issue, different representations, such as real-valued vectors, integers, and permutations, may also be utilized [59].

An **initial population** of potential solutions is created during the startup phase (cf. Figure 1). Both random and domain-specific information may be used to create this population [61]. The choice of population size is based on the complexity of the issue at hand and the preferred ratio of exploitation to exploration [62].

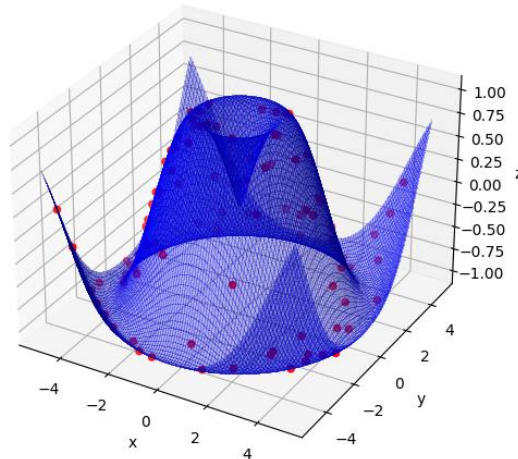


Figure 1: Initial population on Wave function

The **fitness function** is a way to measure the “quality” of each individual in the population. It acts as a gauge of how effectively the solution fulfills both the objectives and the constraints of the challenge [58]. The fitness function must be created to represent the intended result and to direct the search for the best solutions [63].

**Selection** is the process of choosing individuals from the present population to engage in reproduction in order to have the population aggregate around an ideal solution (cf. Figure 2). This mechanism has a preference for those with greater levels of fitness, which is consistent with the concept of “survival of the fittest” [58]. Numerous selection methods have been put forward in the literature, including proportional selection [59], tournament selection [64], and ranking-based selection [65], have been proposed in the literature.

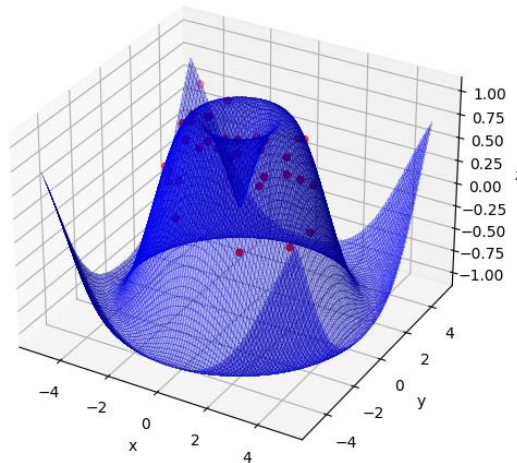


Figure 2: Selected individuals from the initial population (cf. Figure 1). The individuals closest to the peak are preserved since they have the best fitness

The act of integrating the genetic material from two parent solutions to produce one or more child solutions is known as a **crossover**, often referred to as recombination. Crossover aims to explore the search area by developing new solutions that may have higher fitness values [58]. Common crossover operators include single-point, multi-point, and uniform crossover [59].

**Elitism** is an optional element of genetic algorithms that guarantees the preservation of the best person(s), called incumbent, in each generation [60]. Elitism works to stop the loss of the best solutions brought on by genetic operators (e.g., crossover) and to direct search efforts in the direction of the ideal solution by keeping a copy of the fittest individual(s) [59].

### 2.2.2 Variants

In order to improve their efficiency and customize them for certain problem domains, many variations of genetic algorithms have been presented. Below is a discussion of a few of the more common variations:

- **Real-valued Genetic Algorithms (RVGAs):** employ real-valued representations rather than binary strings, enabling a more accurate and effective description of certain problem domains [66]. Arithmetic crossover [67] and non-uniform mutation [68] are two examples of the specific crossover and mutation operators needed for RVGAs.
- **Constraint-Handling Techniques:** GAs must take into account restrictions in order to effectively solve optimization issues in the real world. Numerous methods for

addressing constraints have been put forward, such as penalty functions [69], repair algorithms [70], and multi-objective approaches [63].

- Hybrid Genetic Algorithms (HGAs): combine GAs with additional optimization methods to enhance convergence and search effectiveness [71]. Hill climbing or simulated annealing are two examples of local search techniques that are often used into HGAs to improve the solutions produced by GAs [72].
- Parallel Genetic Algorithms (PGAs): make use of GAs' built-in parallelism to improve performance [73]. PGAs may be implemented using a variety of parallelization techniques, including island models, fine-grained parallelization, and global parallelization.

### 2.2.3 Strengths and Weakness of Genetic Algorithms

Strengths:

- Global search capability: due to their lower propensity to get stuck in local optima than gradient-based approaches, GAs are well-suited for identifying global optima in complicated search domains [59].
- Applicability: GAs can be applied to a wide range of optimization problems, as they only require the definition of a fitness function and an appropriate representation [58].
- Robustness: GAs are resilient and simple to apply in real-world problems since they are comparatively insensitive to parameter selection [60].
- Parallelism: GAs may be significantly speed up by leveraging parallel computer resources since they are inherently parallelizable [73].

Weakness:

- Slow convergence: GAs may take a while to converge, particularly in cases where the search spaces are big and complex, or the population is huge [59].
- Premature convergence: GAs can sometimes converge prematurely to suboptimal solutions, particularly if the selection pressure is too high or the mutation rate is too low [60].
- Problem-dependent performance: depending on the problem domain and the selected representation, crossover, and mutation operators, the performance of GAs might vary dramatically [59].

Parameter tuning: although GAs are generally reliable, determining the ideal set of parameters for a given issue may be difficult and time-consuming [62].

## 2.3 Interpolations Methods

Test

## 2.4 Model Overview

### 2.4.1 Initial Population

The ongoing transition towards sustainable transportation solutions has been marked by the proliferation of electric vehicles (EVs). However, a critical challenge remains in ensuring an adequate and efficiently distributed network of charging stations. This study addresses this challenge by utilizing Machine Learning (ML) techniques, specifically Random Forest (RF) and K-Nearest Neighbors (KNN), to predict the optimal locations for future charging stations. Machine Learning is a branch of artificial intelligence that learns patterns in data and makes predictions or decisions without explicit programming. Random Forest and K-Nearest Neighbors are two widely-used ML algorithms. Random Forest, a bagging-based ensemble learning technique, builds multiple decision trees and aggregates their outputs, resulting in improved accuracy and control of over-fitting [74]. KNN is a type of instance-based learning or lazy learning, where the function is approximated locally, and all computation is deferred until prediction [75]. It uses the feature similarity approach to predict the values of new data points, which further means that the new point will be assigned a value based on how closely it matches the points in the training set. Initially, both models were trained and tested using a dataset containing information about existing charging stations, including location coordinates and the year of installation. The predictive performance of each model was evaluated based on three metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and R2 score. The MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. MSE, similar to MAE, punishes larger errors, which tends to be useful in the real world as it punishes large errors. Lastly, the R2 score, also known as the coefficient of determination, quantifies the proportion of the variance in the dependent variable that is predictable from the independent variable(s) [76]. Upon evaluation, the Random Forest model outperformed KNN on all metrics, suggesting that it is better suited for this prediction task. The RF model achieved an R2 score of 0.921 for latitude and 0.867 for longitude, indicating that it was able to explain approximately 92.1% and 86.7% of the variance in the test dataset for latitude and longitude, respectively. Following the evaluation, the chosen RF model was trained on the entire dataset, divided by year. This process allows for the capture of annual trends in the establishment of charging stations,

thereby providing a robust model that accounts for temporal variations. The trained models were then deployed in a genetic algorithm to generate an initial population, which suggests promising sites for new charging stations. Genetic algorithms are a type of optimization algorithm that mimics the process of natural selection, using methods such as mutation and crossover to generate new generations of solutions [58]. In this application, each “individual” represents a potential layout of new charging stations. The predictive models were used to estimate the location of new stations in each federal state, based on the state’s proportion of total stations. This approach ensures that the stations are distributed in a way that reflects the historical patterns of station placement, while also considering the need for more stations in areas with higher demand. The integration of predictive models into the genetic algorithm allowed for a data-driven approach to generate initial populations, potentially improving the efficiency and effectiveness of the optimization process. In conclusion, the implementation of ML techniques, particularly Random Forest, in conjunction with genetic algorithms, presents a promising methodology for predicting the optimal placement of EV charging stations. This study adds to the growing body of research on ML-based decision support systems in the field of sustainable transportation.

### 3. Results

Test

#### 3.1 Pre-Processing

The raw dataset, procured from the Federal Network Agency, underwent meticulous preprocessing to render it suitable for subsequent analysis. This preprocessing involved several steps aimed at enhancing the quality and readability of the data, thereby facilitating more accurate and effective analysis. One key aspect of the preprocessing was the elimination of duplicate entries from the dataset. It is not uncommon for datasets, particularly those aggregated from multiple sources or entered manually, to contain duplicate entries. Duplicate entries, if not removed, can lead to redundancy in the data and distort the subsequent analysis. Thus, duplicate entries in the dataset were identified and carefully pruned to create a streamlined and precise representation of the unique electric vehicle charging stations distributed across the regions. Following this, the data underwent a process of transformation aimed at standardizing its structure and making it more conducive to analysis. A prime example of this is the transformation of the ‘*type\_of\_charger*’ variable. The original values, ‘*Schnellladeeinrichtung*’ and

'*Normalladeeinrichtung*', were remapped to 'fast' and 'normal' respectively. This alteration simplified the task of classifying charging stations based on their charging speed, thereby paving the way for more straightforward subsequent analysis. In the original dataset, geographical coordinates were presented in a format unsuitable for computational processing, with commas employed as decimal points. This posed significant challenges for any computational or spatial analyses that relied on these coordinates. To address this, the commas were replaced with decimal points, and these columns were converted to the float data type. Consequently, calculations involving distances became significantly more straightforward, and the feasibility of creating detailed geospatial visualizations was substantially improved. Another vital transformation step involved the '*commissioning\_date*' column, which stored the commissioning date of each charging station as a string in the day-month-year format. For a more detailed and useful chronological analysis, it was necessary to convert this data into a datetime format. This modification facilitated an overview of the temporal progression of charging station installations, offering valuable insights into their spread over time. Additionally, leading and trailing spaces found in several columns of the dataset were removed to maintain uniformity in the data. Ensuring this consistency was especially important for object columns, such as city names, where minor differences in formatting could lead to inaccurate grouping or comparison of values. The city names present in the dataset were also standardized for improved accuracy and simplicity. Distinct neighborhoods or districts within a city, initially represented separately, were consolidated under the name of the main city. This step significantly reduced geographical complexity during the analysis, fostering a more coherent representation of data. In a further move to streamline the dataset, certain columns containing public keys were dropped. Although these keys are commonly used for cryptographic operations, they were deemed irrelevant to the intended study and were therefore excluded from the dataset, leading to a more simplified data structure. In the final stage of preprocessing, the refined dataset was saved into a new CSV file termed '*ChargingStationCleaned.csv*'. This file stands as a meticulously cleaned and preprocessed version of the original dataset, primed for a detailed examination of the distribution, characteristics, and evolution of electric vehicle charging stations across Germany.

### 3.2 Data analysis

Test

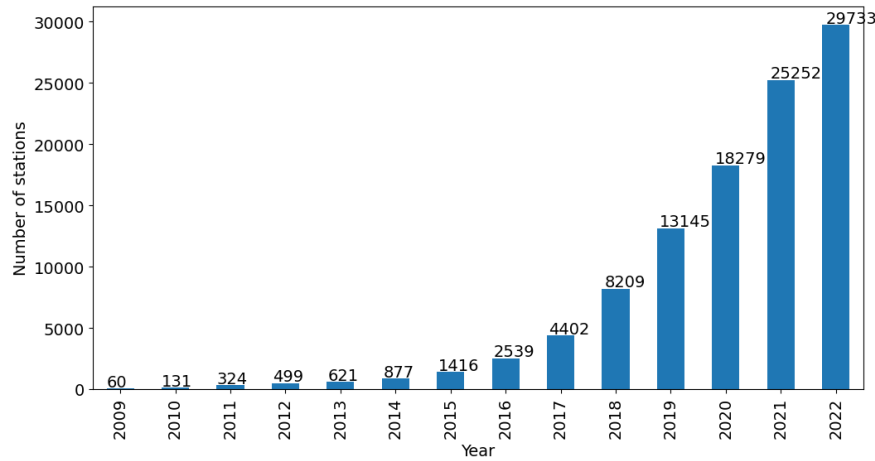


Figure 3: Cumulative histogram per year

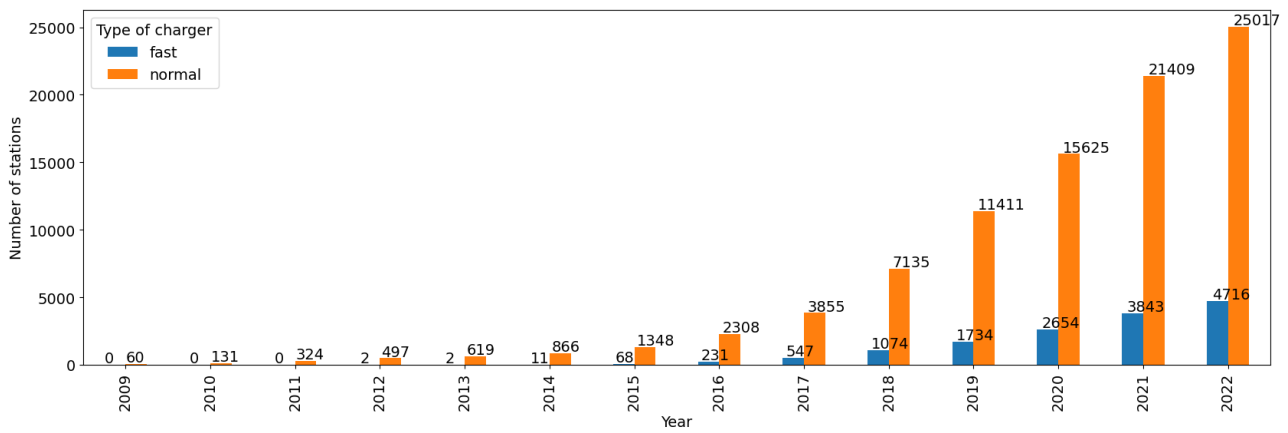


Figure 4: Cumulative histogram per year divided into Normal and Fast charging

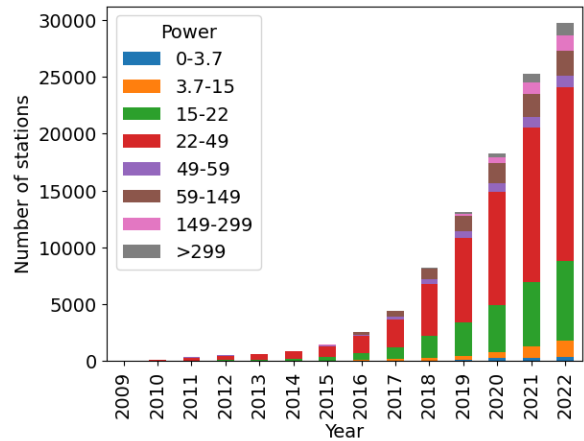


Figure 5: Power clustering histogram per year



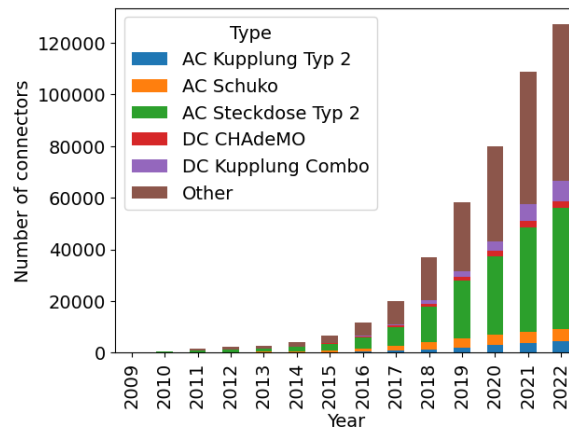


Figure 6: Charging Type clustering per year

### 3.3 Network construction

To further scrutinize the distribution and accessibility of electric vehicle charging stations across various geographical regions, a meticulous process for network creation was deployed. The outcome was a detailed and comprehensive graphical representation, visualizing connections between the charging stations for specified years and within user-determined distance parameters. Several programming libraries, each with a unique role, were brought into play in this complex process. The `sqlite3` library provided the means for interaction with a SQLite database. The `requests` library was employed to handle HTTP requests required for distance calculation, whereas the `math` library was used to compute intricate mathematical operations, including trigonometric functions necessary for distance calculations. The `urllib3` library, an HTTP client for Python, managed and streamlined HTTP protocol details. The `Transformer` module from the `pyproj` library was crucial for geographic coordinate conversions. An important part of this procedure was the calculation of the Haversine distance, a method utilized to determine the ‘great-circle’ distance between two points on the Earth’s surface given their longitudes and latitudes. Here, the Earth was assumed to be a perfect sphere, and its radius was taken as 6371 kilometers. The function `get_osrm_distance` was developed for more accurate distance measurements. This function initially made a quick estimation based on the Haversine formula. If this approximated distance was found to be less than or equal to 100 kilometers, the Open-Source Routing Machine (OSRM) service was employed. OSRM is an open-source service that uses data from the OpenStreetMap project to find the shortest routes between coordinates. Efficiency and speed were prioritized by creating a SQLite database named ‘distances.db’, intended to save previously calculated distances. This efficient system considerably reduced the need for repetitive API calls to the OSRM service. If a previously calculated distance value was found in the database, it was

retrieved and returned. If not, the function executed an API call to the OSRM service, acquired the precise distance, and subsequently stored this new distance value in the database for future use. The subsequent phase of the process was encapsulated in the `create_network` function. This function utilized the previously described distance calculations to construct an undirected graph, which served as a representation of the network of charging stations for a particular year and within a user-specified distance threshold. Each node in the graph corresponded to an electric vehicle charging station, assigned with specific attributes like latitude, longitude, and federal state. Edges between these nodes were added based on the distance between them, calculated by the `get_osrm_distance` function. After the graph's construction, it was visualized on a map. For geographical reference, the boundaries of Germany were used as a backdrop. These boundaries were acquired from a GeoJSON file. The resulting visual output was a graph overlaid on Germany's geographic boundaries, portraying the spread of charging stations and the connectivity between them. The final phase of this process was storing the constructed graph for future uses. The graph was saved in the GraphML format, a comprehensive and easy-to-use file format for graphs, enabling potential future network analysis. Moreover, a visual representation of the graph was saved as a PNG image. This image served as an easily accessible, ready-to-view snapshot of the network for the designated year and distance threshold, aiding in immediate analysis and comparison.

Year	Diameter	Average Distance	Average Clustering	Density	Total nodes	Subnetwork size
2009	1.00	15.10	0.93	1.00	60	[2, 2, 23, 4, 26]
2010	4.20	36.71	0.90	0.64	130	[14, 77, 38]
2011	8.27	41.38	0.86	0.42	320	[256, 61]
2012	11.00	43.65	0.85	0.18	494	[494]
2013	11.96	47.52	0.83	0.17	615	[613, 2]
2014	12.00	51.92	0.81	0.15	861	[861]
2015	11.00	50.75	0.80	0.11	1393	[1393]
2016	11.00	51.70	0.78	0.10	2503	[2503]
2017	10.00	53.26	0.77	0.09	4350	[4350]
2018	09.00	56.99	0.75	0.09	8135	[8135]
2019	09.00	57.93	0.76	0.09	13012	[13012]
2020	09.00	58.24	0.74	0.09	18103	[18103]
2021	09.00	58.43	0.77	0.10	25040	[25040]
2022	09.00	58.36	0.74	0.10	29481	[29481]

Table 1: Characteristics of the different network created

### 3.4 Optimization

Test

### 3.5 Test Cases

Test

	Optimized Network 2015	Real Network 2015
Density	0.11	0.11
Average Distance	52.3	50.7
Diameter	10	11
Average Clustering	0.724	0.831
Num. of stations	1393	1393

Table 2: Comparison between the obtained network and the real network in 2015

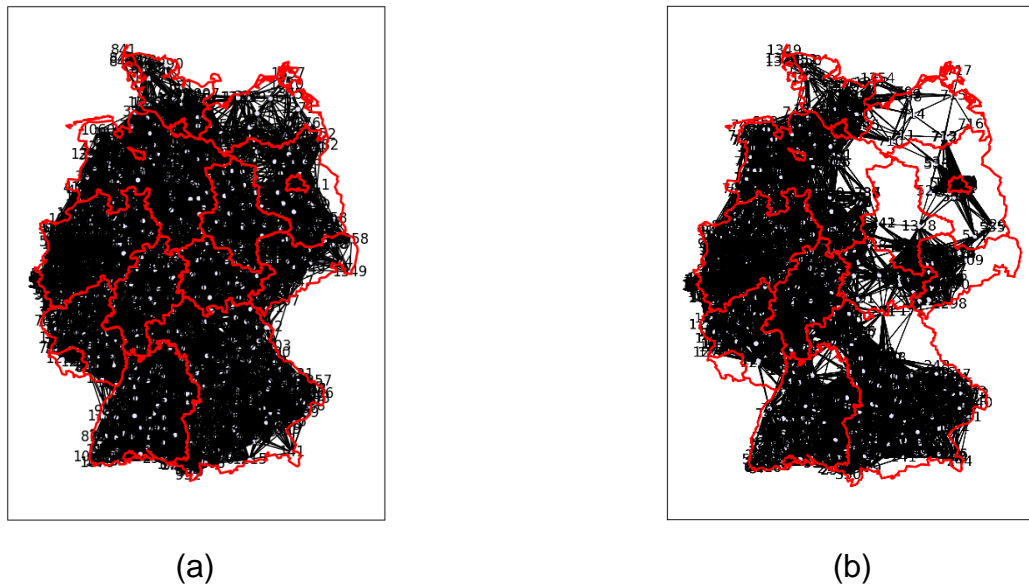


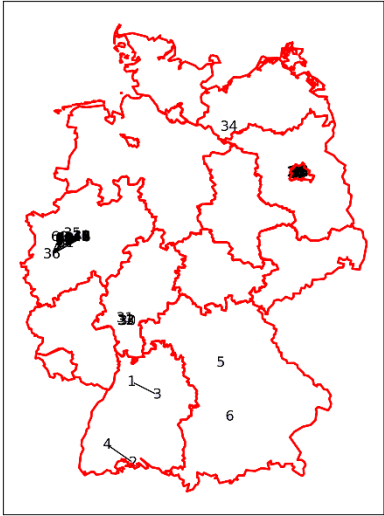
Figure 7: Optimized network (a) and real network (b) for year 2015

## 4. Conclusion and Further Implementations

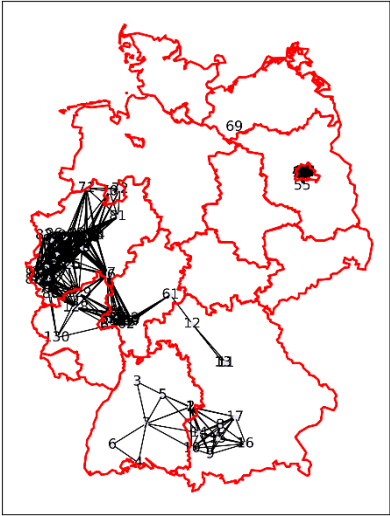
Test

# 5. Appendix

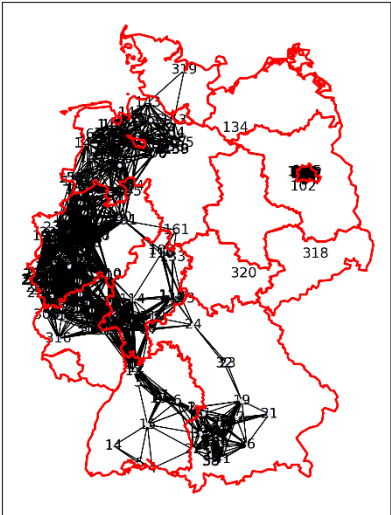
## 5.1 Network evolution of Germany



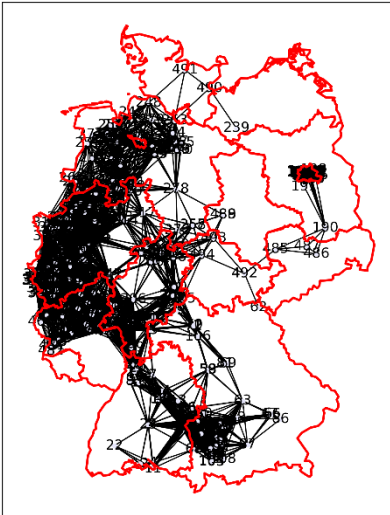
(2009)



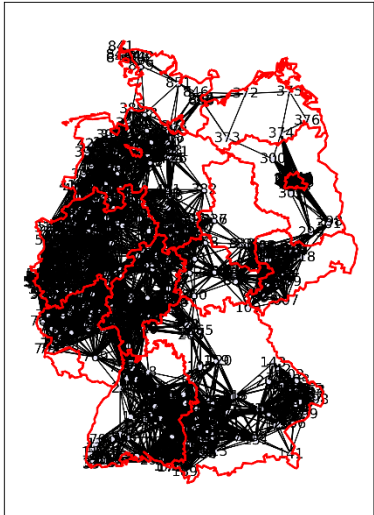
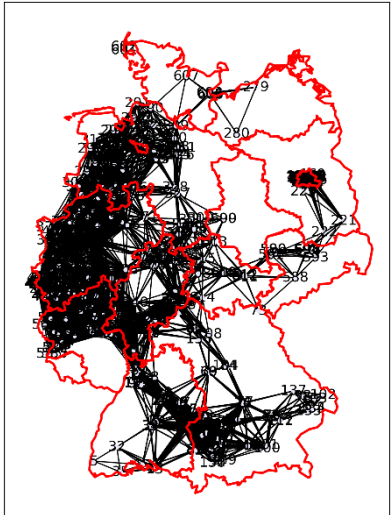
(2010)



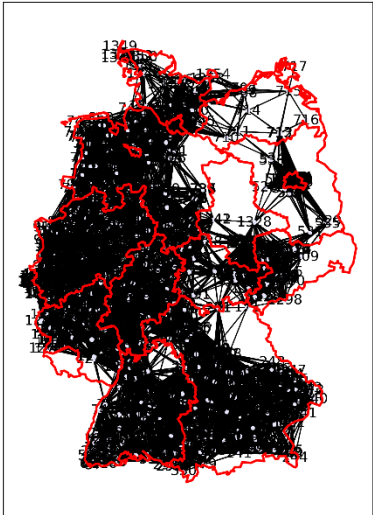
(2011)



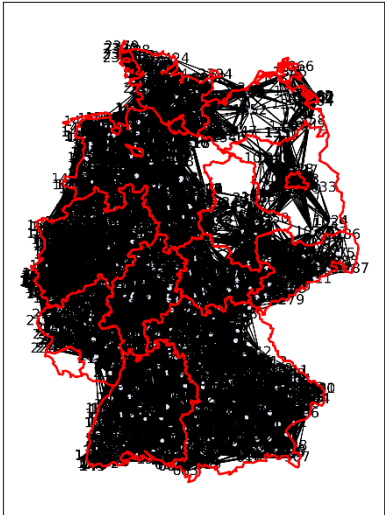
(2012)



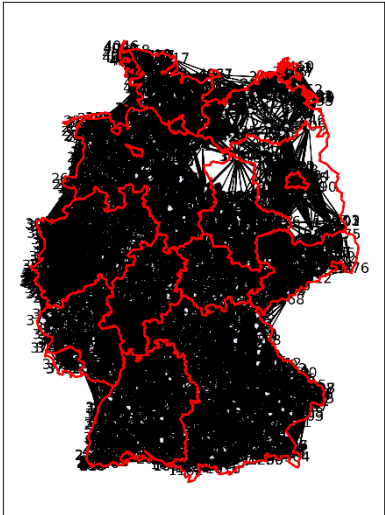
(2013)



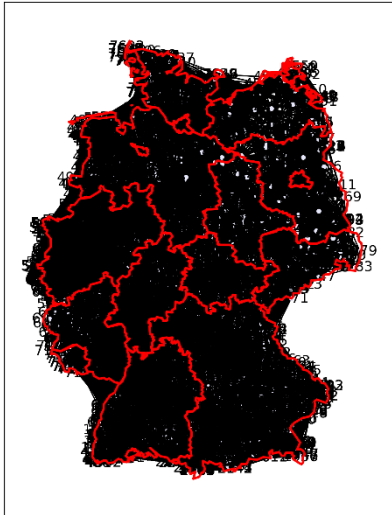
(2014)



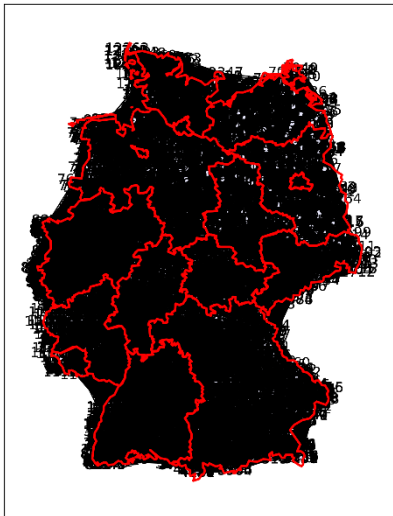
(2015)



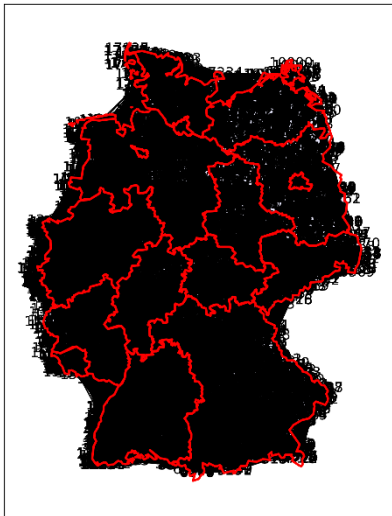
(2016)



(2017)



(2018)



(2019)



(2020)



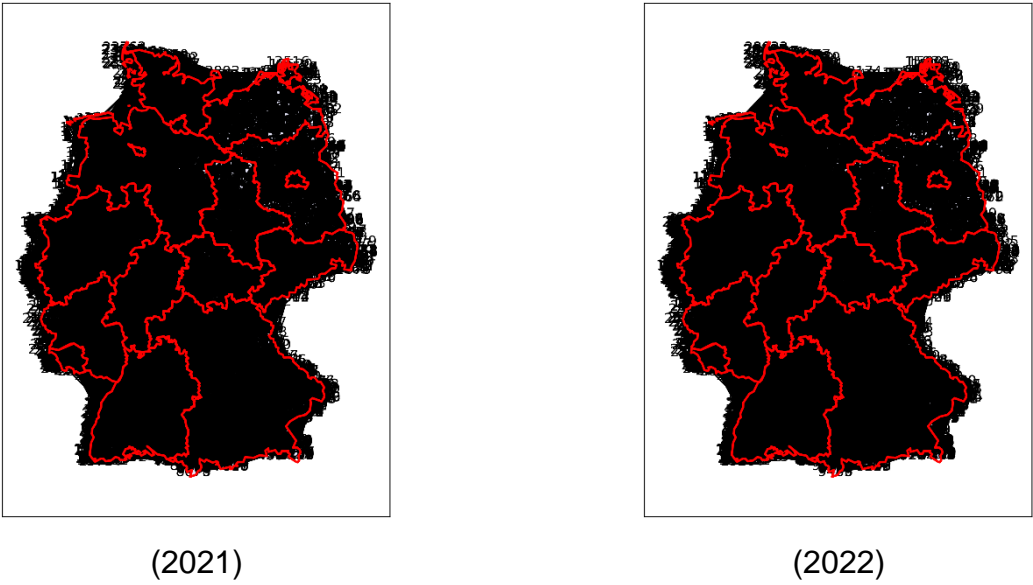


Figure 8: Evolution of the charging station network in Germany from 2009 to 2022

5.2 Per-year optimization results

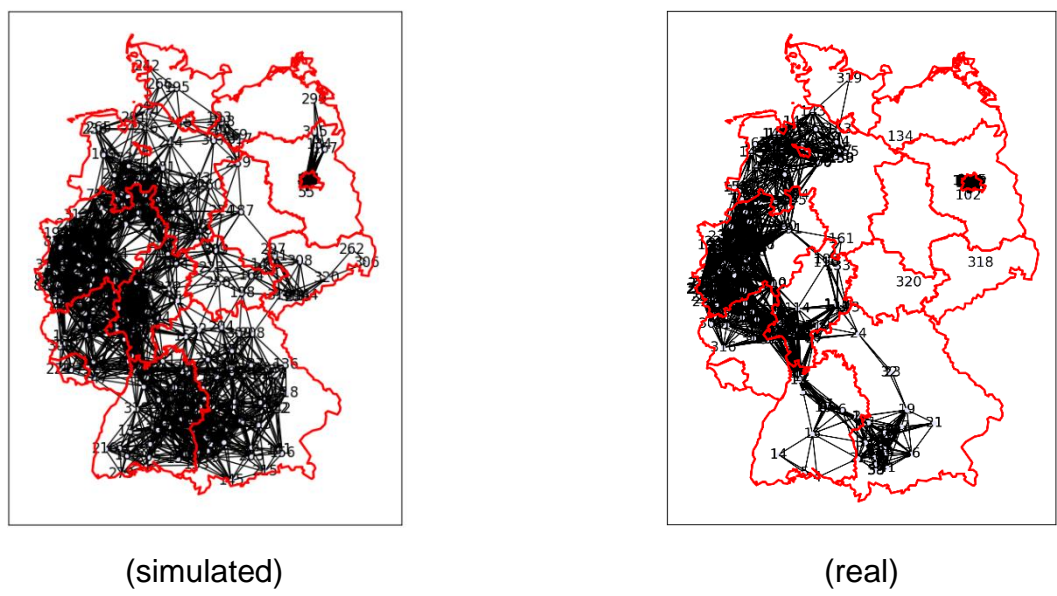


Figure 9: Simulated and real network in 2011

Parameters	Opt	Real
Density	0.24	
Average Distance	54.06	
Diameter	8.95	
Average Clustering	0.7438	
Num. of stations	[278,42]	

Table 3: Parameters comparison between the obtained network and the real network in 2011

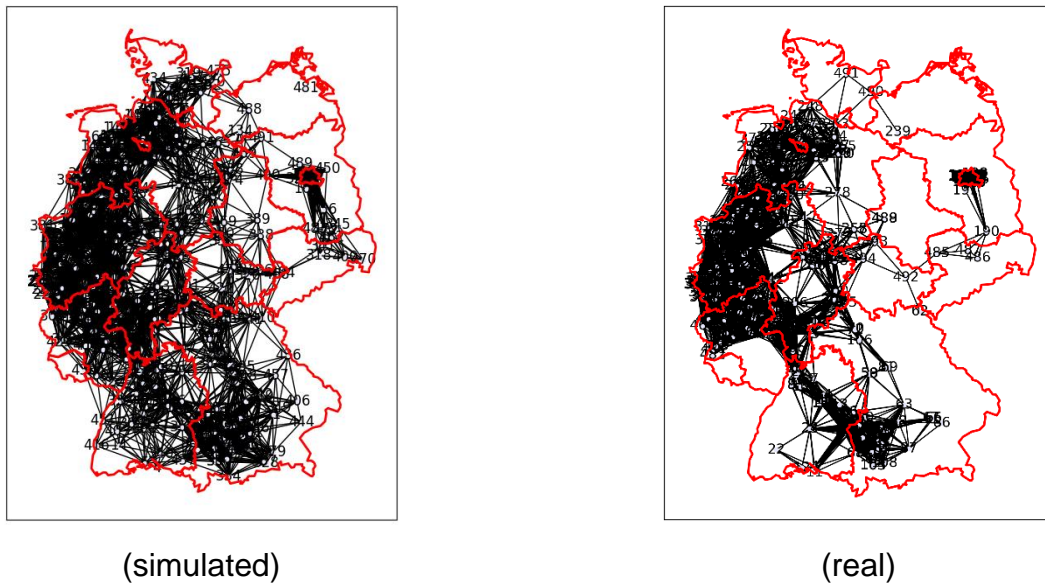


Figure 10: Simulated and real network in 2012

Parameters	Opt	Real
Density	0.14	
Average Distance	50.16	
Diameter	9.0	
Average Clustering	0.76	
Num. of stations	494	

Table 4: Parameters comparison between the obtained network and the real network in 2012



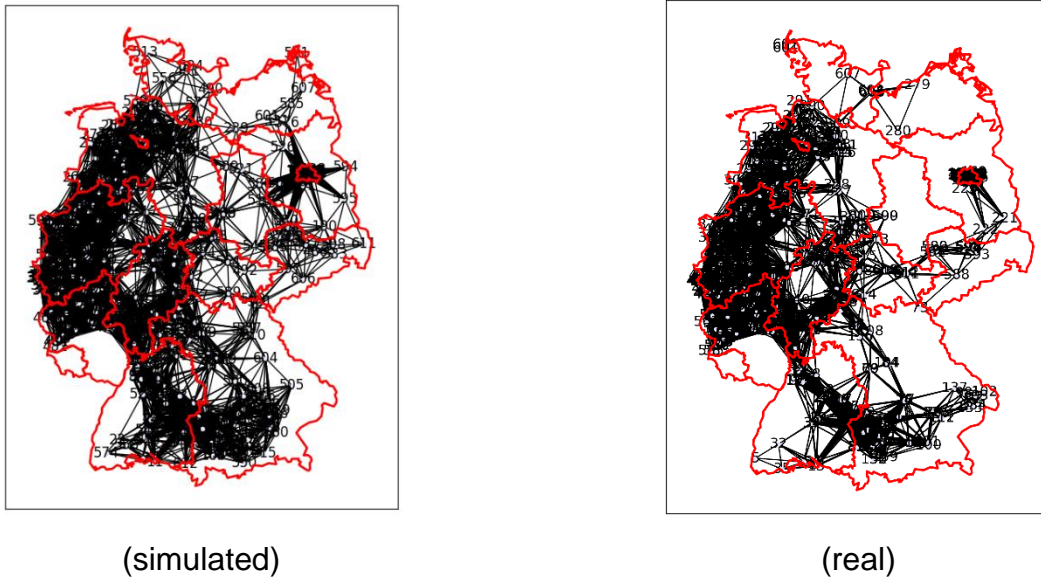


Figure 11: Simulated and real network in 2013

Parameters	Opt	Real
Density	0.144	
Average Distance	48.08	
Diameter	10.0	
Average Clustering	0.813	
Num. of stations	615	

Table 5: Parameters comparison between the obtained network and the real network in 2013

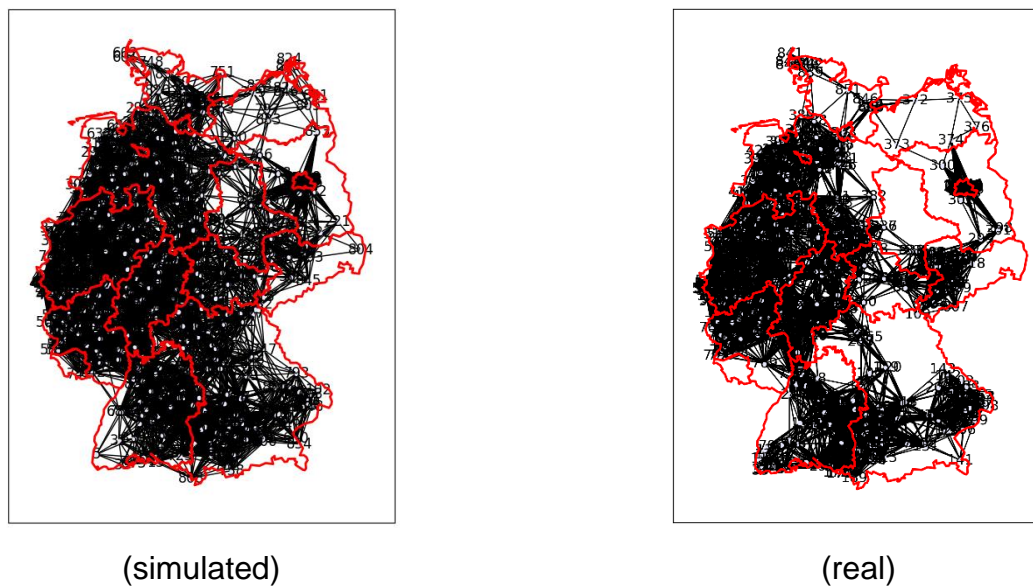


Figure 12: Simulated and real network in 2014

Parameters	Opt	Real
Density	0.13	
Average Distance	53.96	
Diameter	10.0	
Average Clustering	0.781	
Num. of stations	861	

Table 6: Parameters comparison between the obtained network and the real network in 2014

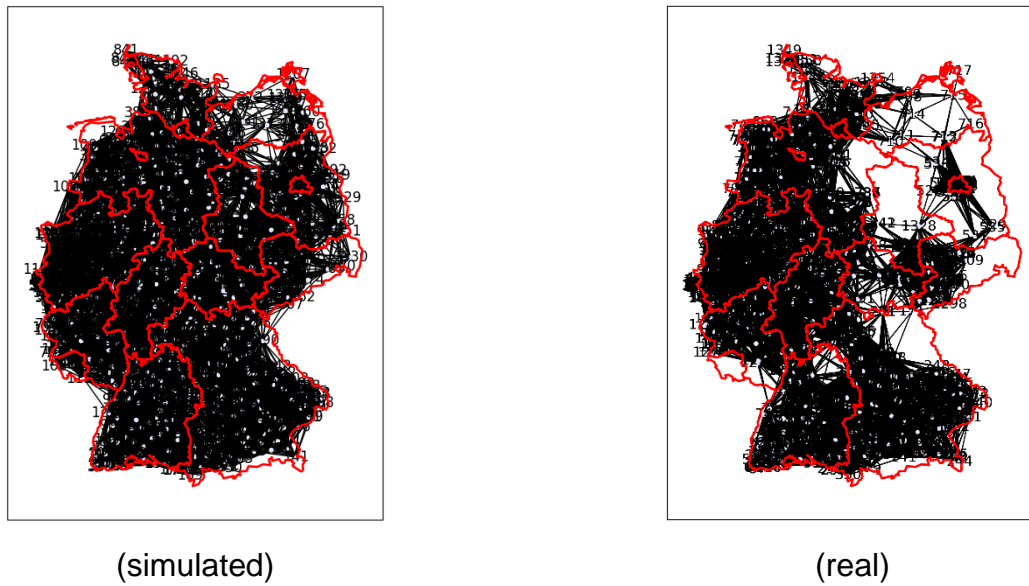


Figure 13: Simulated and real network in 2015

Parameters	Opt	Real
Density	0.1127	
Average Distance	58.153	
Diameter	10.0	
Average Clustering	0.738	
Num. of stations	1393	

Table 7: Parameters comparison between the obtained network and the real network in 2015

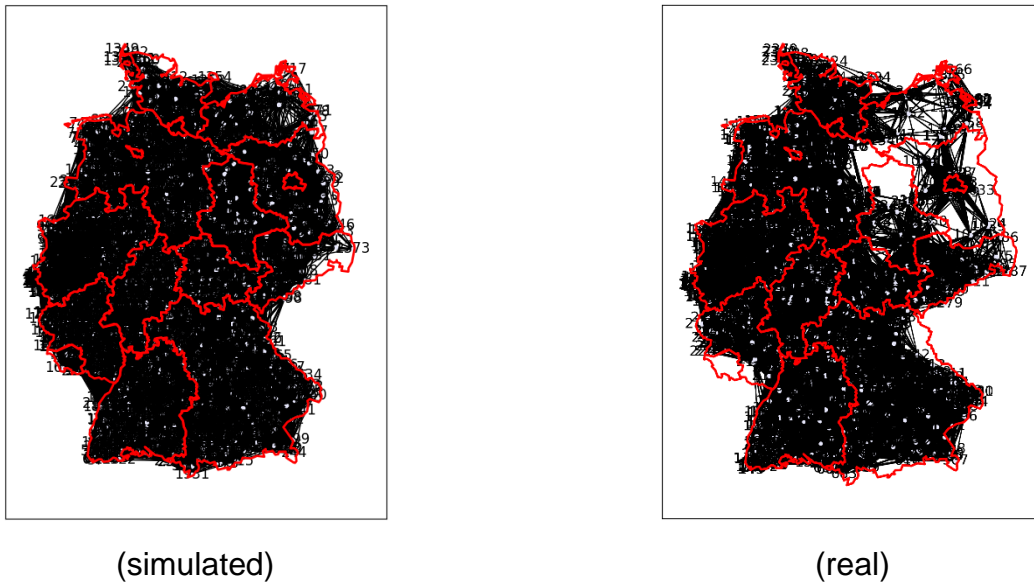


Figure 14: Simulated and real network in 2016

Parameters	Opt	Real
Density	0.094	
Average Distance	59.563	
Diameter	8.0	
Average Clustering	0.73	
Num. of stations	2503	

Table 8: Parameters comparison between the obtained network and the real network in 2016

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