Master Thesis

A MODEL APPROACH: QUANTIFYING QUALITY OF NORWAY'S EV CHARGING INFRASTRUCTURE

by

Anton Olav Glad
Filip Moen Nilsen

supervised by

Johannes Langguth
Dr. Karim Tamssaouet

a thesis submitted for the degree of
Master of Science in Business Analytics
at
BI Norwegian Business School,
Department of Accounting, Auditing and Business Analytics

2nd July 2023

Abstract

This thesis presents a study of Norway's electric vehicle (EV) charging infrastructure. It proposes a flexible, data-driven model for assessment and planning of EV charging infrastructure. By integrating real traffic data into a simplified representation of Norway's road network, considering variables such as the EV ratio, vehicle range, and battery capacity, this model is a tool for simulating current state and future EV-scenarios. The study identifies gaps in the existing charging network by categorizing roads as served, partially served or underserved. It reveals that approximately 76% of roads with at least one existing charger have adequate infrastructure. However, when considering the entire road network, including roads without chargers, the percentage of adequately served roads decreases to 47%. To bridge this infrastructure shortfall, an estimated 1709 additional chargers in the 50 kW category, or 795 chargers in the 150 kW category, are required. The proposed model could be useful for stakeholders involved in EV infrastructure planning. It enables anticipation of future demands and evaluation of different scenarios, contributing to evidence-based decision-making and guiding strategies for meeting the increasing demand for electric vehicles in Norway.

Keywords: *Electric Vehicles (EV), Charging Infrastructure, Norway, Traffic Data, Road Network, EV Adoption, Charging Station, Vehicle Range, Battery Capacity, Infrastructure Planning, Sensitivity Analysis, Future EV Projections, EV Charging Demand, Infrastructure Investment, Data-Driven Model, Sustainable Mobility, EV Policy-making, Charging Technology*

Acknowledgments

We are thankful to have had the opportunity to collaborate with an incredible group of individuals during our research project. This work would not have been possible without their assistance, and we would like to express our heartfelt thanks to each one of them.

Firstly, we would like to thank Johannes Langguth, our supervisor from Simula Research Laboratory, for his invaluable guidance, patience, and expertise. His mentorship was indispensable throughout this research project, and we are deeply appreciative of his support.

Secondly, our supervisor from BI, Karim Tamssaouet, also deserves our gratitude. He always seemed to have just the right insights at just the right time. His input was vital and helped shape our perspective and approach.

We extend our appreciation to three individuals whose timely assistance helped advance our research. Samuel Berntzen, the pioneer of the first thesis on this topic, patiently guided us through our inquiries about the road network. Jan Kudlicka, who assisted us in overcoming a challenging programming issue early on in our project, and Thomas Melkeraaen for his assistance with LaTeX issues. We thank each of them for their contributions to our progress.

Finally, we wish to express our appreciation towards our families. Their support extends far beyond the task of proofreading our work and providing feedback. They have also been our steadfast pillars, supporting us throughout our master's studies.

Contents

List of Figures

List of Tables

List of Algorithms

1 Introduction

According to the International Energy Agency (IEA), roughly 16% of global CO_2 emissions are transport related. Consequently, reducing CO_2 emissions from transport systems will play a crucial role in creating a more sustainable future for coming generations (International Energy Agency, 2022). One of the major technologies that can assist in decarbonizing road transport is the adoption of electric vehicles (hereby referred to as EVs). There are mainly two deciding factors when it comes to a country's EV adoption rate. One of these being the political and economic incentives for the purchase and use of said vehicles, while the second being the quality of the charging infrastructure in the respective country. When assessing the European EV car sales share in 2021, we find that Norway boasts the highest market share of 86% of new car sales being EVs (Figure 1; (SSB, 2023b)), followed by Iceland with 72%, Sweden with 43%, Netherlands with 30%, France with 19% and Italy with 9% (International Energy Agency, 2022).

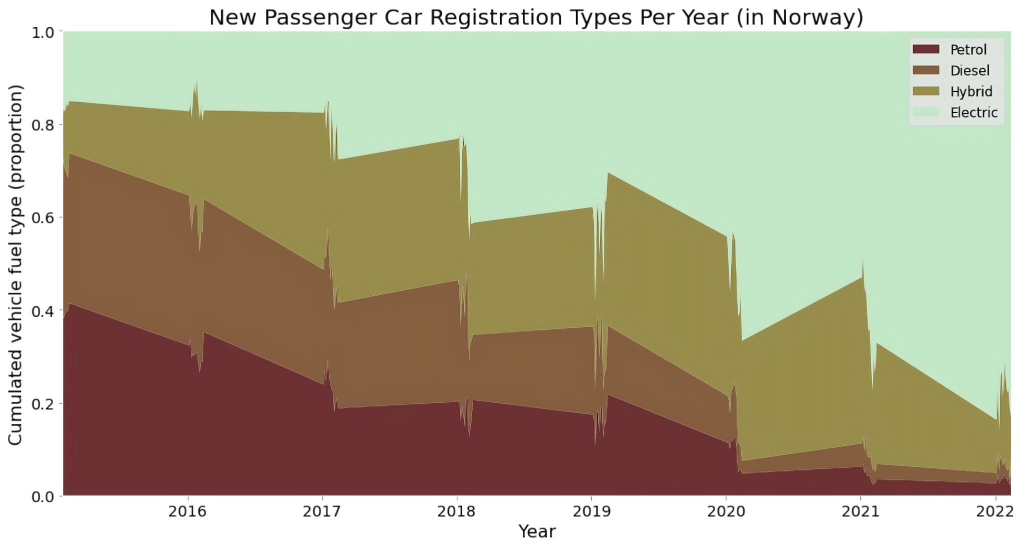


Figure 1: New car registrations by vehicle type

The phase in of a stricter CO_2 emission target in 2020 and 2021, among other factors, are the dominant drivers propelling the adoption of EVs in Europe. Regulation (EU) 2019/631 was proposed and entered into force, to improve CO_2 emission performance standards for passenger cars (EU, 2023). This regulation includes incentive mechanisms for zero- and low-emission vehicles and penalties on manufacturers for excess emissions. The extension of purchase subsidies and tax incentives in Norway also contributed to sales growth. There are dozens of these incentive mechanisms that affect automotive technology selection and Norway's carbon footprint that include, exemptions from VAT and one-off registration tax, parking, ferry and road fee discounts, as well as EV's access to bus lanes on highly congested roads (Fridstrøm & Østli, 2021). Collectively, these benefits have shown to be effective and can be viewed by close and far-off neighbors as practical examples for advancing global climate goals.

From the preceding paragraph, we can establish a case that one of the two deciding factors for a country's EV adoption rate has been efficacious. The remaining factor in regard to the charging station infrastructure is associated with a quality-metric that is not as clearly quantifiable. It is a factor that necessitates a more thorough analysis of geospatial information of the actual charging stations, a realistic grasp of the Norwegian traffic network, and the travel behavior of Norway's citizens. This decisive component will be examined in this research. We will model the Norwegian road network using real-world data, while inserting the present fast charging stations on the graph and retrieving actual traffic volumes on their corresponding road segments. The available traffic volume is measured from fixed position detectors; hence we will present our estimates of domestic travel behavior. Consequently, we will undertake geographical and statistical analysis on the completed model, yielding quantitative metrics that may be used to evaluate the performance of Norway's charging infrastructure. Norway is already in the vanguard of the drive to embrace EVs, making it a benchmark for other nations conducting their own adoptions. This thesis will hopefully shed light on whether the high adoption rate is solely the outcome of governmental incentives, a reflection of a highly effective infrastructure, or influenced by other yet to be identified factors.

1.1 Objective

The utmost ambition for this thesis is to develop a functional model capable of systematically identifying congestion points and high-demand routes within Norway's EV charging network. The intention behind this identification is to facilitate a comprehensive evaluation of the quality of the entire EV infrastructure, thereby informing strategic planning.

In a country such as Norway, with its dispersed population, mountainous terrain, and vast rural areas, the key factors in deciding the acceptance and use of EVs are the availability and accessibility of charging stations (CSs). This observation is supported by the prevalent term "range anxiety", indicating a concern among potential EV users about the distances they can travel before requiring a charge (Loveday, 2013).

Despite these apprehensions, we can observe a continuous increase in the proportion of EV traffic relative to other fuel types. This trend, demonstrated by the annually increasing distances travelled by EVs (Figure 2), emphasizes the critical need for an effective and comprehensive EV charging infrastructure that can support the transition from internal combustion engine (ICE) vehicles to EVs (SSB, 2023c).

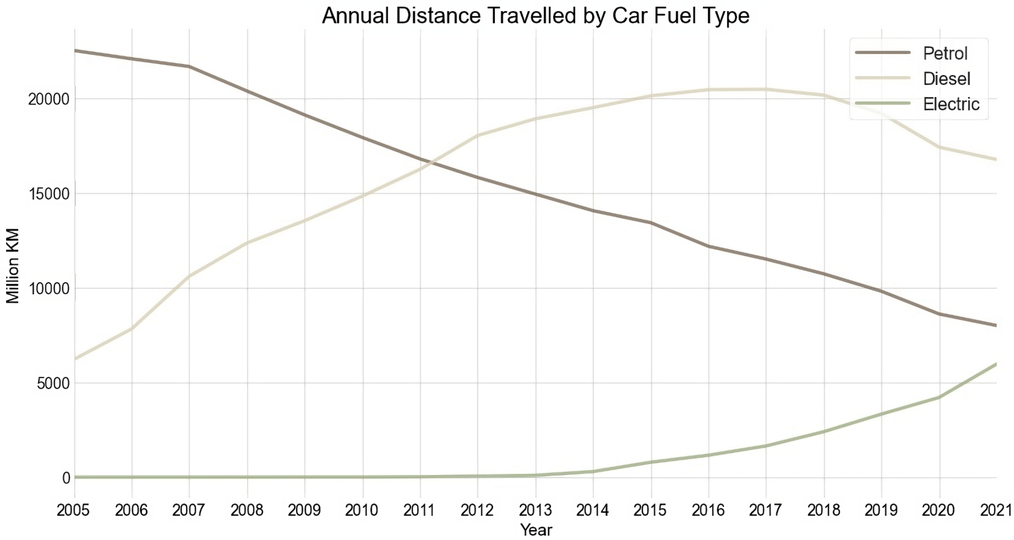


Figure 2: Distances travelled by various vehicle types

As the proportion of EVs on the road continues to rise, it is crucial to establish a comprehensive and efficient infrastructure for charging these vehicles. This infrastructure should be comparable in both size and accessibility to the gasoline station infrastructure it will replace. Our objective of this thesis is to offer a methodology for minimizing gaps in charging supply and maximize accessibility. Our goal is not only to provide a theoretical framework but to offer practical insights and recommendations for the strategic planning of EV charging infrastructure in Norway.

1.2 Research Question

The transition towards electrified transportation opens a significant window to mitigate environmental concerns. Nonetheless, this transition is not without challenges. In countries such as Norway, where EV adoption rates are particularly high, these challenges are more pronounced. The infrastructure to support this transformation, namely the charging station network, plays a pivotal role in the transition process. The effectiveness of this network, particularly in satisfying the EV charging demand, is a central aspect of this thesis. The core of our study focuses on developing a model suitable for examining the adequacy of Norway's existing EV charging infrastructure and exploring strategies, possible scenarios and sensitivities of further development in anticipation of increased future demand.

With the aid of our model, we seek to answer the following research question:

How does the present and future demand for EV charging stations align with the supply of EV charging?

To answer this, we will employ a systematic approach, incorporating public data to build a graph model of the Norwegian road network. Each road segment will be evaluated for EV charging demand and charging station supply. Scenario analyses will be employed to study the potential evolution of the supply-demand landscape and the effect of advancements in EV technology. Finally, a sensitivity analysis will allow us to understand the implications of increasing the EV proportion of the total vehicle fleet, providing an understanding of how increasing demand affects the adequacy of charging infrastructure on the Norwegian roads.

2 Literature Review

This section surveys the landscape of studies concerning electric vehicle charging infrastructure. It supports our research, providing context and insights that help shape our approach and places our study within the larger research field.

Extensive years of research have been devoted to the optimization of charging station allocation and road network modeling for EVs. Using a range of mathematical models and optimization methods, research has focused on locating the ideal position of charging stations on road networks (Kuby & Lim, 2005; Lim & Kuby, 2010; Nicholas et al., 2004; Shi et al., 2021). These models frequently incorporate variables such as traffic volume and patterns, population density, and current infrastructure availability (Capar et al., 2013). In addition, several studies have advocated the use of spatio-temporal models to forecast the need for charging stations based on the movement patterns of EVs (Dong et al., 2019). This approach can aid in identifying spots with the greatest demand for charging infrastructure and optimizing resource allocation. In addition, a few studies have examined the possible advantages of deploying mobile charging stations (Afshar et al., 2021), which may be relocated to various sites dependent on demand. Furthermore, several studies have examined the economic elements of charging station infrastructure, such as the cost of establishing and maintaining stations (Huang & Kockelman, 2020), pricing models for usage (L. Zhang et al., 2018), and the distribution of costs among various stakeholders (Lorentzen et al., 2017). Also discussed are the effects of government regulations and incentives on the adoption of electric vehicles and the construction of charging infrastructure (Langbroek et al., 2016).

2.1 FCLM & FRLM

The Flow Capturing Location Model (FCLM) is a mathematical model developed by Hodgson in 1990, primarily aimed at addressing problems where the focus is on capturing the flow of traffic along network edges, rather than demand at nodes (Hodgson, 1990). In the context of EV infrastructure planning, the FCLM can be used to identify optimal locations for deploying EV charging stations by capturing the maximum possible flow of EV traffic at the lowest cost. The FCLM, however, has some limitations. The model overlooks the limited driving range of EVs and the potential need for multiple charging stops during a trip. These limitations drove Kuby and Lim to develop the Flow Refueling Location Model (FRLM) in 2005 (Kuby & Lim, 2005).

The FRLM builds on the FCLM by incorporating the concept of range anxiety, or the fear of running out of charge while on the road, and the need for multiple charging stations to refuel a trip. The FRLM is designed to optimally position refueling stations so as to maximize the total flow volume refueled. It takes into account various factors such as the limited range of vehicles, the path length, and node spacing. These factors are considered to determine all possible combinations of nodes that can refuel a given path. The model also acknowledges the importance of developing a cost-effective infrastructure for alternative-fuel refueling stations and strives to minimize these associated costs. The FRLM aims to identify the optimal locations for EV charging stations in a way that balances the need for range assurance with the costs and revenues associated with EV charging. Kuby and Lim developed the Flow Refueling Location Model (FRLM) as a mixed-integer linear program (MILP) to identify the optimal locations for alternative fuel stations in road networks. However, this MILP requires a sub-model to pre-generate exogenously all possible combinations of refueling stations for each route (Lim & Kuby, 2010). Unfortunately, even for medium-sized networks with hundreds of nodes, this algorithm must analyze a vast number of facility combinations along routes with numerous nodes. As a result, the MILP becomes impractical for larger networks, as it is impossible to even pre-generate the combinations, let alone solve the MILP. To address this limitation, Kuby and Lim also developed heuristic algorithms for the FRLM, including greedy-adding, greedy-adding with substitution, and genetic algorithms. The advantage of these heuristic methods is that they do not include the prerequisite of pre-generating the combination of facilities that can refill the routes and can solve the FRLM in a reasonable amount of time for actual networks.

2.2 Prior Work on the Norwegian Road Network

In the process of shaping the research direction for this thesis, inspiration was derived from two important studies addressing the issue of reachability and optimal charging station placement within the context of the Norwegian road network.

In the first study (Berntzen, 2021), Berntzen proposed a framework aimed at ensuring reachability of all parts of a road network, given specific EV battery capacities. Two methods were explored: k-Dominating Set and a Connected k-Dominating Set. The testing of these methods on the Norwegian road network revealed that the latter approach, when computed using a greedy algorithm, offered more efficient and desirable solutions. A noteworthy conclusion was the identification of a coverage gap in remote, non-urban areas, which offered important insights into the geographical nuances of charging station allocation. This study's overall concept and findings provided a solid base from which our initial explorations and model building could begin.

The second study (Peratinos & Piene, 2022) deployed a flow-refueling location model to determine optimal charging station placements based on traffic flows of inter-city and long-distance travel. The authors designed two heuristic algorithms — a greedy-adding algorithm and a genetic algorithm — to solve this problem effectively. Their results highlighted that current charging infrastructure was suitable for longer EV ranges but insufficient for shorter ranges below 200km. Their interest in traffic flow data was a big inspiration for our approach on using real traffic data.

The previous theses have provided insights and methodologies that have guided and shaped our research. These works have contributed to our understanding of the EV charging infrastructure and road network in Norway, while identifying potential areas of further study. Leveraging this existing research, our thesis seeks to deliver a present and future evaluation of the Norwegian EV charging infrastructure. Our goal is to enhance the existing knowledge base and contribute to the ongoing discourse around EV adoption in Norway, with particular emphasis on actual traffic data among other factors.

2.3 Road Network Generalization

Road networks present complex data structures that can be processed in different ways. The Canada Centre for Remote Sensing (CCRS) has proposed a method for creating geographic databases, which includes three levels of processing: The User Level, The Generalization Model level, and Logical Data Structures Level (Thomson & Richardson, n.d). Although the CCRS method focuses on remote sensing data integration, some aspects of their approach are applicable to this thesis.

At the user level, it is essential to identify the requirements and specifications for the final outcome. In the context of road networks, this involves understanding the needs of users and considering factors such as data density reduction, consistent generalization techniques for specific representation scales, and an information-based approach. By incorporating these considerations, the user level ensures that the system provides flexibility and logical approaches to process the road network data effectively.

The generalization model, as proposed by CCRS, can be adapted to simplify and smooth the road network. This involves reducing the complexity of the network while preserving the essential information. The generalization techniques employed can help create a more understandable representation of the road network, facilitating further analysis.

The data model used in the CCRS method, based on geometry, topology, object-oriented classification, and aggregation hierarchies, can also be utilized in adding new relevant geographical features to the road network. This allows for the integration of additional information that enhances the output model. By incorporating these new features, the road network can be enriched and provide more comprehensive insights for various applications.

In summary, the CCRS method provides insights into the creation of geographic databases and generalization of road networks. The user level helps define the requirements and specifications, while the generalization model and data model contribute to simplifying and enhancing the road network representation. By leveraging these concepts, it is possible to develop a systematic approach to process the road network data, making it easier to understand and incorporating new relevant features.

2.4 The EV Charging Demand Model

Addressing the restrictions posed by traditional deterministic methods, Jun et al. (2019) put forth a strategy utilizing a probabilistic framework to gauge electric vehicle (EV) charging demand distribution within a specified region. This model holds significance as it adeptly encapsulates the fundamentally unpredictable facets of vehicle movement and charging needs. Hence, it underscores the necessity of incorporating predefined parameters in a deterministic fashion within our approach to the EV charging station location problem, while still recognizing the relevance of the probabilistic perspective.

The paper presents a stochastic model to predict spatio-temporal EV charging demand allocation in the distribution network. The process involves two primary steps: the acquisition of EV spatio-temporal moving parameters, and the calculation of charging demand using the formulated model. This approach effectively captures the non-homogenous daily travel patterns of EVs and takes into account multiple factors, including the number and parameters of each type of EV in a region, the traffic area zone (TAZ) division, and daily origin-destination (OD) matrix data. Jun et al.'s model assumes an area with 30 TAZs and offers charging demand curves and property-classified charging demand curves for every TAZ in the area under examination. It carefully considers different travel scenarios by modifying the corresponding input data, thereby making it a flexible tool for various circumstances. This model's versatility and adaptability make it a strong candidate for operation and planning of power systems with high EV penetration. The model's strength lies in its probabilistic nature and avoidance of the need for traffic network information, making it particularly feasible during the planning stage. The findings from the paper are convincing and suggest that this probabilistic approach can provide more accurate insights into the spatio-temporal allocation of EV charging demand, which subsequently can inform better decision-making around charging station placement and network planning.

However, it should be noted that this model, like any other, has room for further development. A limitation in this area of research is that more detailed data on exact charging locations and trips might exist, but is often private or proprietary, making it inaccessible for researchers. Future studies could benefit from such data if accessible. Jun et al. also suggests that future research could focus on incorporating strategies around smart charging and vehicle-to-grid (V2G) systems, which can offer further refinements to the model and may provide additional insights. In summary, Jun et al.'s probabilistic approach provides a compelling argument for the use of stochastic methods in determining EV charging demand and station locations. Acknowledging the success of the probabilistic approach, we aim to incorporate a similar methodology in our research, albeit in a more deterministic manner. We firmly believe that our deterministic approach, while operating within predefined parameters, will yield robust results and hold promise for offering new insights into the Norwegian EV charging infrastructure.

3 Methodology

The following section outlines the methodological approach used in this thesis, offering a synopsis of the research procedures that were deployed. It will explain our initial ideas shaping the research design we aim to adopt, thereby providing insight into our methodological choices and reasoning. Furthermore, this section will describe the data sources chosen to support our model and guide the subsequent analysis.

3.1 Research Design

The research design employed in this study serves as a strategic blueprint for addressing and deciphering the posed research question. Our design can be characterized as a combination of descriptive and explorative research methods. Descriptive components enable the systematic collection and examination of data to capture the characteristics of a given population or phenomenon. Concurrently, the explorative aspect allows us to simulate future scenarios and sensitivities, taking into account possible changes in the landscape of EV adoption and infrastructure. Our approach leans heavily on complex network theory, as elucidated by Zhang, to quantitatively describe the structural and dynamic properties of traffic networks (M. Zhang et al., 2022).

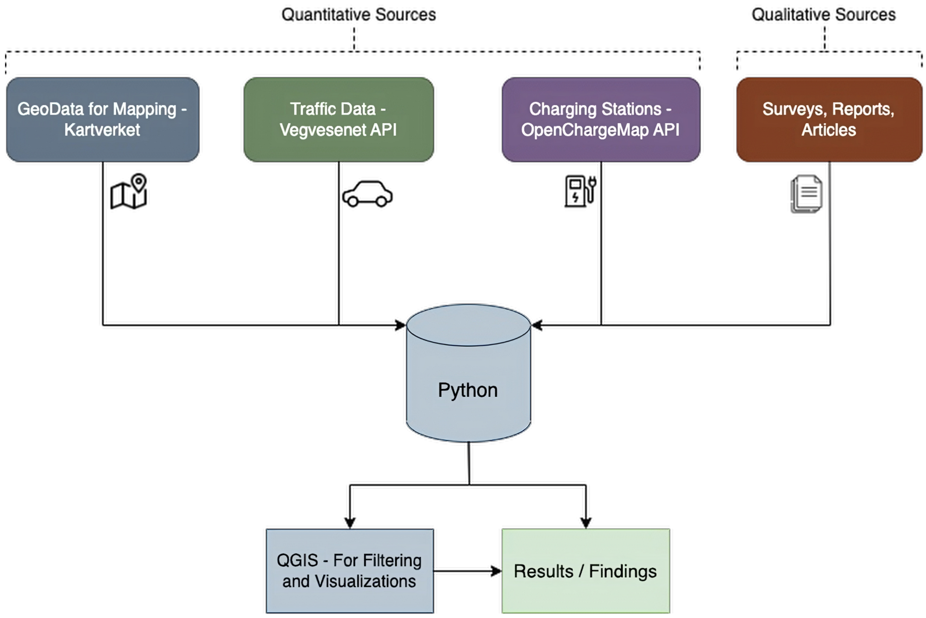


Figure 3: Diagram of sources used

While quantitative methods provide the backbone of our analysis, an integral part of our research hinges on qualitative insights necessary for understanding and shaping the parameters, assumptions, and constraints intrinsic to our study. The aim of our research is not only to map out the prevailing traffic flow within Norway but also to employ the results to identify gaps in the EV charging infrastructure and subsequently with the addition of new model features enable identification of optional locations for charging stations throughout Norway's road network. Therefore, the research strategy employed in this thesis can be characterized as a blend of descriptive and explorative research design, marrying quantitative data with qualitative methodologies. This approach allows for a comprehensive understanding of the investigated phenomenon while facilitating the exploration of various scenarios and sensitivities. This explorative facet aids us in preparing for potential shifts in traffic flow, EV adoption rates, and infrastructural changes.

3.2 Network Construction and Simplification

Transportation networks, characterized by their complex systems of interconnected routes, are fundamental to urban planning and development. The intricate nature of these networks, however, poses considerable computational and interpretative challenges. In the context of our research, the initial data collected from the network was exceedingly complex for immediate analysis, necessitating a process of simplification while ensuring the preservation of crucial network attributes such as topology and traffic flow patterns. This simplification aimed to improve the data's readability and computational efficiency, enabling a precise representation of traffic flow through the network. By reducing complexity, we facilitated a more comprehensive understanding of the network's overall structure and functionality, thereby enhancing our capacity for analysis. This chapter details the process of transitioning from raw data collection to the development of a simplified transport network. It provides an overview of the methodologies used, highlights the challenges faced, and outlines the solutions devised to address these issues.

3.2.1 Network Model Generalization

Before diving into the specifics of our process, it is essential to provide an overview of the three distinct phases involved in our approach to the road network model generalization and simplification. These phases include data visualization using a geographical information system (GIS), network construction and simplification, and finally, the incorporation of traffic volume and charging station data into the model. While these steps resonate well with the general principles of Road Network Generalization as proposed by the CCRS (Thomson & Richardson, n.d), they are tailored specifically to the context of our study and the analytical requirements at hand.

The initial phase is marked by our utilization of a GIS for data visualization, serving a similar role to The User Level in The Road Network Generalization Model. However, our aim in this phase differs subtly. Instead of seeking to reduce complexity for better visual understanding at varying scales, we leverage the GIS to gain an overview and fundamental understanding of our road network data at hand. This knowledge guides the design of the next phases.

The second phase encompasses the construction and simplification of the network, drawing parallels with The Generalization Model in Road Network Generalization. Here, our method diverges from the typical approach of relying on predefined criteria such as road class. Instead, we customize the simplification process to match our analytical needs. While this phase simplifies the network, it also structures it in a way that supports the specific traffic analysis we aim to undertake, creating a bridge between the physical network representation and our analytical goals.

Our concluding phase, Traffic and Charging Station Data Processing, shares some conceptual parallels with The Logical Data Model, a network generalization strategy proposed by the CCRS. However, our methodology is designed with a particular emphasis on associating traffic volume and charging station data with the corresponding network edges. While this bears some resemblance to general attribute assignment, it highlights our method's emphasis on the specific traffic volume and charging attributes, making this a specialized aspect of our data handling process compared to a more conventional, broader attribute assignment approach. In conclusion, our approach upholds the core principles of Road Network Generalization while incorporating phases tailored to handle the complexities and meet the analytical demands of our study on the Norwegian road network. Each phase is designed to build upon the precision and utility of the previous one, resulting in a comprehensive analysis of supply and demand.

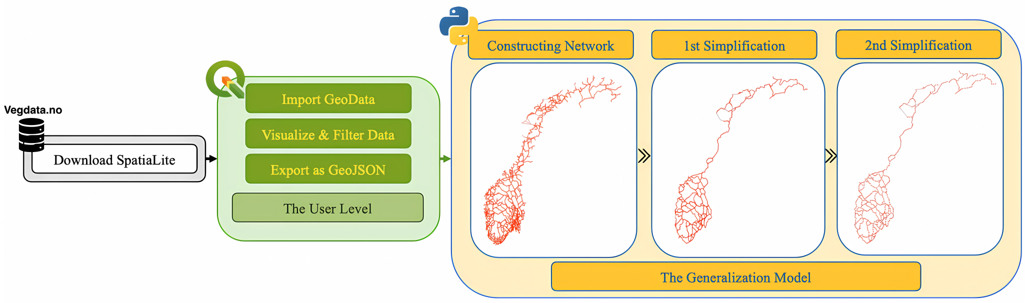


Figure 4: Network Model Generalization (Phase 1 and 2)

A visual representation of the first two stages in our network generalization approach is provided above in Figure 4 for better comprehension. It lays the groundwork for the subsequent, more detailed, discussions in the following sections.

3.2.2 Data Acquisition

Our primary data source was an open-source platform offering intricate and geo-referenced data about the Norwegian road network (GeoNorge, 2022). This dataset encapsulated essential details about the transportation pathways, the junctions, and associated attributes. Significantly, the data was procured as a SpatiaLite file. SpatiaLite is an SQLite database engine with spatial functions added, making it a powerful tool for handling large-scale geospatial data. This format enables management and utilization of spatial data, a feature crucial to our project.

To process this geospatial information effectively, we utilized QGIS, an open-source Geographic Information System (GIS)(QGIS, 2023). With its capacity to handle spatial data, QGIS became instrumental in visualizing, exploring, and manipulating our data within its geographical context. The initial step within QGIS involved importing our acquired SpatiaLite data. The import procedure allowed us to visualize the road network and interact with the data intuitively. This gave us an immediate understanding of the network's structure and complexity, illuminating the challenges that were to follow.

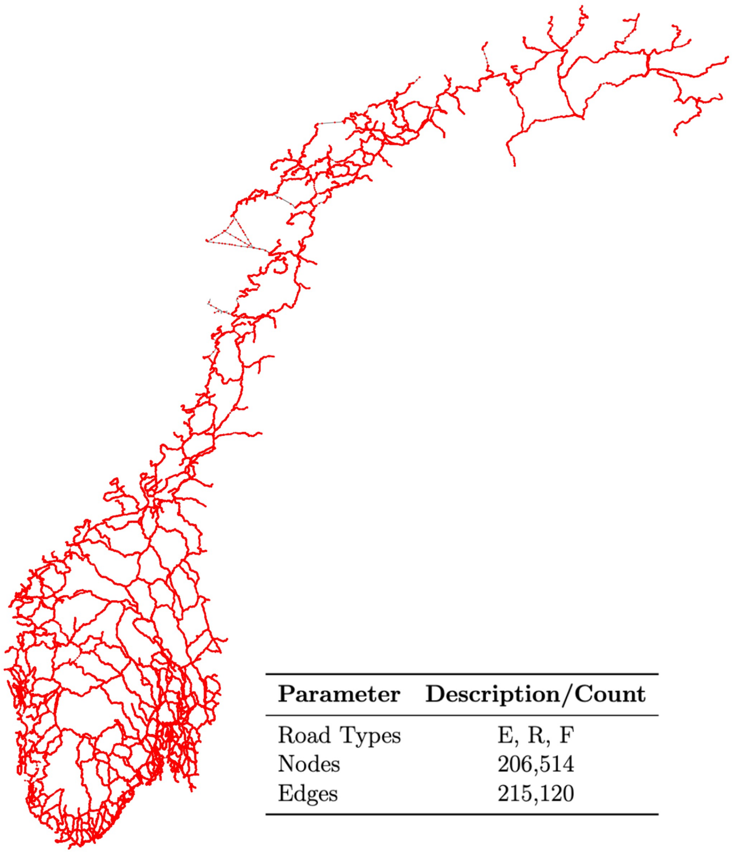
The subsequent phase of data filtering formed the modelling of our project. It necessitated the cleaning and pre-processing of data to ready it for the ensuing stages. The sheer volume of data and the diverse attributes of each point in the network made it imperative to filter out irrelevant or redundant information. This filtration process enabled us to concentrate on key data attributes required for our analysis, including node coordinates, road type, and length, among others.

Upon successful filtering, we prepared the data for additional processing. This involved retrieving our filtered data as a GeoJSON file, a format well-suited for interaction with Python and the much used geo-libraries, NetworkX and OSMnx (NetworkX, 2023)(OSMnx, 2023). Notably, the data was filtered to encompass E, R, and F-roads (European, national, and county roads), providing a focus for our study and removing smaller less important road segments. Though these preliminary stages might seem straightforward, it was a laborious process that played an important role in ensuring the precision and efficiency of the subsequent network construction and simplification processes.

3.2.3 Network Construction

In our study, we initiated the construction and modelling phase by building a network from the pre-processed data. This procedure involved transforming the refined data into an interconnected and structured network representation suitable for further analysis. A significant tool aiding us in this process was a Python implementation of an algorithm, originally introduced in an earlier similar master's thesis (Berntzen, 2021). Although the research shared similarities with ours, the primary reason for integrating the algorithm into our study was its effectiveness in facilitating a structured network from raw data. Essentially, the algorithm functioned to convert the GeoJSON file obtained from QGIS into a format that the NetworkX library could interpret. This algorithm read the GeoJSON file and converted the parsed data into two GeoPandas GeoDataFrames - one for nodes and one for edges. The attributes from the GeoJSON file were incorporated into the corresponding nodes and edges within these GeoDataFrames. Subsequently, these GeoDataFrames were integrated together to form a NetworkX graph.

In effect, the algorithm allowed us to transform the geospatial data of the Norwegian road network into an interconnected and structured graph. Each road segment in this graph was represented by an edge that connected two nodes, thus preserving the topological properties of the road network. This representation served as a snapshot of the structure of the road network and represented a significant step in the research. The resulting NetworkX graph closely mirrored the structural properties of the Norwegian road network. This graph, serving as a sturdy foundation for the forthcoming simplification process, underscored the importance of a well-constructed initial network as a starting point. The constructed base graph is visualized in Figure 5. Notice the substantial quantity of nodes and edges, along with the tightly clustered nodes along the graph.

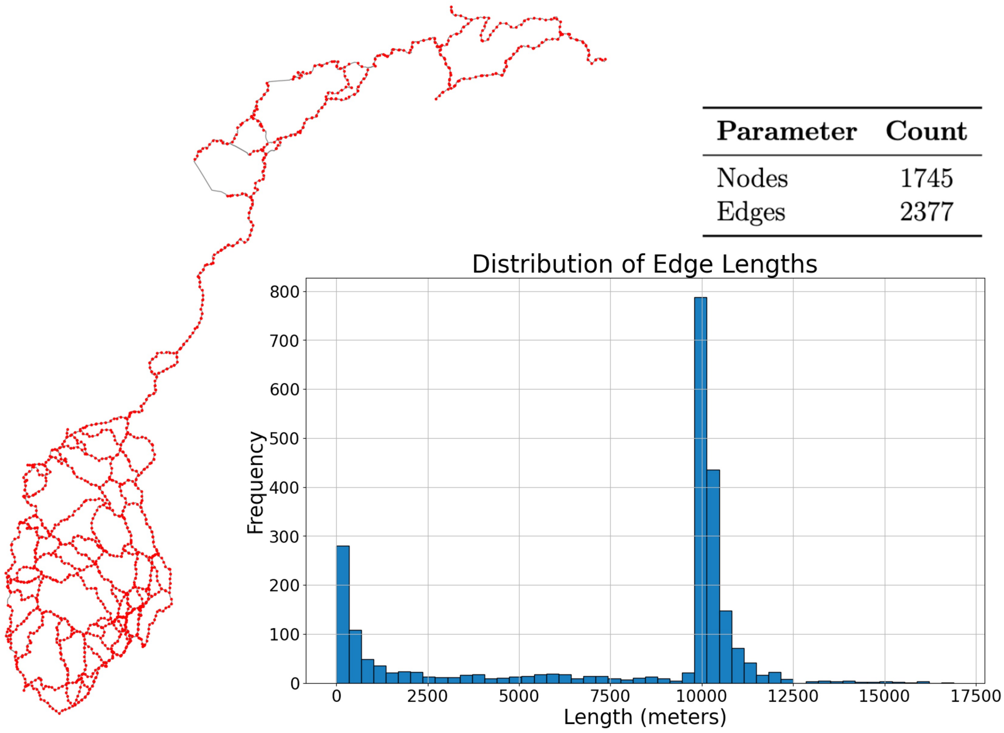


Parameter	Description/Count
Road Types	E, R, F
Nodes	206,514
Edges	215,120

Figure 5: Original network construction

3.2.4 Network Simplification

In addressing the complexity of the Norwegian road network for our analysis, we applied a two-step simplification process using two algorithms constructed in Python. The first simplification algorithm, also adapted from a related master's thesis (Peratinos & Piene, 2022), was our first tool for enhancing the efficiency of our network. The result enhanced interpretability and computational efficiency by emphasizing significant routes throughout the network. Following its application, we had a refined graph consisting of 1745 nodes and 2377 edges. Figure 6 presents the graph following the initial simplification process, accompanied by the corresponding edge length distribution that we will further explore.



Parameter	Count
Nodes	1745
Edges	2377

Figure 6: Graph after first simplification

Our modeling led us to confront another issue: the traffic volume count points along the graph did not precisely align with the network's edge information. This discrepancy, much related to the short edge lengths and further detailed in the following chapter, led us to develop the second simplification algorithm - "simplify_network_v2". This algorithm, specifically designed to tackle the alignment problem, also significantly improved the visibility of edges and traffic flow. The algorithm operates by merging nodes within a predetermined radius and standardizing a minimum edge length of 10 kilometers. This systematic approach to node merging and edge length regulation ensures improved alignment with traffic count points and enhances network simplicity. Moreover, the algorithm incorporates the initial attributes of the original edges being merged, preserving crucial information about the network even after the simplification process.

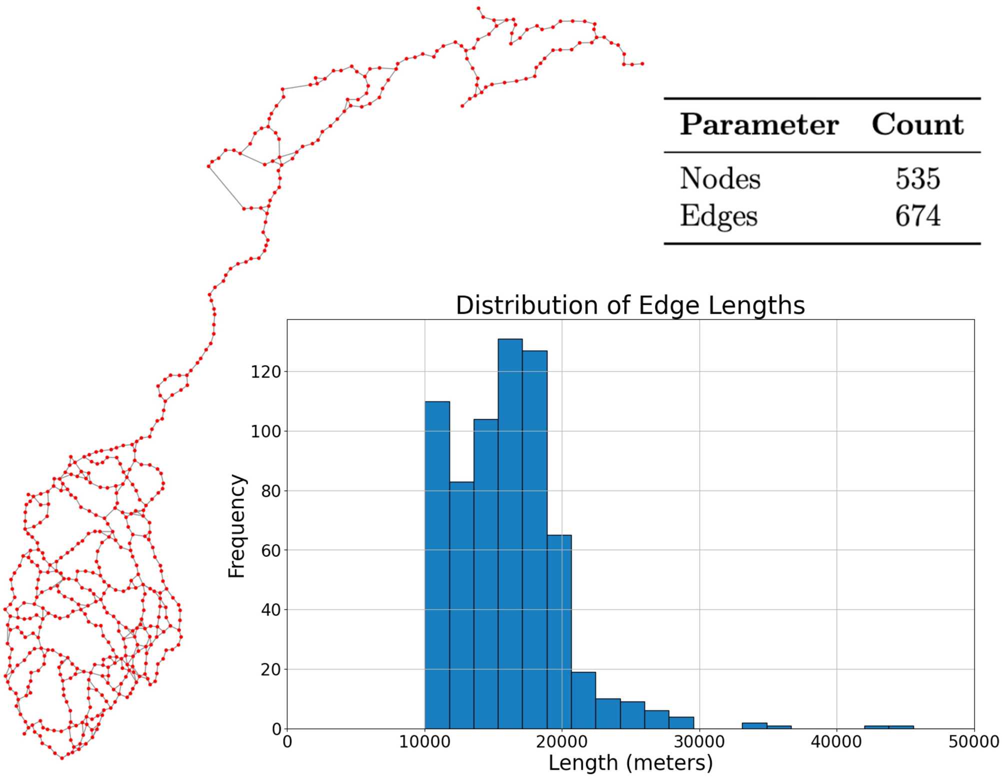
The "simplify_network_v2"-algorithm and a brief explanation can be viewed below.

Algorithm 1 Simplify Network v2

```
procedure SIMPLIFY_NETWORK_V2(G, mergeRadius)
    Initialize simpG, nodeGroups
    for each node not in any nodeGroups do
        Form newGroup within mergeRadius from node
        Append newGroup to nodeGroups
    end for
    for each group in nodeGroups do
        Add a new node to simpG from group
    end for
    for each group in nodeGroups do
        Get neighbors of nodes in group
        for each neighbor do
            Identify neighborGroup containing neighbor
            if neighborGroup exists and no edge to neighbor in simpG then
                Get edgeAttributes, calculate distance
                Add edge to simpG with distance and edgeAttributes
            end if
        end for
    end for
    return simpG
end procedure
```

The "simplify_network_v2" algorithm aimed to minimize a graph's complexity by merging nearby nodes within a specified merge radius. The procedure starts by initializing an empty graph, *simpG* (abbr. simplified graph), and an empty list, *nodeGroups*. It iterates over each node in the original graph G, forming a group of nodes (*newGroup*) within the merge radius, which is then appended to *nodeGroups*. Each group in *nodeGroups* is then represented by a new node in *simpG*, simplifying the graph's structure. The algorithm identifies the neighbors of nodes within each group, determining the group (*neighborGroup*) that each neighbor belongs to. If *neighborGroup* exists and is not yet linked to the group in *simpG*, the algorithm calculates a new edge based on the original edge's attributes and distance. This edge is added to *simpG*, effectively maintaining the original connectivity while reducing the graph's complexity.

The result is a simplified graph, displayed in Figure 7 below, that preserves the fundamental properties of the original graph. An evident shift in edge length from the observations in Figure 6 should be acknowledged.



Parameter	**Count**
Nodes	535
Edges	674

Figure 7: Graph after final simplification

Applying this dual-layer simplification had notable benefits. While the first algorithm emphasized the most crucial routes, the second simplification algorithm dealt with the specific analytical challenge of aligning traffic points and edges. After the whole simplification was applied, the final graph consisted of 535 nodes and 674 edges which made it manageable for further modeling.

In conclusion, the transformation of complex geospatial data into a simplified and comprehensible transport network was achieved through a meticulous process of data acquisition, management, and transformation. This process allowed us to successfully address the complexities inherent to the Norwegian road network. The process of simplification underscored the importance of strategic data reduction in our analysis, offering a potentially replicable methodology for similar network studies.

3.3 Traffic and Charging Station Data Processing

This chapter delves into the detailed process of extracting and processing traffic volume and charging station data for the Norwegian road network. This road network, owing to its extensive geographical span and varied terrain, presents a set of challenges that necessitate data handling and problem-solving approaches. Therefore, an exploration of this process offers insights not only into the technicalities of data extraction and processing but also into the broader theme of addressing complex, real-world data issues. We will examine the traffic volume data source and discuss the interpretation and preparation of the data for subsequent analysis. The chapter will then pivot to the challenges encountered in this process, ranging from ambiguities in the raw data to the intricacies of assigning traffic volumes and charging stations to specific network edges. We will detail the methods developed to overcome these obstacles, including the creation of a custom Python implementation of an algorithm which proved instrumental in successfully resolving one of the most significant challenges.

3.3.1 Traffic Volume Data Source: NPRA

The Norwegian Public Roads Administration (NPRA) is the primary body responsible for the management of roads in Norway. As part of its mandate, NPRA maintains an exhaustive database that covers a variety of data, including information about road networks and traffic volumes (NPRA, 2023). Through the NPRA Application Programming Interface (API), we aimed to extract traffic volume data for selected roads in Norway. The NPRA data, owing to its reliability, accuracy, and extensive coverage, served as one of the cornerstones for this research and a key resource in understanding and modeling the traffic patterns throughout the Norwegian road network.

3.3.2 Data Challenges and Data Processing

In our process of extracting and processing the traffic volume data from NPRA, we encountered a range of challenges. These challenges stemmed primarily from the inherent complexities and ambiguities in the raw data. Each challenge necessitated examination, problem-solving, and the development of custom methodologies for resolution. This sub-section delves into these challenges and illustrate the methods we used to overcome them.

Selecting Roads and Time-frame of Data

Our first challenge was twofold, involving both the selection of specific roads for data collection and deciding on an appropriate timeframe for traffic data. The road selection process was rather straightforward as we gathered traffic data from roads already included in our network (E, R, and F roads). This choice was facilitated by the filtering capabilities of the NPRA API, which allowed us to focus only on relevant roads, ensuring the data's relevance and applicability to our research.

The choice of timeframe also posed a challenge. Our goal was to gather a comprehensive data set without compromising its accuracy and consistency. Therefore, we opted to use data from the entire year of 2018. This decision was informed by the prevalence of missing data in the 2019 data set and our desire to avoid any distortions due to the COVID-19 pandemic's effects on traffic patterns in 2020 and beyond. This ensured that our data was reflective of typical traffic patterns, enhancing the reliability of our subsequent analysis.

Data Granularity

While we initially aimed to gather exact hourly data to discern daily traffic fluctuations, we found that only a minority of traffic points on our chosen roads offered this level of granularity. This restriction led us to revise our approach. Instead of seeking exact hourly data, we used the monthly average day traffic volume for each month of 2018. Furthermore, to enhance the representation of the hourly traffic volume, we extracted all available hourly volume traffic counts from four different weeks in 2018, each representing a different season. Following this strategy, the derived hourly distribution (ref. Figure 8) from these four representative weeks was subsequently utilized to effectively distribute the gathered average daily traffic data across specific hours of the day. We recognized that this strategy might involve some compromises on the precision of hourly traffic data. However, we believe that this methodology still provides valid insights and preserves the overall reliability of our data, given the representative nature of the four selected weeks from different seasons.

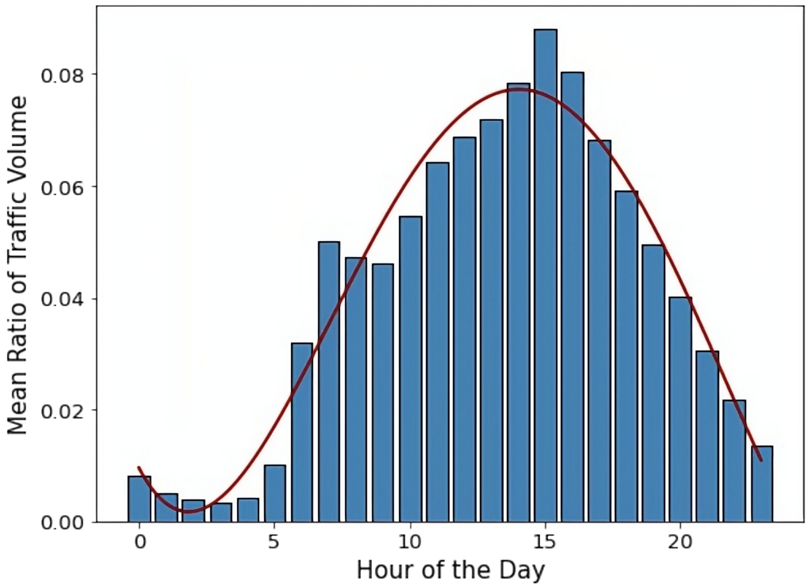


Figure 8: Hour traffic distribution

Assigning Traffic Volume to Edges

The task of correlating traffic volume data with the appropriate network edge was problematic due to the significant differences in data structures between GeoNorge's network data and NPRA's traffic data. These data sources being from two distinct entities posed a challenge to their consolidation in a single process, thus complicating the process of aligning the traffic volume data with the correct network edge.

After cleaning the NPRA data, we ended up with traffic points, complete with point geometries (coordinates), in a GeoJSON file, which was then flattened to a GeoPandas GeoDataFrame. Unfortunately, neither the utilized packages, NetworkX nor OSMnx, have built-in functions that can effectively "snap" point data attributes from a separate GeoDataFrame to the nearest edge in a network. This feature was critical for our data handling process, as our traffic points were somewhat evenly distributed along our network, and we needed a way to accurately associate the volume data with the correct edge. To overcome this hurdle, we created a custom Python function that was designed to perform this specific task. The Python implementation of this algorithm is capable of "snapping" the attributes from a point data frame to the nearest edge in a given network, provided that the distance between the point and the edge is within a specified threshold. This functionality proved to be a major breakthrough in our data handling process, enabling us to accurately associate traffic volume data with the correct edges in our network.

Algorithm 2 Assign Volume To Edges

```
procedure ASSIGN_VOL_TO_EDGES(points_df, N, threshold)
    for each row in points_df do
        point ← row[geometry]
        nearest_node ← None
        min_distance ← Inf
        for each node in N.nodes do
            node_point ← Point(N.nodes[node]['x'], N.nodes[node]['y'])
            distance ← Distance(point, node_point)
            if distance > min_distance then
                nearest_node ← node
                min_distance ← distance
            end if
        end for
        nearest_edge ← None
        min_distance ← Inf
        for each edge in N.edges do
            node1 ← N.nodes[edge[0]]
            node2 ← N.nodes[edge[1]]
            line ← LineString([(node1['x'],node1['y']),(node2['x'],node2['y'])])
            distance ← Distance(point, line)
            if distance < min_distance then
                nearest_edge ← edge
                min_distance ← distance
            end if
        end for
        if min_distance < threshold then
            edge_attrs ← 'point_ID': row['id']
            N.edges[nearest_edge].update(edge_attrs)
        end if
    end for
end procedure
```

Algorithm 2, above, efficiently handles complexities associated with data format mismatches between network data and traffic data, specifically for traffic volume modeling on a road network. The algorithm takes a GeoDataFrame of geometry points, representing spatial data on the road network. It then identifies the nearest edge to each point, using the latitude and longitude coordinates. Uniquely, it can "snap" a point to the closest edge within a specified threshold distance. This means that if the distance to the nearest edge is less than this threshold, the algorithm associates the point's ID with the edge's attributes, effectively appending the traffic volume data to the edges instead of the nodes. This ensures a more precise representation of traffic volumes along routes, making it an adaptable and scalable solution for various contexts where traffic data, or data with similar context, must be mapped accurately along edges.

Challenges with Missing Volume Edges

Addressing the assignment of traffic points to appropriate network edges has been an essential aspect of our study, a challenge that was overcome in the previous step. However, a persisting issue related to the completeness of the network remained unresolved. To clarify, our network had instances of edges lacking volume data, leading to gaps in our analysis.

A manual method was adopted to tackle this predicament, focusing on ensuring the most accurate volume estimations. It was observed that the edges with missing volume data were invariably surrounded by neighboring edges that possessed volume data. Consequently, our chosen approach involved manually appending new registration points, drawing on the attributes of the neighboring registration points (ref. Figure 9). This process could be performed in QGIS by enabling editing on the traffic registration point layer, selecting the relevant point, and duplicating its attributes. The copied point would then be pasted with updated location coordinates and volume values, either replicated or averaged from the neighboring points. The adoption of this method was the outcome after extensive deliberation and testing of various data-filling algorithms. We provide further details about these testing procedures on the associated GitHub page for this thesis (GitHub, 2023d). It's noteworthy that the necessity for this intervention was limited to a minimal number of edges. Therefore, we remain confident that this approach preserves the validity of our results.

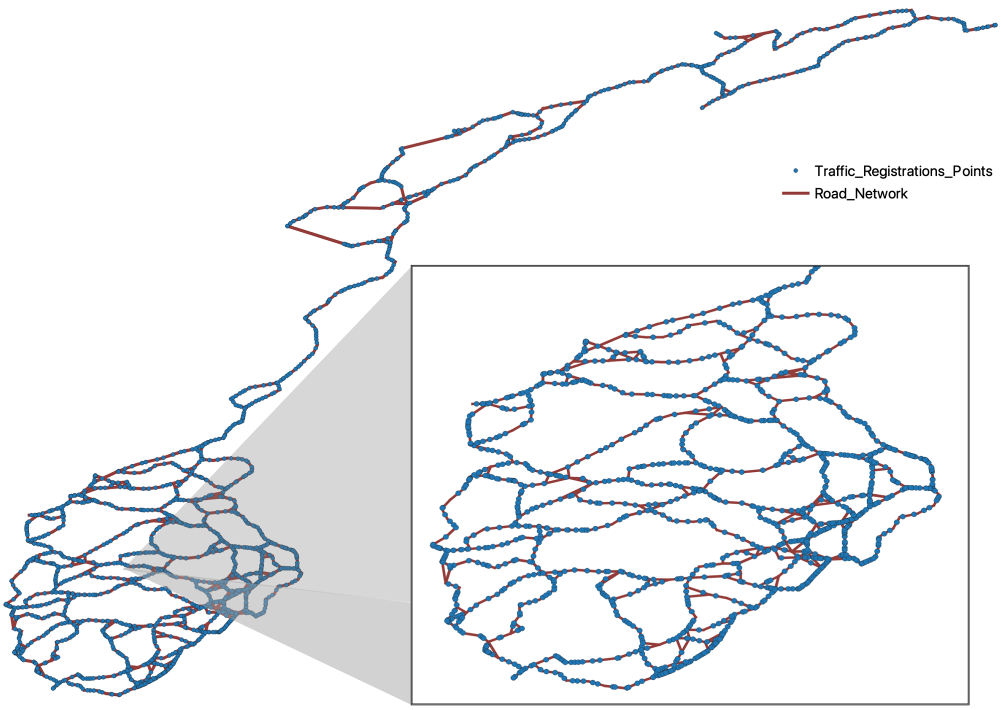


Figure 9: Traffic registration points on network

After successfully integrating traffic data into our network and weighing the edges accordingly, we generated a representation of traffic flows across Norway. This visualization, presented in Figure 10 below, reveals a clear pattern: the highest traffic volumes are predominantly located around the country's major urban centers. This includes areas such as Oslo in the east, southern cities of Kristiansand and Stavanger, western hubs of Trondheim and Bergen, and northern regions such as Bodø and Tromsø. This pattern is in line with our expectations and validates the correctness of our data integration process, further reinforcing the accuracy of our overall network representation.

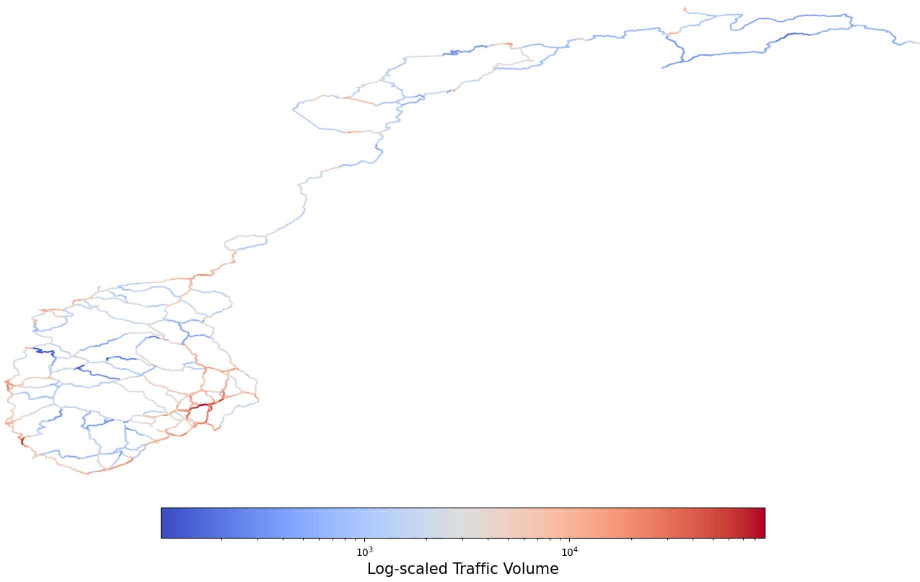


Figure 10: Edges weighted by traffic volume

3.3.3 Gathering Charging Station Data

Following the successful retrieval and assignment of traffic volume data to identify demand, the next step was to accumulate data about the charging stations, which delineates supply. We employed an API query tailored to fetch only the specific data we required from OpenChargeMap (OCM, 2023). This direct approach allowed us to bypass irrelevant information, focusing solely on stations within Norway, and exclusively on chargers with an output of 43 kWh or more. We maintained this specific criteria throughout our thesis, as lower efficiency chargers do not accurately mirror the behavioral patterns we aimed to study. The specifics of our investigation centered around charger details, such as geographical coordinates, number of chargers per station, and individual charger efficiency. Following the compilation of a concise dataset, it was exported to QGIS for additional data processing stages. In QGIS, we carried out several operations, which included eliminating stations that fell outside the range of the roads under study (E, R & F) and, eventually, aligning the chargers with the edges of the road network. Finally, we merged attributes from the charging station dataset with the network dataset. This process created a combined network dataset comprising comprehensive information about the roads and corresponding data about the chargers present on each road. A visualization of the charging stations on the network can be seen in Figure 9.

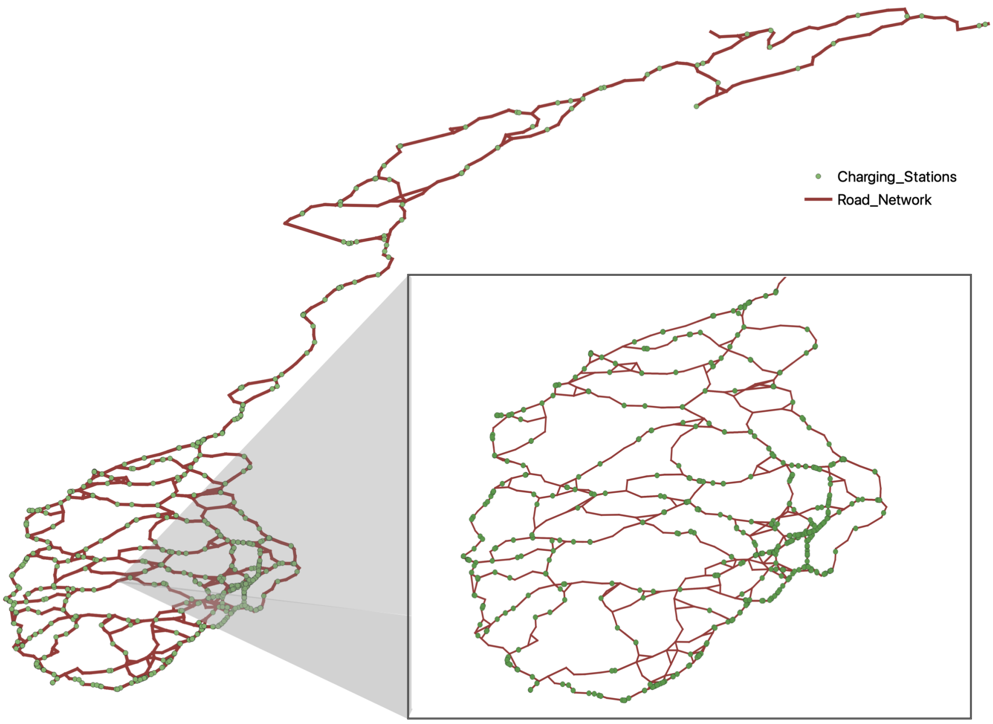


Figure 11: Charging stations on network

3.4 Modeling Approach for Supply and Demand

In this section, we present a deterministic method for estimating the adequacy of an electric vehicle charging infrastructure, in relation to its demand. This involves a series of computations and assumptions, with data encompassing various metrics. Firstly, a comprehensive dataset was constructed which encompasses data for each road section within the network. This data includes the average daily traffic volume for each month on every edge. Subsequently, we set about creating range parameters for EVs, adjusted monthly. Considering an initial fixed average EV range of 300 kilometers, we take into consideration temperature fluctuations that impact battery capacity and subsequently affect the driving range. This analysis is informed by a Recurrent study conducted on 7,000 cars during the winter season (Recurrent, 2022). This involves creating a dictionary of factors corresponding to each month. These factors are informed by average temperatures from five major Norwegian cities: Oslo, Bergen, Kristiansand, Trondheim, and Tromsø (CTT, 2023). The factors were derived from the analysis of 5.2 million trips taken by over 4,000 EVs, representing over 100 different models (GeoTab, 2020). This analysis was based on a graphical representation that elucidates the relationship between temperature and battery capacity.

Month	**Range Factor***
January	0.8
February	0.8
March	0.8
April	0.9
May	1
June	1.05
July	1.1
August	1.1
September	1.02
October	0.92
November	0.82
December	0.8

Table 1: Dictionary indicating the effective range per season
* *The calculation can be found on our GitHub page (GitHub, 2023b)*

As shown in Equation 1, the adjusted EV driving range for a specific month can be calculated using the formula.

$$\text{Range}_{\text{month}} = \text{FixedRange} \times \text{Factor}_{\text{month}} \tag{1}$$

In the next stage, we computed the probability of an EV needing to charge on a specific edge (Equation 2). This was achieved by dividing the edge length by the actual driving range (adjusted for temperature and multiplied by 1000).

$$\text{Charging Probability}_{\text{month}} = \frac{\text{Edge Length}}{\text{Range}_{\text{month}} \times 1000} \tag{2}$$

Utilizing these probabilities, we calculated the number of EVs that would need charging on each edge, based on the proportion of EVs within the vehicle fleet and the observed traffic volume on the corresponding edge.

$$\text{Charging EVs}_{\text{month}} = \text{Charging Probability}_{\text{month}} \times \text{Volume}_{\text{month}} \times \text{EV Ratio} \quad (3)$$

The resulting output was a dataset that provided the daily charging demand for each month, distributed across every hour of the day. The hourly traffic volume data were obtained from traffic registration points for E, R, and F roads, as mentioned previously. Next, we defined the supply capacity of each edge, based on charging station data. We transformed the charging station data into a JSON-formatted data structure that contained edge ID pairs (source and target), nested within these were charging station IDs, and within each station ID was a list of power capacities in kilowatts. Following this, we created another dictionary that computed the theoretical number of cars that could be charged per hour, taking into account setup and exiting times.

Consideration of how drivers typically charge their vehicles is a key factor in our calculations. Several electric vehicle manufacturers recommend that owners refrain from charging their batteries beyond 80% to prevent accelerated battery degradation. Others avoid explicitly stating this recommendation, instead subtly limiting their battery status indicator to show a maximum of 100%, which in reality corresponds to 80% of the battery's full capacity (Kostopoulos et al., 2020). However, it's worth noting that not all drivers heed these guidelines, with some choosing to charge their vehicles to full capacity, either out of disregard for the manufacturer's recommendations or simple unawareness. Many drivers also refrain from fully charging their batteries because of the significant charging time required to top up the battery, according to Kostopoulos et al. This behavior certainly calls for further exploration to ensure more accurate estimates in future studies.

In the context of our research, we have incorporated a factor of 0.9 into our calculations. By multiplying this factor with the battery capacity, we effectively account for the tendency among drivers to charge their batteries to less than full capacity. This pragmatic adjustment allows our model to more closely mirror real-world EV charging behaviors, despite the inherent variability and potential for further refinement through future research.

Algorithm 3 and the resulting dictionary (ref. Table 2) are shown below.

Algorithm 3 Calculating Theoretical Number of Cars Charged per Hour

Require:
kW_list: List of charging kW types
avg_bat_cap: Average battery capacity of EVs
$setup\_takedown\_time$: Time required for setup and takedown
$aging\_ratio$: Battery aging factor
Ensure:
$cars\_per\_hour\_dict \leftarrow \{\}$ ▷ Initialize an empty dictionary
for kW **in** kW_list **do**
    $adj\_bat\_cap \leftarrow avg\_bat\_cap \times aging\_ratio$ ▷ Adjust battery capacity
    $charging\_time \leftarrow \frac{adj\_bat\_cap}{kW}$ ▷ Calculate charging time
    $setup\_takedown\_time\_hours \leftarrow \frac{setup\_takedown\_time}{60}$
    $total\_time \leftarrow charging\_time + setup\_takedown\_time\_hours$
    $cars\_per\_hour \leftarrow \frac{1}{total\_time}$ ▷ Calculate cars per hour
    $cars\_per\_hour \leftarrow \mathrm{Round}(cars\_per\_hour, 1)$ ▷ Round to one decimal
    $cars\_per\_hour\_dict[kW] \leftarrow cars\_per\_hour$ ▷ Add to dictionary
end for
return $cars\_per\_hour\_dict$

kW Charger	Cars per/Hour
350.0	3.9
300.0	3.5
250.0	3.0
200.0	2.6
180.0	2.4
175.0	2.3
150.0	2.0
135.0	1.9
129.0	1.8
125.0	1.7
120.0	1.7
100.0	1.4
75.0	1.1
62.5	0.9
62.0	0.9
60.0	0.9
55.0	0.8
50.0	0.8
48.0	0.7
44.0	0.7
43.0	0.7

Table 2: Dictionary indicating cars per hour

A column for each edge's total hourly supply capacity was generated by integrating the dictionary with chargers present on each edge.

$$\text{Supply Capacity}_{\text{edge}} = \sum_{\sum_{\text{p\_list} \in \text{kW\_list}}}^{\sum_{\text{power} \in \text{p\_list}}} \text{cars\_per\_hour\_dict[power]} \tag{4}$$

Finally, to evaluate the sufficiency of the charging infrastructure, we classified each edge based on its supply status. This classification was set to 1 (*served*) if the edge was adequately supplied for all hours, 0 (*partially served*) if it was partially supplied, and -1 (*underserved*) if it was inadequately supplied. This classification allows us to understand if and when there is an imbalance between demand and supply on the network, providing valuable insight for the optimization of EV charging infrastructure. Figure 12 below demonstrates the rules of classification more intuitively as we see the orange line going from a positive value to a negative value hence being labeled as *partially served*. We also see that *served* roads are never beneath 0 and *underserved* are never above 0. Further information regarding the methodology used to determine charging demand, supply, and classification rules can be found in our GitHub repository (GitHub, 2023c).

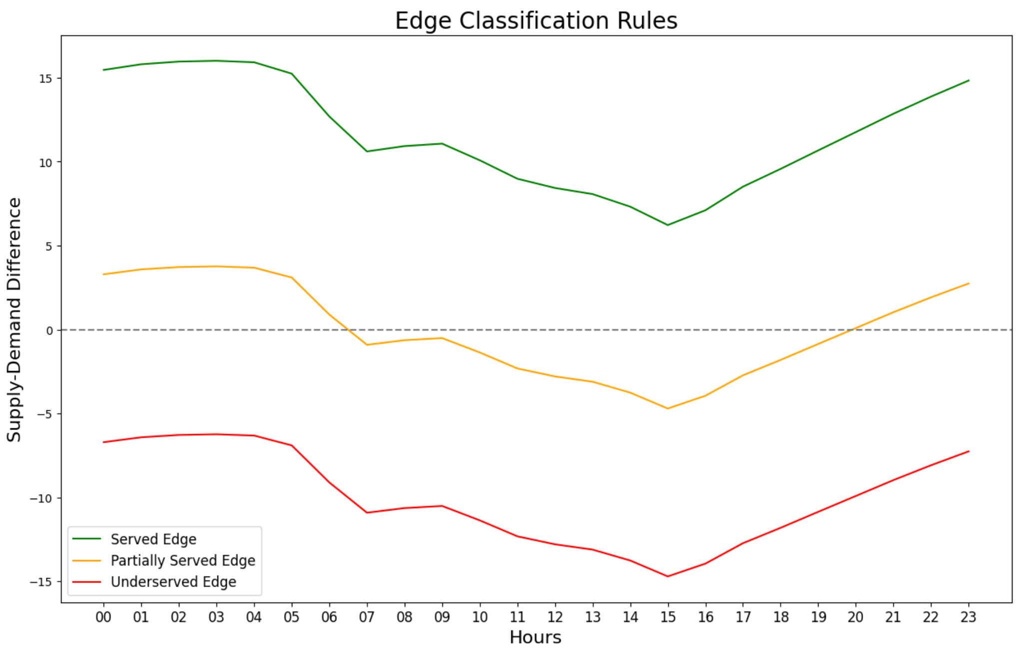


Figure 12: Depiction of classification rules

4 Baseline Results

In this section, we will outline the baseline model outcomes, followed by the insights derived from supplementary analyses, including cost and sensitivity assessments. The objective is to highlight the model's adaptability to cater to diverse stakeholders, underscoring its capacity to incorporate new parameters. The focus is also on presenting the quality metric of the charging infrastructure. Through this approach, we strive to demonstrate the model's practical relevance and potential for tangible real-world applications.

4.1 Parameters used in Baseline Model

To start off, we will outline the principal parameters and assumptions underpinning the results of the baseline model. Critical factors encompass the average range of EVs, the proportion of electric vehicles in the Norwegian vehicle fleet, temperature impact on travel range, hourly charging capacities per charger type, and ratios for the distribution of daily traffic across various hours. The baseline model commences with an assumption of an average EV range of 300 kilometers (Hildonen, 2023; TOI, 2023), a value derived from an aggregation of older and newer vehicles in the Norwegian fleet, though this can be manipulated for sensitivity analysis. The EV ratio, set at 20%, draws on data from SSB (SSB, 2023a). We also used an average battery capacity of vehicles at 68 kWh (Brakels, 2022; OFV, 2023b). In our pursuit of robust and credible outcomes, we opted for a conservative approach when selecting parameter values, thereby mitigating the risk of overly optimistic projections.

Parameter	**Value**
EV-Ratio	20 %
Range	300 km
Battery Capacity	68 kWh
Actual Charge	90 %

Table 3: Baseline parameters

4.2 Identifying Underserved Roads

The model, when run using baseline parameters such as today's average EV-range and EV-ratio of the vehicle fleet among others, reveals that out of 416 roads, 318 are *served*. This implies that approximately 76% of roads fall under the *served* category. This calculation is based solely on the roads that already have at least one charging station. Roads without charging stations are excluded from this calculation, and for the purposes of our study, we regard these as *underserved*. Should we decide to include the 258 roads without CSs in our calculations, the proportion of served roads would decline to 47%. The rationale behind maintaining the *underserved* roads as a separate category is to provide a clearer view of the current status of charging infrastructure and to identify the magnitude of the gap to be addressed.

In Figure 13 we can observe how the classification of edges fluctuate across the months of the year.

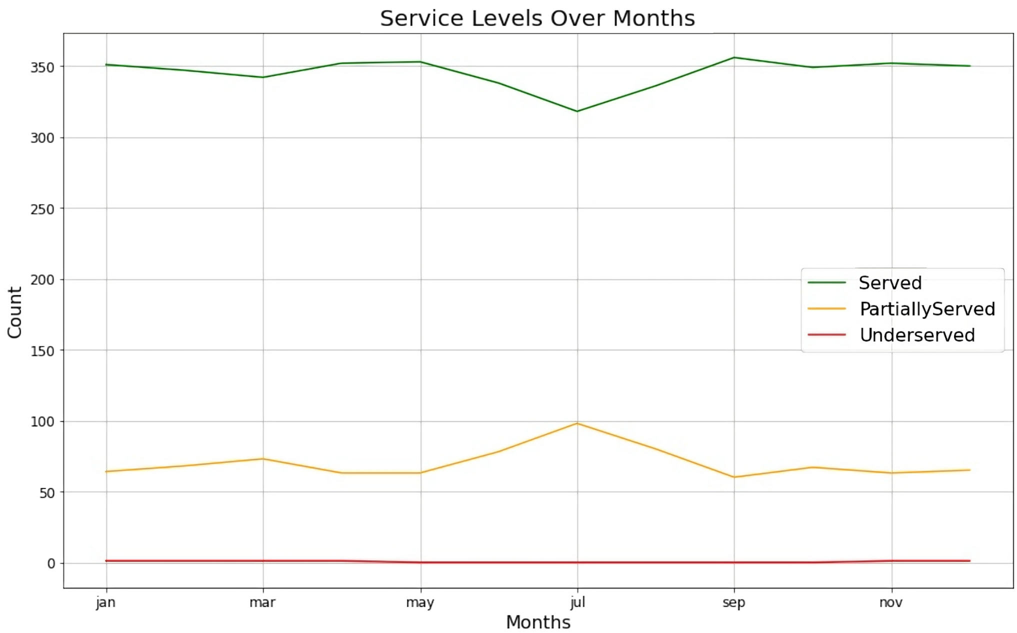


Figure 13: Classified roads on map: Only edges w/CS

Edge	**Only Edges $^{w}/$CS**		**All Edges**	
Served	318	76%	318	47%
Underserved	98	24%	356	53%
Total	416	100%	674	100%

Table 4: Baseline results

The tabular representation presented in Table 4 illustrates the baseline results, encompassing both included and excluded edges with missing charging stations. To visually depict the *served* and *underserved* edges from a geographical perspective, refer to Figure 14 below.

Figure 14: Classified roads on map
* *Underserved = Partially Served & Underserved*

In light of recent user experiences, as captured by the Elbilforeningens elbilundersøkelse (2022), our model's findings on the current state of EV charging infrastructure align closely with real-world perceptions. The survey uncovers user frustrations with non-functional charging stations and queues, with half of the respondents reporting instances of encountering inoperable rapid chargers or experiencing frequent or occasional waiting lines. These real-world experiences underscore the urgency of our study's findings on the *underserved* roads and the pressing need to enhance charging infrastructure. According to the "*Kunnskapsgrunnlag om hurtigladeinfrastruktur for veitransport*" published by the Norwegian Government, ensuring sufficient charging infrastructure, particularly in areas with high EV density, poses a significant challenge (Statens Vegvesen and Miljødirektoratet, 2022). Concerns also exist regarding the equitable accessibility of charging infrastructure, irrespective of individuals' residential or travel locations.

To meet the increasing demand for EVs, substantial investments are required in both public charging stations and private home charging points, coupled with the development of rapid and ultra-rapid charging technology. This government report underscores the necessity for public-private collaboration, the incorporation of renewable energy into charging infrastructure, and the development of smart grids to manage the increased electricity demand from EVs. Furthermore, regulatory measures are deemed essential to ensure that the development of charging infrastructure is equitable, universally accessible, and sustainable (Statens Vegvesen and Miljødirektoratet, 2022). These topics highlight the pressing need for concerted efforts and strategic planning to address the current shortcomings in EV charging infrastructure and which are further strengthened by our results.

Upon a thorough analysis of the edge data, we observe variations in supply and demand at distinct hours of the day, categorized by the months of the year. Using a color-coded representation, based on the monthly average 'temperature', a pattern surfaces: warmer months demonstrate a higher surplus of supply compared to demand. This could be due to several factors, a noteworthy one being the increased battery longevity in warm temperatures. While one could argue that the lighter traffic during winter months should logically result in a higher supply surplus, our analysis suggests that the surplus, albeit noticeable during winters, does not exceed that of the warmer months. Figure 15 below displays this finding for a better understanding.

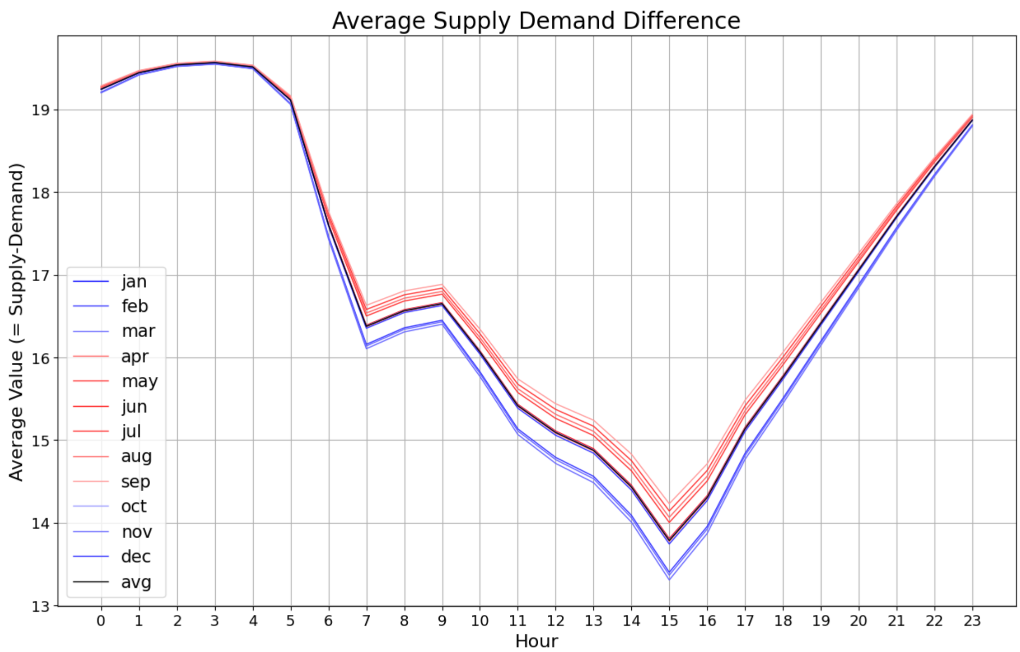


Figure 15: Average supply demand difference based on hours of the day

Additionally, we note a significant decrease in average supply and demand balance transitioning from morning to afternoon, aligning with the common 'rush hour' periods. This indicates that these are pivotal times for the charging infrastructure, necessitating careful planning for efficient operations. Significantly, the visualization presents average figures, yet it provides the capability to scrutinize each road individually, allowing us to discern the precise moments when the supply-demand difference drops below zero. This granular view holds value for strategic planning and informed evaluation of the road network, underscoring the role of detailed data analysis in optimizing electric vehicle infrastructure.

4.3 Quantifying Charging Infrastructure Needs

The analysis and quantification of the charging infrastructure needs, particularly on roads that currently lack charging stations, reveal insights into future investment requirements. The task of evaluating the adequacy of the charging infrastructure is a multifaceted issue, with diverse stakeholders having their own distinct goals and KPIs. Our strategy thus hinges on aligning future infrastructure development with the careful predictions of supply and demand. Utilizing our model's data, we analyzed the current charging stations' adequacy on all roads, their insufficiencies, and the roads bereft of any charging stations. The roads were segmented into two categories: the served roads and the underserved or partially served roads (classified as 0 or -1). For the latter, we focused on identifying the hour with the maximum supply deficit vis-a-vis the demand to understand the extent of investment required to upgrade them to the *served* category.

Our findings unveiled that a total of 98 edges were classified as partially served or not served at all. To transform them into fully served edges, an additional charging capacity equivalent to 564 cars per hour is required. Applying the charging capacities of 50 kW and 150 kW chargers, we found that this translated into the need for an additional 758 chargers for the 50 kW category, or 335 chargers for the 150 kW category. For roads devoid of any chargers, a similar methodology was employed, with the focus being on the hour with the maximum demand throughout the year. To meet the peak demand, and thereby convert these roads into *served* roads, a total of 951 chargers of the 50 kW category, or 460 of the 150 kW category, would be needed. Combining the infrastructure needs for both the underserved roads and roads without any chargers, we established a requirement of 1709 chargers of the 50 kW category, or 795 of the 150 kW category. Leveraging commercial cost metrics for fast chargers in the United States, we could then estimate the financial implications of these needs (DiNello, 2023; Manager, 2021). The cost for setting up 795 of the 150 kW chargers is calculated to be 795 million NOK, while the cost for 1709 of the 50 kW chargers is expected to reach 854.5 million NOK.

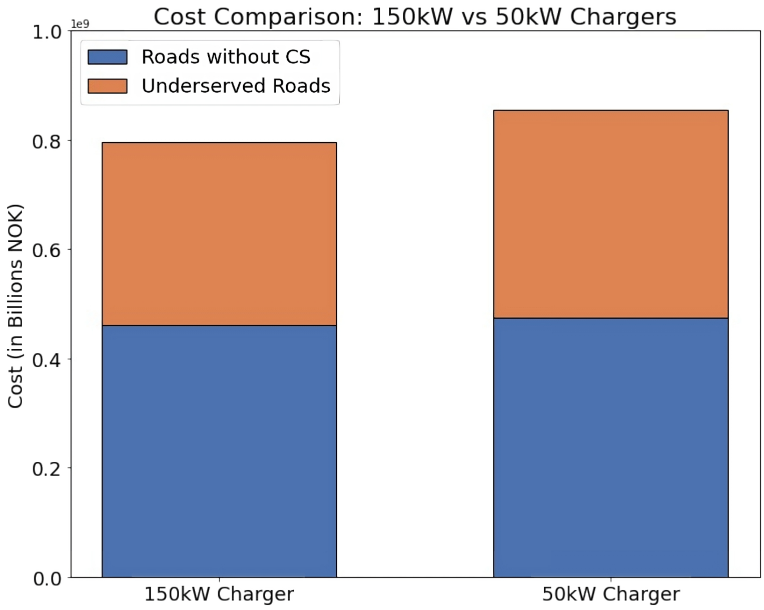


Figure 16: Cost sorted by charger type

Charger Type	Edges $^{w}/$CS	No CS Edges	Total	Cost (MNOK)
50kW	758	951	1709	795
150kW	335	460	795	854.5

Table 5: Needed chargers and costs

It is important to note that these figures represent a rough estimate, but they serve to illustrate the scale of investments required to ensure adequate charging infrastructure on all roads. The strategic placement of these additional charging stations will need to take into account a number of factors, such as the volume of electric vehicle traffic and the proximity to electrical grid infrastructure, which could present additional challenges. Additionally, the cost metrics under consideration pertain exclusively to the chargers. Therefore, when evaluating costs for roads currently devoid of charging stations, these metrics do not incorporate the potential ancillary construction expenses. These additional costs could include paving the platform, creating access roads to the charger locations, among other potential expenditures. It's worth noting that these values can be challenging to estimate due to their site-specific nature. However, model users with access to such detailed cost data could more readily incorporate them into their own analyses.

4.4 Sensitivity Analysis

In our endeavor to authenticate and refine the findings of our model, we have performed sensitivity analyses on the key parameters. The primary aim of such an analysis is to understand the influence of variations in an independent variable on a specific dependent variable, given certain assumptions. This process is vital for robust decision-making, and it enables us to understand the reliability and validity of our model. The parameters we subjected to the sensitivity analysis encompass alterations in the EV ratio and variations in vehicle range. Each of these parameters was analyzed individually and in tandem to obtain a comprehensive view of their combined impact.

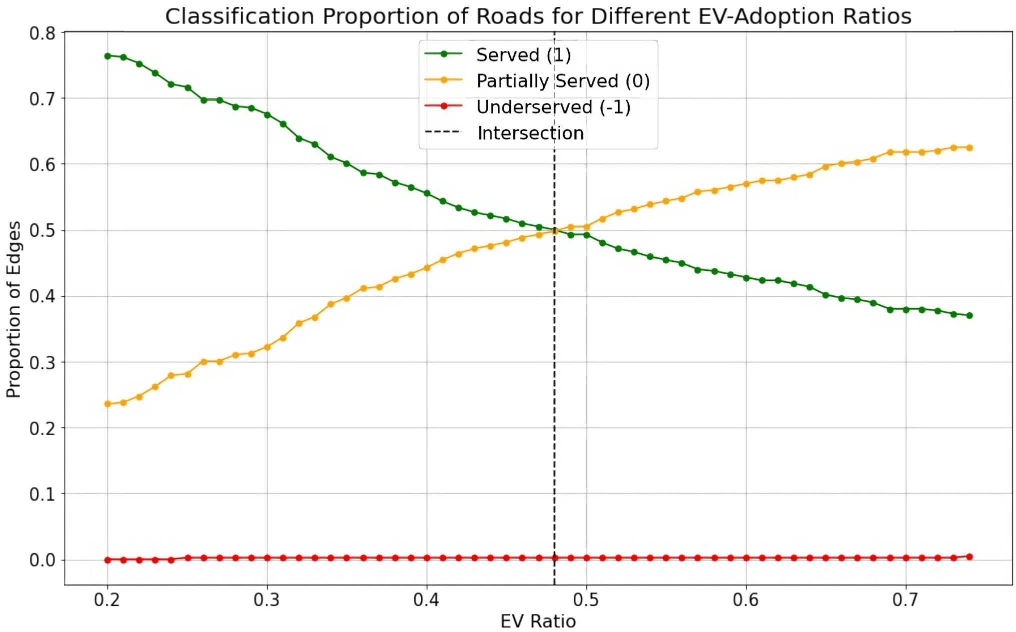


Figure 17: Sensitivity of EV-ratio parameter on model

The data obtained from our sensitivity analysis on the EV-ratio parameter yields informative insights (Figure 17). The graph reveals that approximately 76% of roads can be considered *served* when using today's EV-ratio of 20%. An inflection point is observed when the EV ratio reaches 47%, where there is a balance between *served* and *partially served* roads. These findings support the internal logic of our model, as an increase in the rate of EV usage is expected to escalate demand naturally. With a steady supply, the uptick in demand will inevitably cause a intersection between *served* and *partially served* roads. Another sensitivity displayed in Figure 18 focuses solely on the range of vehicles. The results from this study highlight an enhancement in infrastructure quality as there is reduced demand for chargers with an increase in vehicle range. This ties back to the calculation probability of a car requiring charging.

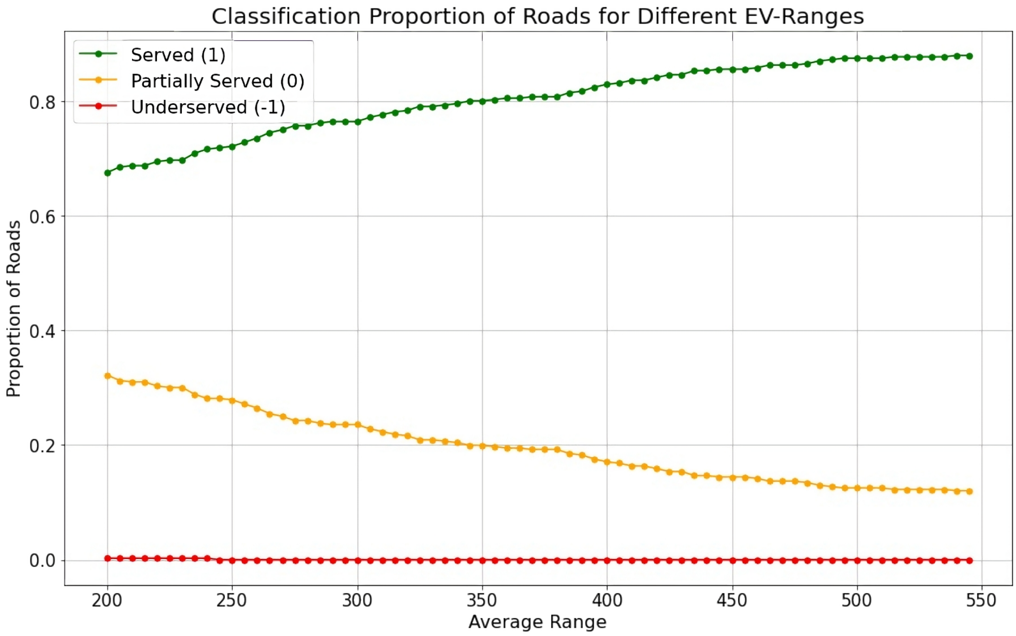


Figure 18: Sensitivity of range parameter on model

Though this particular sensitivity analysis in isolation may not add substantial value, it corroborates the rationale of our model. Furthermore, when used in conjunction with other parameters and variables, it can significantly enhance the accuracy of infrastructure requirement projections.

The final sensitivity analysis we performed involved a concurrent modification of EV range and EV adoption rate. This combination offers insights into a likely scenario, wherein the adoption of EVs may increase as people see an improvement in vehicle range. The outcome of this analysis is displayed in Figure 19.

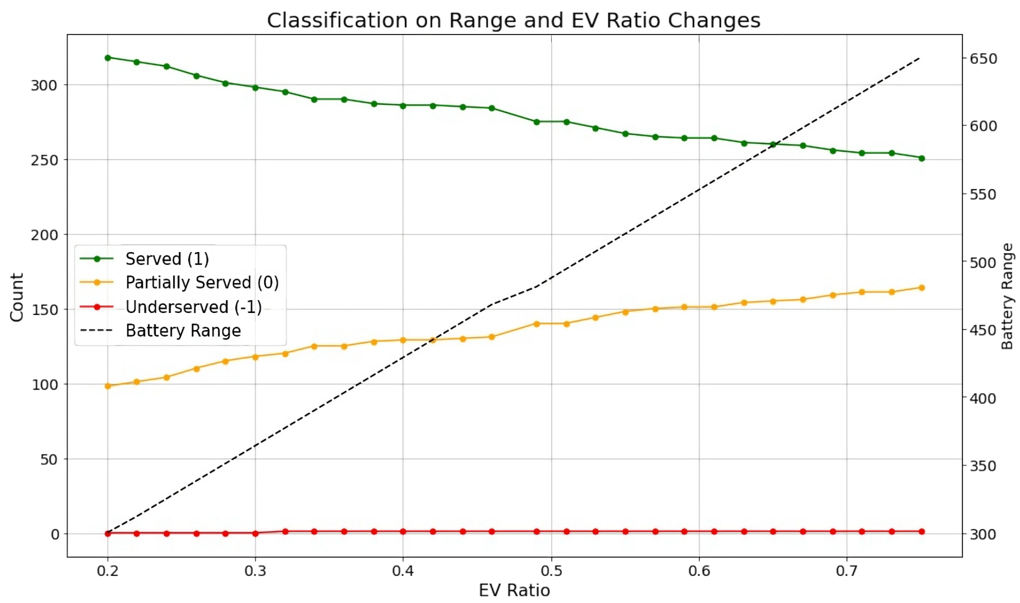


Figure 19: Sensitivity of battery range and EV-ratio parameter on model

The data demonstrates that when the EV adoption ratio increases from 20% to 70%, the number of roads classified as *served* decreases from approximately 318 to around 250. Despite the EV range doubling during the same time period (from 300 to 600), this increase in range does not sustain or enhance the count of *served* roads. This implies that under the current charger infrastructure, an increase in EV adoption will lead to a reduction in the number of *served* roads, regardless of these significant improvements in the average range of EVs. In other words, our model suggests that a rise in the adoption of EVs coupled with advancements in range does not necessarily translate into a greater number of adequately served roads under the current charging infrastructure.

4.4.1 Implications of Sensitivity Analysis

Sensitivities of parameters like the ones we have analyzed here can have implications and applications across various sectors and disciplines. They can serve as aids to decision-making tools, guiding stakeholders through various scenarios and enabling them to predict future trends based on changes in input parameters.

Firstly, for governmental bodies, these models could provide insights into planning and implementing infrastructure policies. By analyzing different scenarios using the sensitivity parameters, they can gain a better understanding of the implications of various investment decisions. For example, the trade-off between investing in more charging stations versus encouraging the development of EVs with a higher range or capacity could be better evaluated.

Secondly, automakers can use these models to understand market trends and the potential demand for EVs under various circumstances. Changes in the EV ratio, vehicle range, and battery capacity have significant effects on the required charging infrastructure. Recognizing these trends can guide automakers in their product development, helping them to tailor their offerings to meet projected demands and infrastructure capabilities.

Lastly, these models serve as a resource for the broader community, aiding in the demystification of the challenges and requirements associated with a larger-scale transition to electric vehicles. While they do not endorse specific sustainable transport modes, they provide a data-driven examination of the potential infrastructure implications. The models shed light on the challenges of establishing and expanding an EV charging network, contributing to a more informed public discourse and academic discussion on planning for an EV-centric infrastructure.

However, while creating these models, it's crucial to consider that they are simplifications of reality. The choice of parameters, the assumptions made, and the interplay between variables all influence the model's outputs. The models should therefore be robust, able to handle changes in inputs or conditions, and transparent, meaning that the assumptions and parameters are clearly stated and justified. This helps to ensure the model's findings are reliable and valid. Moreover, as the future can often be unpredictable, these models should not be seen as a perfect forecast, but rather as a guide that can inform and support decision-making. By integrating continual data updating and refining the sensitivity of the parameters, the model can remain relevant and accurate over time.

5 Scenarios

This section explores two key scenarios within our model. The first scenario provides a comprehensive analysis of the EV charging infrastructure's evolution until 2050. Drawing inspiration from national budget predictions, we align our projections with the expected increase in electric vehicle adoption.

The second scenario examines the differentiation between urban and rural areas in terms of charging infrastructure, using an automated process based on traffic volume classification. By analyzing these scenarios, we may gain specific insights into the future of EV charging infrastructure, aiding policymakers and stakeholders in developing targeted strategies and solutions.

5.1 Charging Ahead: Projections for 2050

This portion of the analysis seeks to expand upon the earlier sensitivity examination by providing a more comprehensive projection of the evolution of the EV charging infrastructure from the present year to 2050. The main variables shaping our model will be the EV-ratio, the EV range, and the EV battery capacity. The choice of a timeline extending to 2050 is inspired by the report "*Electrifying the vehicle fleet: Projections for Norway 2018-2050*" by the Norwegian Institute of Transport Economics (Fridstrøm, L., 2019). According to the national budget predictions of 2019 included in this report, it's expected that by the year 2050, 75% of the vehicle fleet will be fully electric, with chargeable hybrids making up an additional 22%. Using this timeframe and the projected EV-ratios, we can incorporate additional variables. One such variable is vehicle range. With continuous advancements and the increasing affordability of battery technology, it is reasonable to anticipate an enhancement in the vehicle range. We have taken a conservative approach in our estimate, projecting an average range of 650 kilometers by the year 2050, increased from a baseline of 300 kilometers (Carlier, 2023). While this estimate might seem somewhat modest, it accounts for uncertainties surrounding future battery technology developments and raw material availability. Similarly, we considered the average battery capacity of electric vehicles as another variable. Our model assumes an average capacity of 68 kWh today and, based on estimates from various sources, projects this to increase to an average of 90 kWh by 2050 (Samferdselsdepartementet, 2023).

Year	**EV Ratio**	**Vehicle Range**	**Avg. Battery**	**-1***	**0***	**1***
2023	0.20	300.0	61.2	0	98	318
2031	0.36	403.0	67.1	1	127	288
2039	0.53	507.0	72.9	1	170	245
2047	0.69	611.0	78.8	1	184	231
2050	0.75	650.0	81.0	1	199	216

* *-1 = Underserved, 0 = Partially Served, 1 = Served*

Table 6: Numeric results, every 8th and last year

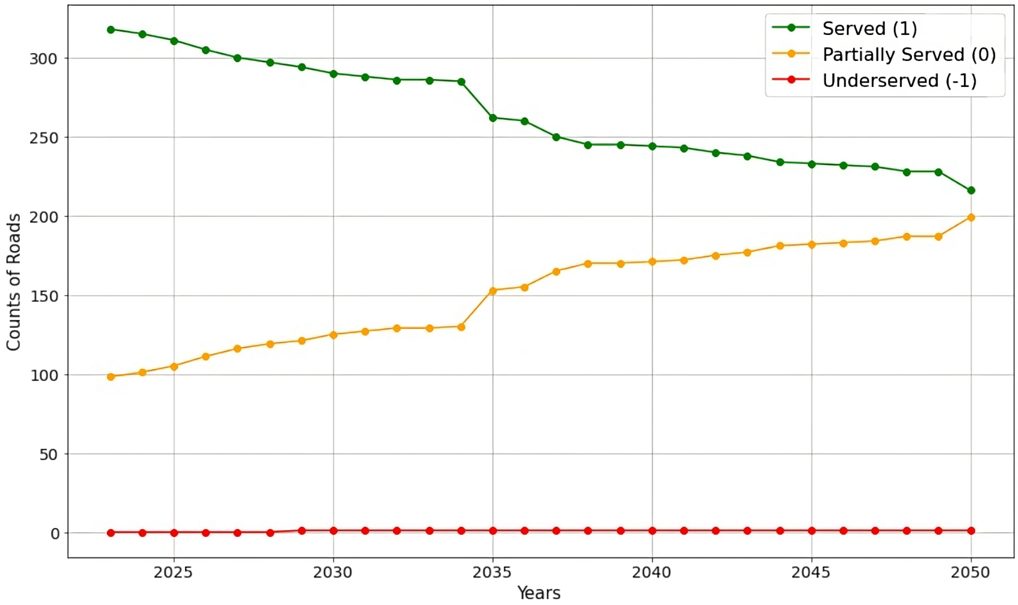


Figure 20: Projections with adjusted variables

Running the model annually from 2023 to 2050, with these three variables gradually increasing, yields some findings. For instance, the number of roads classified as *served* appears to be decreasing steadily, whereas *partially served* roads are on the rise. This trend indicates that the enhancements in range and battery capacity significantly influence the road classification. If we revisit our sensitivity analysis, wherein the EV-ratio was the sole variable adjusted, we recall that the count of *served* roads dipped below that of *partially served* roads. However, this scenario does not play out once we factor in changes in both vehicle range and battery capacity.

However, it is essential to acknowledge that there are other potential factors, not included in this analysis due to their uncertain nature, which could significantly impact these results. For instance, as battery capacities increase, might the quantity of vehicles that can be charged per charger decrease due to the increased charging time? This is uncertain as charger technology may also evolve, potentially leading to faster charging times. Furthermore, increasing the baseline traffic could also have an impact. Predicting a moderate increase in overall traffic over the next 30 years would seem logical. However, we chose to exclude this variable due to the myriad of complex factors involved, which risked exceeding the scope of our thesis.

5.2 Urban vs. Rural Infrastructure: Future Focus

As another scenario of our study, we have developed a pragmatic method to differentiate between urban and rural roads. Our automated process bases its assessment on the traffic volume, offering a swift and efficient way to ascertain the degree of urbaneness of any given road.

Our method commences with the identification of roads with the highest and lowest traffic volumes. Subsequently, we segment the range between these two extremes into six intervals. Each road is then classified into one of these intervals, based on its traffic volume, creating a new categorical classification feature for our dataset. It's worth noting that our distribution is skewed towards the lowest interval, representing rural areas.

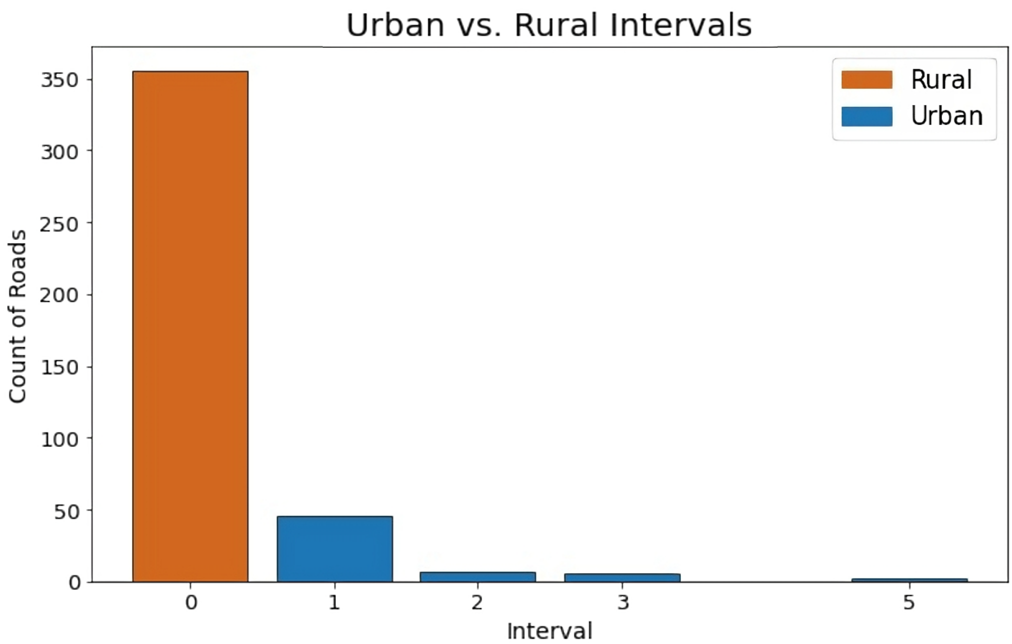


Figure 21: Urban vs. Rural distribution

A trial-and-error approach revealed that the remaining five intervals combined (1-5) could be considered representative of urban roads, resulting in a binary classification (0,1) for rural and urban areas respectively. To visually examine the classification, we again utilized QGIS to map out and visualize the data. The results can be found in Figure 22 below. The results showed a correlation between our classifications and the actual geographical nature of the areas. Major urban centers in Norway were classified as urban, while mountainous regions and farmland were appropriately identified as rural. While our approach is not flawless, it serves as a viable means of preliminary differentiation between urban and rural roads. It allows us to analyze disparities in charging infrastructure, providing insight into the state of accessibility for EV users in diverse geographical settings.

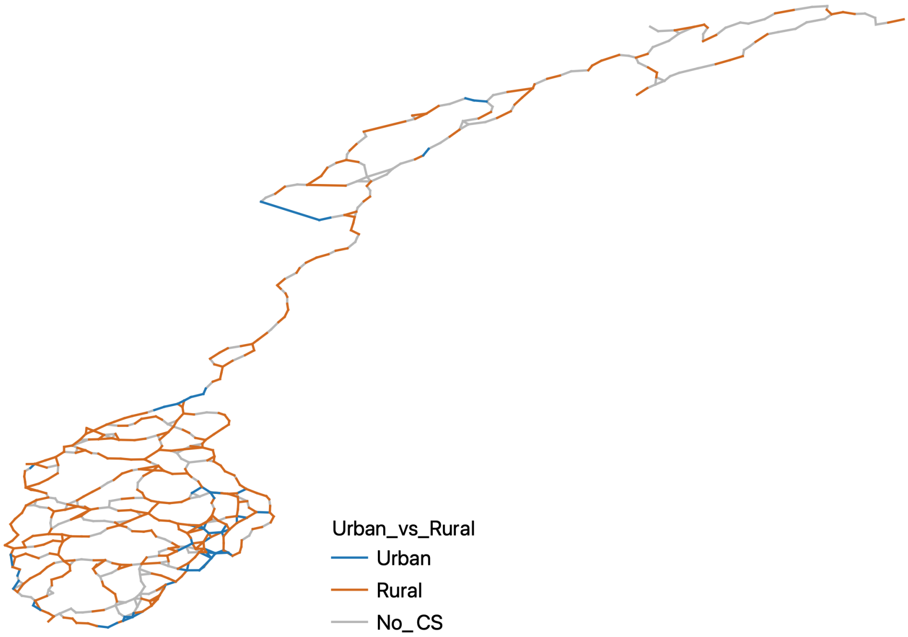


Figure 22: Urban vs. Rural classified roads

Upon grouping our dataset by the urban/rural classification and service status (i.e., *served*, *partially served*, *underserved*), we examined the ratios of roads based on their service status within each category. Out of the 355 rural roads, 85.9% were *served*, whereas for the 61 urban roads, the percentage *served* dropped to 75.4%.

Urban	Edge Classification	Percentage
0	Served	0.85915
	Not Served	0.14085
1	Served	0.75410
	Not Served	0.22951

Table 7: Service status based on urban (1) and rural (0) categories

This apparent discrepancy in the availability of charging stations between rural and urban areas might be attributed to several factors. Our hypothesis is that it might be related to differing travel behaviors between urban and rural inhabitants. While urban areas generally experience higher traffic volumes, the shorter distances traveled by urban dwellers often allow them to rely on home charging facilities. On the other hand, rural inhabitants tend to rely more heavily on public charging infrastructure due to their longer commutes. However, further research is needed to substantiate this hypothesis. A more extensive study into travel behavior and the ratio of public versus home charging based on geographical areas could shed light on the observed disparity in service percentages between urban and rural roads. The insights gained from such research could guide policymakers and planning authorities in designing a more equitable charging infrastructure for both urban and rural EV users.

6 Discussion

This section details key limitations of our study. These limitations must be factored in when interpreting our results. They delineate the scope within which our findings are valid and draw attention to areas where assumptions were necessary, hence requiring careful interpretation. The aim is not to devalue our work but to provide a holistic understanding of the research context. Acknowledging these constraints lends greater depth to our findings, enabling practitioners, policymakers, and subsequent researchers to utilize our work effectively and responsibly.

6.1 Limitations

Firstly, the simplifications made in our model, including the selection of factors and parameters such as the EV-ratio, battery capacity, and vehicle range, may not capture the full complexity of the real-world EV charging infrastructure. Factors such as advancements in charging technology, policy changes, and consumer behaviors are not accounted for, leaving room for future research to explore additional parameters and their impact on the charging infrastructure. An example of a significant limitation of our study stems from the assumptions made in our algorithm that calculates the theoretical number of cars capable of charging per hour for each charger type. The algorithm, in its current form, presumes that all vehicles can utilize the same charging efficiency on every charger type. This is not the case in reality; while a vehicle can technically charge on various chargers, the charging effect will differ based on the car's own charging capacity. For instance, a car with a maximum charging efficiency of 100kW can utilize a 350kW charger but will only achieve the charging rate of a 100kW charger, reflecting the battery's maximum efficiency. We made adjustments to this algorithm, showcased on our GitHub (GitHub, 2023a), but chose to exclude it from the main model due to its shortcomings. A more accurate model would need detailed vehicle fleet information, such as percentages of different brands, car model years, and corresponding maximum outputs. This data is accessible from OFV but it is not without costs (OFV, 2023a). Another important point is that modern vehicles feature significantly higher battery efficiency. Therefore, even without updating the algorithm, the anticipated trend in future vehicle sales indicates a larger number of cars will be able to utilize higher-efficiency charger types.

Secondly, the data used in our research, while sourced from reputable sources, may have limitations in terms of reliability, accuracy, and currency. Addressing data gaps, such as obtaining more specific information on daily driving patterns, individual charging behavior, regional variations in EV adoption, public charging point usage, and the influence of climate on EV performance and charging behavior, would enhance our understanding of the dynamics of the EV charging infrastructure.

Additionally, the prediction of future technological advancements, which play a crucial role in our study, is inherently uncertain. While our analysis assumes linear improvements in battery technology and charging infrastructure, breakthroughs or unforeseen innovations could significantly alter the landscape of EV technology. Advancements in renewable energy, energy storage, and grid management also have the potential to impact the demand for and efficiency of the charging infrastructure.

A key limitation of our model also lies in its evaluation metric and the inherent assumptions it makes about the real-world conditions. The metric is based on probabilities calculated from road segments of approximately 16 km (*avg.edge length*). Consequently, when we label a short road segment as *underserved*, it's crucial to remember that there may be other factors at play. For example, charging stations may exist on adjacent segments, which in reality are just a short distance away. Furthermore, actual usage scenarios present complex economic and behavioural considerations that our model does not fully address. Real-world conditions often involve trade-offs between system efficiency and associated costs. For instance, behavioural adaptations, such as shifting preferred travel times or "premature charging" in anticipation of *underserved* road sections, can have a significant impact. Many electric vehicles are coming equipped with advanced traffic and charging assistance systems, which aid drivers in making decisions regarding travel times and recharging optimization. These variables introduce another layer of complexity that our model, which does not factor in economic optimization or behavioural adaptation optimization, is unable to capture.

It is important to recognize these limitations and the potential implications they may have on our research findings. While our study provides insights based on current knowledge, future developments in technology and data availability may lead to different outcomes and necessitate adjustments to our projections.

6.2 Further Research

Our thesis reveals potential pathways for further expansion and the following section outlines some of these areas.

6.2.1 Parameter Exploration

While our study utilized certain parameters based on our assessment and available data, a different set of parameters might yield different outcomes. Further research could explore a variety of parameter choices, including different battery capacities, EV-ratios, and vehicle ranges. Furthermore, the consideration of more complex parameters or even nonlinear parameter relationships might add additional depth and realism to the analysis. Integrating our data-driven approach with live data from sources such as NOBIL (2023) could yield even more precise insights, given NOBIL's comprehensive repository of charging station data. Looking ahead, the European Commission's proposition of open data requirements, as outlined in the Alternative Fuels Infrastructure Directive, holds promise for enhancing the precision and applicability of these models. This highlights the crucial role of open and accessible data in advancing our comprehension and strategic development of EV charging infrastructure (European Parliament and Council of the European Union, 2014). With future developments also set to accommodate alternative fuels within these databases, our model's versatility and readiness to adapt to such changes underlines its sustainable value in this dynamic context.

6.2.2 Incorporation of Additional Variables

There is potential for future research to extend our model by incorporating additional variables. This could include factors like increasing baseline traffic and potential changes in charging technology. While some of these variables were outside the scope of our study due to their complexity or uncertainty, they could significantly influence the charging infrastructure needs. One prime example of this is that in our research, we deliberately omitted home charging stations from the model's considerations, focusing instead on public charging infrastructure. This decision, while seemingly a deviation from reality, was grounded in our objective to model the journey of electric vehicle drivers navigating the real-world network and their interactions with public charging stations. Including home charging in this model would have introduced an extra layer of complexity, and any metric or ratio used to represent it would be inherently fraught with assumptions and uncertainties. However, we acknowledge that this is a significant simplification of the real-world scenario, where home charging plays a vital role, especially in urban settings. Notably, our findings indicating a higher percentage of *underserved* or *partially served* roads in urban areas compared to rural areas might be influenced by this model limitation. In actuality, a substantial proportion of urban electric vehicle users are likely to rely heavily on home charging, reducing their dependency on public charging infrastructure. This aspect, not accounted for in our model, could potentially alter the interpretation of our results. Therefore, we propose that future research should expand on our model by incorporating the impact of home charging.

6.2.3 Wider Geographical Scope

Our study focused on Norway, a country with unique geographical, climatic, and societal conditions. Extending the geographical scope of this research could provide different insights. Future work could apply the developed model to different countries or regions, thereby comparing and contrasting the charging infrastructure needs across different geographies. Such a comparison could help to identify region-specific challenges and solutions.

6.2.4 Traffic Flow Modeling

Our existing network, with bidirectional edges and designated volumes, offers a strong basis for implementing a multitude of modeling approaches such as gravity models or machine learning techniques. The inclusion of origin-destination (O-D) flow dynamics could enable a detailed understanding of travel patterns, enhancing the accuracy of our deterministic model. The integration of such methods would add depth and complexity to the comprehension of EV usage and needs, thus aiding in the identification of gaps in the charging infrastructure.

7 Research Conclusion

Our study set out to evaluate the adequacy of existing electric vehicle charging infrastructure in Norway and to establish a flexible, data-driven model that can simulate various scenarios and analyze different parameters impacting charging station infrastructure. In achieving these goals, we have not only identified gaps in the current EV charging network but also provided a tool that can guide future research and strategic planning in the realm of EV infrastructure development.

To reiterate our research question, *"How does the present and future demand for EV charging stations align with the supply of EV charging?"*, our study reveals clear disparities between current supply and demand. Furthermore, projections indicate potential future misalignment if infrastructure development does not keep pace with the growth in EV adoption.

The baseline model presented a snapshot of the current state of EV charging infrastructure in Norway, identifying approximately 76% of roads as *served* when considering roads that already possess at least one charging station. When observing the quality of all roads, this *served* ratio of roads decreases to 47%. We also highlighted the limitations of the current network, with a significant number of roads falling into the *underserved* or *partially served* categories. Our findings align with real-world user experiences and underscore the need to enhance charging infrastructure across the country. Our sensitivity analysis also revealed an inflection point at an EV ratio of 47%, beyond which the balance shifts towards more roads falling under the *partially served* category.

Based on these baseline results, our model predicts a requirement for 1709 additional chargers of the 50 kW category, or 795 of the 150 kW category, to convert all the *underserved* and currently *partially served* roads into the *served* category. This prediction emphasizes the scale of investment required to match the growing demand

A cornerstone of our research, and where much of its value lies, is rooted in the model which presented these results. It's capacity to adjust to diverse parameters and assumptions makes it a possible asset for a range of stakeholders involved in EV infrastructure planning and policy-making. The model also has potential to serve as a reference for more granular studies and for integration with real-time data sources which could offer more accurate insights. In terms of future direction, we recognize certain limitations in our study that may pave the way for further research. These limitations stem from our choice of parameters, data sources, geographical focus, and assumptions about future technology advancements. Exploring these potential avenues could lead to further model refinement, geographical expansion, and exploration of additional variables and technologies.

In conclusion, our study emphasizes the need for a strategic and informed approach to planning and investing in EV charging infrastructure in Norway. By leveraging our data-driven model, we can anticipate future demand, understand the implications of different scenarios, and ultimately make more informed decisions to ensure a sustainable and equitable transition towards electric mobility.

References

Afshar, S., Macedo, P., Mohamed, F., & Disfani, V. (2021). Mobile charging stations for electric vehicles — a review. *Renew. Sustain. Energy Rev.*, *152*(111654), 111654 (cit. on p. 4).

Berntzen, S. (2021). Optimal allocation of electric vehicle charging stations: A case study of the norwegian road network. *BI Norwegian Business School - Campus Oslo* (cit. on pp. 6, 13).

Brakels, R. (2022). Norway Has So Many EVs Their Battery Capacity Averages 13kWh Per Household [Accessed: 2023-06-17]. https://www.solarquotes.com.au/blog/norway-ev-batteries/. (Cit. on p. 29)

Capar, I., Kuby, M., Leon, V. J., & Tsai, Y.-J. (2013). An arc cover–path-cover formulation and strategic analysis of alternative-fuel station locations. *Eur. J. Oper. Res.*, *227*(1), 142–151 (cit. on p. 4).

Carlier, M. (2023). Electric vehicles - Average range forecast [Accessed: 2023-06-17]. https://www.statista.com/statistics/970998/range-trends-electric-vehicles/. (Cit. on p. 39)

CTT. (2023). *Climate in norway*. https://www.climatestotravel.com/climate/norway. (Cit. on p. 25)

DiNello, S. (2023). WHAT DOES A LEVEL 3 CHARGER COST? [Accessed: 2023-06-17]. https://futureenergy.com/ev-charging/what-does-a-level-3-charger-cost/. (Cit. on p. 34)

Dong, G., Ma, J., Wei, R., & Haycox, J. (2019). Electric vehicle charging point placement optimisation by exploiting spatial statistics and maximal coverage location models. *Transportation Research Part D: Transport and Environment*, *67*, 77–88 (cit. on p. 4).

Elbilforeningen. (2022). Elbilundersøkelse 2022 - 16.500 respondenter [Accessed: 2023-06-17]. https://www.regjeringen.no/no/dokumenter/nasjonal-ladestrategi/id2950371/?ch=7#fn14_doc. (Cit. on p. 31)

EU. (2023). EUR-Lex - 02019R0631-20210301 - EN - EUR-Lex [Accessed: 2023-5-31]. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:02019R0631-20210301. (Cit. on p. 1)

European Parliament and Council of the European Union. (2014). Directive 2014/94/EU of the European Parliament and of the Council of 22 October 2014 on the deployment of alternative fuels infrastructure [Accessed: 2023-06-17]. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32014L0094. (Cit. on p. 45)

Fridstrøm, L., & Østli, V. (2021). Slow, fast or extra fast exploring decarbonization pathways for road transportation in norway [Accessed:

2023-5-31]. https://www.toi.no/getfile.php/1368504-1630928367/Publikasjoner/T%7B%5CO%7DI. (Cit. on p. 2)

Fridstrøm, L. (2019). *Electrifying the vehicle fleet: Projections for Norway 2018-2050* (Research report) [Accessed: 2023-06-17]. Norwegian Institute of Transport Economics (TØI). https://www.toi.no/getfile.php/1350199-1553693924/Publikasjoner/T%5C%C3%5C%98I%5C%20rapporter/2019/1689-2019/1689-2019-sum.pdf. (Cit. on p. 39)

GeoNorge. (2022). Kartkatalogen [Accessed: 2023-5-31]. https://kartkatalog.geonorge.no/metadata/statens-vegvesen/nvdb-ruteplan-nettverksdatasett/8d0f9066-34f9-4423-be12-8e8523089313. (Cit. on p. 12)

GeoTab. (2020). The ultimate guide to electric vehicle range. https://www.geotab.com/blog/ev-range/. (Cit. on p. 25)

GitHub. (2023a). *Changing Charge Efficiency -Testing* [Accessed: 2023-06-17]. https://github.com/AntonOlav/ev-charging-infrastructure/blob/main/Drafts/Draft%20-%20Anton/Additional_Exploration/altering_chargetype.ipynb. (Cit. on p. 43)

GitHub. (2023b). *Effective Range Calculation* [Accessed: 2023-06-17]. https://github.com/AntonOlav/ev-charging-infrastructure/blob/main/Main_Folder/3.Data_Processing/Data/Battery_Range_and_Charge_Time.xlsx. (Cit. on p. 25)

GitHub. (2023c). *Ev-Charging-Infrastructure* [Accessed: 2023-06-17]. https://github.com/AntonOlav/ev-charging-infrastructure/blob/main/Main_Folder/3.Data_Processing/Code/Mainframe_Model.ipynb. (Cit. on p. 28)

GitHub. (2023d). *Volume Filling Algorithm -Testing* [Accessed: 2023-06-17]. https://github.com/AntonOlav/ev-charging-infrastructure/blob/main/Drafts/Draft%20-%20Anton/VolumeFill_Algorithm.ipynb. (Cit. on p. 22)

Hildonen, T. (2023). Elbilene har i snitt 130 kilometer bedre rekkevidde [Accessed: 2023-06-17]. https://bil24.no/elbilene-har-i-snitt-130-kilometer-bedre-rekkevidde/. (Cit. on p. 29)

Hodgson, M. (1990). A flow-capturing location-allocation model. https://www.researchgate.net/publication/285022113_A_flow-capturing_location-allocation_model (cit. on p. 5)

Huang, Y., & Kockelman, K. M. (2020). Electric vehicle charging station locations: Elastic demand, station congestion, and network equilibrium. *Transp. Res. D Transp. Environ.*, *78*(102179), 102179 (cit. on p. 5).

International Energy Agency. (2022). *Global EV outlook 2022*. OECD. (Cit. on p. 1).

Jun, X., Bo, H., Kaigui, X., Junjie, T., & Heng-Min, T. (2019). An ev charging demand model for the distribution system using traffic property. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8654186 (cit. on p. 8)

Kostopoulos, E. D., Spyropoulos, G. C., & Kaldellis, J. K. (2020). Real-world study for the optimal charging of electric vehicles. *Energy Reports*, *6*, 418–426. https://doi.org/https://doi.org/10.1016/j.egyr.2019.12.008 (cit. on p. 26)

Kuby, M., & Lim, S. (2005). The flow-refueling location problem for alternative-fuel vehicles. *Socioecon. Plann. Sci.*, *39*(2), 125–145 (cit. on pp. 4, 5).

Langbroek, J. H. M., Franklin, J. P., & Susilo, Y. O. (2016). The effect of policy incentives on electric vehicle adoption. *Energy Policy*, *94*, 94–103 (cit. on p. 5).

Lim, S., & Kuby, M. (2010). Heuristic algorithms for siting alternative-fuel stations using the Flow-Refueling location model. *Eur. J. Oper. Res.*, *204*(1), 51–61 (cit. on pp. 4, 5).

Lorentzen, E., Haugneland, P., Bu, C., & Hauge, E. (2017). Charging infrastructure experiences in norway - the worlds most advanced EV market [Accessed: 2023-5-31]. https://www.elbil.no/wp-content/uploads/2016/08/EVS30-Charging-infrastrucure-experiences-in-Norway-paper.pdf. (Cit. on p. 5)

Loveday, E. (2013). "range anxiety" in 2nd place on norway's "words of the year" list [Accessed: 2023-5-31]. https://insideevs.com/news/320317/range-anxiety-in-2nd-place-on-norways-words-of-the-year-list/. (Cit. on p. 2)

Manager, P. (2021). How Much Do Commercial DC Fast Chargers Cost? [Accessed: 2023-06-17]. https://propertymanagerinsider.com/how-much-do-commercial-dc-fast-chargers-cost-2/. (Cit. on p. 34)

NetworkX. (2023). Software for complex networks — NetworkX 3.1 documentation [Accessed: 2023-5-31]. https://networkx.org/documentation/stable/index.html. (Cit. on p. 13)

Nicholas, M. A., Handy, S., & Sperling, D. (2004). Using geographic information systems to evaluate siting and networks of hydrogen stations. *Transportation Research Record: Journal of the Transportation Research Board*, *1880*(1), 126–134 (cit. on p. 4).

NOBIL. (2023). API-INFORMASJON [Accessed: 2023-06-17]. https://info.nobil.no/api. (Cit. on p. 45)

NPRA. (2023). Vegvesenet trafikkdata api. (Cit. on p. 18).

OCM. (2023). OpenChargeMap API [Accessed: 2023-06-17]. https://openchargemap.org/site/develop#api. (Cit. on p. 23)

OFV. (2023a). Kjøretøybestand - Kjøretøystatistikk [Accessed: 2023-06-17]. https://ofv.no/produktinfo/ofv-statistikk-norges-beste-verktoy-for-kjoretoystatistikk. (Cit. on p. 44)

OFV. (2023b). OFV Statistikk: Norges beste verktøy for kjøretøystatistikk [Accessed: 2023-06-17]. (Cit. on p. 29).

OSMnx. (2023). OSMnx 1.3.1.post0 — OSMnx 1.3.1.post0 documentation [Accessed: 2023-5-31]. https://osmnx.readthedocs.io/en/stable/. (Cit. on p. 13)

Peratinos, A., & Piene, J. (2022). Optimal location of electric vehicle charging stations in norway using the flow refueling location model. BI norwegian business school, department of accounting (cit. on pp. 6, 15).

QGIS. (2023). QGIS user guide — QGIS documentation documentation [Accessed: 2023-5-31]. https://docs.qgis.org/3.28/en/docs/user_manual/. (Cit. on p. 13)

Recurrent. (2022). Winter ev range loss. https://www.recurrentauto.com/research/winter-ev-range-loss. (Cit. on p. 25)

Samferdselsdepartementet. (2023). *Nasjonal Ladestrategi* [Accessed: 2023-06-17]. https://www.regjeringen.no/contentassets/26d4c472862342b69e8d49803b45c36a/no/pdfs/nasjonal-ladestrategi.pdf. (Cit. on p. 39)

Shi, L., Hao, Y., Lv, S., Cipcigan, L., & Liang, J. (2021). A comprehensive charging network planning scheme for promoting EV charging infrastructure considering the Chicken-Eggs dilemma. *Res. Transp. Econ.*, *88*(100837), 100837 (cit. on p. 4).

SSB. (2023a). Electric vehicles - registered, by type of vehicle and year - 07849 [Accessed: 2023-6-17]. https://www.ssb.no/statbank/table/07849/tableViewLayout2/. (Cit. on p. 29)

SSB. (2023b). Registered Motor Vehicles, by type of vehicle [Accessed: 2023-06-17]. https://www.ssb.no/en/statbank/table/12576/. (Cit. on p. 1)

SSB. (2023c). Road traffic volumes [Accessed: 2023-5-31]. https://www.ssb.no/en/statbank/table/12577/tableViewLayout1/. (Cit. on p. 3)

Statens Vegvesen and Miljødirektoratet. (2022). Kunnskapsgrunnlag om hurtigladeinfrastruktur for veitransport [Accessed: 2023-06-17]. htt ps://www.regjeringen.no/contentassets/a07ef2d3142344989dfddc75f5a92365/kunnskapsgrunnlag_1mars.pdf. (Cit. on pp. 31, 32)

Thomson, R. C., & Richardson, D. E. (n.d). A graph theory approach to road network generalization. https://icaci.org/files/documents/ICC_proceedings/ICC1995/PDF/Cap354.pdf. (Cit. on pp. 7, 11)

TOI. (2023). TOI Elbiler - Traffiksikkerhetshåndboken [Accessed: 2023-06-17]. https://www.tshandbok.no/del-2/4-kjoeretoeyteknikk-og-personlig-verneutstyr/4-35-elbiler/. (Cit. on p. 29)

Zhang, L., Zhao, Z., Xin, H., Chai, J., & Wang, G. (2018). Charge pricing model for electric vehicle charging infrastructure public-private partnership projects in china: A system dynamics analysis. *J. Clean. Prod.*, *199*, 321–333 (cit. on p. 5).

Zhang, M., Huang, T., Guo, Z., & He, Z. (2022). Complex-network-based traffic network analysis and dynamics: A comprehensive review. *Physica A*, *607*(128063), 128063 (cit. on p. 9).

Appendix

A.1 GitHub - Source

The link to the projects GitHub repository:
https://github.com/AntonOlav/ev-charging-infrastructure

A.2 GeoData - Source

The link to the geodata from Kartkatalogen:
https://kartkatalog.geonorge.no