Dissertation

Spatial modeling of charging infrastructure for the origin-destination-flow-based/traffic flow-based/vehicle-based charging demand of battery electric vehicle fleets

by

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Abstract

TODO: think about the title? maybe origin-destination-flow based? The objective of the thesis is to advance the analytical understanding of the demand-driven geographic allocation of charging infrastructure of future electrified vehicle fleets in different road transport segments. The core contribution to the scientific literature is the extension of charging infrastructure capacity planning to consider diverse drivers of charging demand. This includes the long-term battery-electric vehicle (BEV) adoption, consumer-specific utilization patterns and inter-regional traffic flows. This is addressed through four research papers. Three of the four methodologies applied are optimizations, one a simulation-based approach. The central feature of the analytical methods is the use of traffic flow data, leveraging geographic relations of traffic flow to model the spatial distribution of charging demand.

For passenger cars, we first address the planning of fast charging for long-distance passenger car travel at the national level under different decarbonization scenarios for the transport sector. We observe that the highest reduction in required charging infrastructure capacities is achieved in scenarios with high charging efficiencies, while the driving range of BEVs has no significant impact due to the dense network topology of the analysed highway network. Furthermore, we analyze public charging infrastructure for shorter-distance traffic and BEV adoption within and between three regions. Here, the analysis shows income-class differences in charger utilization preferences which are further shaped by the local spatial density of charging stations. The local expansion of rapid public charging infrastructure has a moderate impact on BEV adoption in neighboring regions.

For commercial fleets, the analysis focuses on the spatial heterogeneity of charging loads and flexibility potential. The sensitivity of charging load allocation to spatially varying electricity prices and network fees is analyzed along international road transport routes. Furthermore, this study identifies segments in an international transport corridor where rail infrastructure is cost-effective in contributing to the decarbonization of road freight and reducing the local concentration of charging loads. The temporal flexibility of commercial fleets is analyzed, considering light-duty vehicles, buses, and heavy-duty vehicles at the federal and state levels. The spatial heterogeneity results from geographical variations in regional fleet sizes and in national and international truck traffic flows. Moreover, high temporal flexibility in charging demand allocation is evident on weekends, which, in cases of cost-optimal charging, may result in substantial peak loads in the electricity system.

A central insight of this thesis is that planning of charging infrastructure—accounting for both adoption patterns and cross-regional vehicle movements — is necessary to support the electrification of particularly long-distance BEV application for passenger cars and trucks alike.

Graphical Abstract

Motivation | Problem Statement		Research Question	Scientific publication
passenger car fleets			
• What are required fast-charging capacities along Austria's highway network for long-distance travel with BEV passenger cars and where are these located under different decarbonization scenarios? • Future charging infrastructure demand affected by different decarbonization scenarios for the transport sector (electrification share, technological improvments, shift to other travel modes,. ...)	**RQ1**	What are required fast-charging capacities along Austria's highway network for battery-electric passenger cars under different decarbonization scenarios and where are these located ?	Golab, A., Zwickl-Bernhard, S., & Auer, H. (2022). Minimum-Cost Fast-Charging Infrastructure Planning for Electric Vehicles along the Austrian High-Level Road Network. Energies, 15(6), 2147. https://doi.org/10.3390/en15062147
• Battery-electric vehicles are currently luxory item that are used in higher-income level classes • Unexplored impact of different public charging infrastructure roll-out strategies in two dimensions: on BEV adoption in different income levels and on neighbouring regions (spillover effect)	**RQ2**	To what extent do the speed and spatial distribution of public infrastructure expansion influence BEV adoption rates among various income groups and across neighboring regions?	Golab, A., Zwickl-Bernhard, S., & Auer, H. (2025). Public charger expansion: Impacts across income classes and beyond regional borders [Manuscript submitted for publication]. *Transportation Research Part D: Transport and Environment*.
commercial fleets			
• Cost differences in the installation of charging infrastructure and charging by country and electricity market zone indicate potential for "charging tourism" • Unknown magnitudes of potential charging infrastructure capacity allocations being affected by these differences	**RQ3**	What magnitude of charging infrastructure capacities is affected by geographically varying network fees and electricity prices in the cost-optimal planning of charging infrastructure allocation for long-haul battery-electric trucks?	Golab, A., Bakker, S., Zwickl-Bernhard, S., & Auer, H. (2025). Spatial flexible charging load allocation for inter-zonal long-haul truck electrification [Manuscript submitted for publication]. *Energy Reports*.
• Future impact of charging demand of battery-electric commercial fleet and potential for demand-side flexibility • Quantification of large-scale charging demand of battery-electric fleet at hourly temporal and NUTS-2 level under the consideration of transport flows within the countries and transit traffic in Austria	**RQ4**	What is the expected charging demand of the commercial BEV fleet spatio-temporally distributed in Austria in 2040?	Golab, A., Loschan, C., Zwickl-Bernhard, S., & Auer, H. (2025). The value of flexibility of commercial electric vehicle fleets in the redispatch of congested transmission grids. *Energy*, *316*, Article 134385. https://doi.org/10.1016/j.energy.2025.134385

Figure 1: we have here a repetition of RQ1 in problem statement; needs change! Overview of most important building blocks of the thesis.

Graphical Abstract

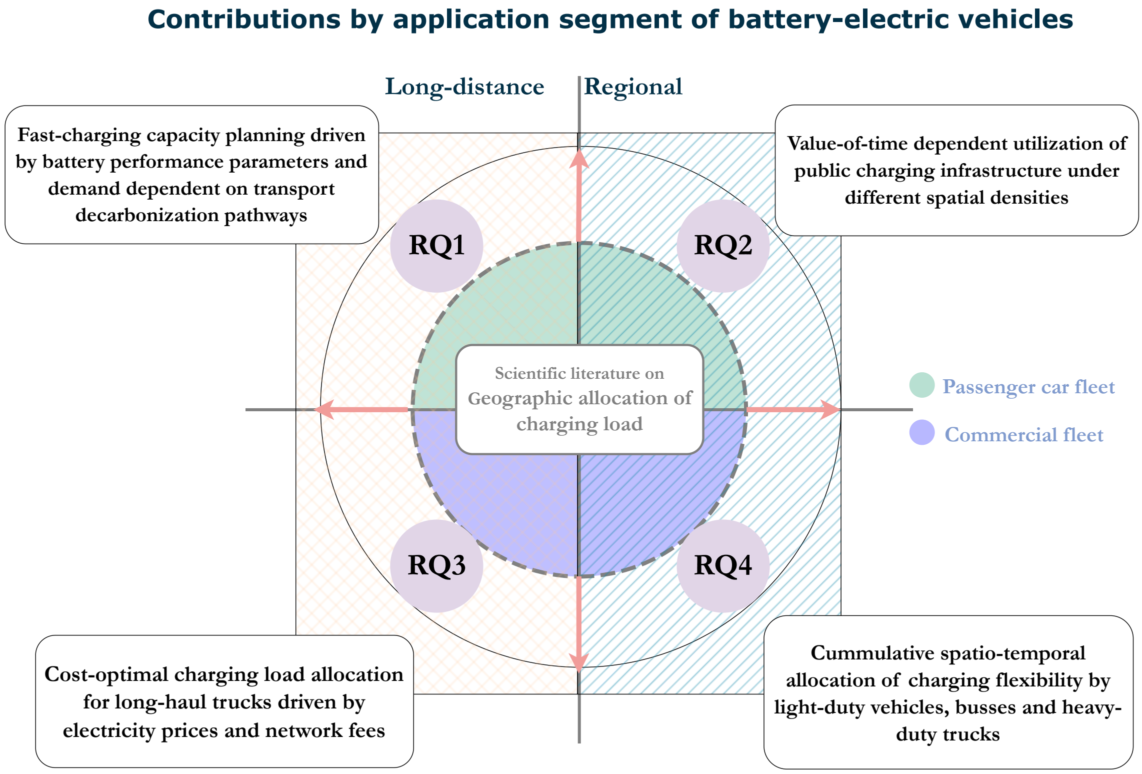

Figure 2: Contributions of Papers 1—4, each reflecting one core research question (RQ1—4): Each research question extends the scientific literature for a different application segment of battery-electric vehicles. The application segments differ in long-distance vs. regional transport as well as between passenger cars and commercial fleet applications. This figure illustrates the relative allocation of the research questions and therefore the scope of this thesis.

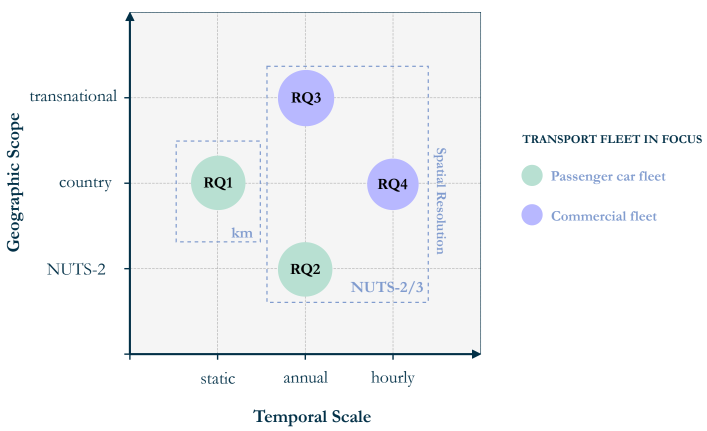

Figure 3: Overview on the temporal scale, and geographic scope and scale as well as addressed application segments of battery-electric vehicles of the methods designed to answer RQ1—4.

Contents

Graphical abstracts

1 Introduction

1.1 Background: Electrification of road transport sector in the context of the European system decarbonization

There is a high urgency in decarbonizing the transport sector to achieve the European Green Deal goals **EC2019GreenDeal**. European countries have committed to reducing 90% of the greenhouse gas emissions from the transport sector by 2050. In 2023, the contribution to total European greenhouse gas emissions remained at 29%, and the road transport sector accounted for around 73% of the total transport-related emissions [1]. To achieve such significant reductions over the next two and a half decades, zero-emission drivetrain technologies need to be rapidly adopted on a large scale. At the forefront of these technologies stands the battery-electric drive-train.

A transition towards electrification in the transport sector has long been established as the cost-optimal pathway for effectively reducing fossil fuel demand in the transport sector [2]. This is primarily driven by the energy efficiency of direct electrification, as well as the low cost of electricity provided through renewable energy sources [3]. In particular, the battery-electric drivetrain has achieved significant technological and market maturity over the last decade, marked by substantial advances in charging speed, driving range, and continuously decreasing costs [4]. A clear trend is emerging, as evidenced by the rapidly increasing market share of battery-electric vehicles in new registrations across all road transport segments. In 2023, battery electric vehicles accounted for nearly 15% of all new car sales, while 40% of newly bought buses were electric and 10% of light and medium-haul commercial vehicles were battery-electric [5]. Yet this gradient in adoption has only begun to transform the existing fleet: as of 2023, just 1.8% of the EU passenger car fleet, 0.1% of trucks, and 2.5% of buses were electric [6]. This gap between zero-emission fleet numbers and total fleet composition underscores both the progress made and the scale of transformation still required.

This required transition towards electrified fleets is recognized and supported by European Union (EU) level policies. The EU Sustainable and Smart Mobility Strategy was published in 2020 [7]. This document presents a comprehensive view of decarbonizing and modernizing all transport modes, along with generalized milestones for achieving a 90% reduction in emissions. For road transport, it is specified that two systematic levers are essential. These include the uptake of zero-emission drive-train technologies, primarily battery-electric vehicles, and the shift of transport demand to lower-carbon modes, for example, rail[1]. This strategy paper was followed by the Fit for 55 Package in 2021 [8]. This policy package encompasses regulations that aim for a reduction of at least 55% by 2030. To achieve this, regulations address CO_2 emission standards for road vehicles of different segments, regulations on the introduction of alternative fuels in

[1] Another important lever is the reduction in service demand, achieved through decreased travel or transport of passengers and goods, and increased shared mobility.

the maritime and aviation and for charging and alternative fueling infrastructure. A significant regulation in this framework is the 100% CO_2 emission reduction target for new passenger cars from 2035. A central element in this framework is the Alternative Fuels Infrastructure Regulation (AFIR; Regulation (EU 2023/1804) [9], which sets binding targets on expanding charging infrastructure for battery-electric vehicles, including passenger and heavy-duty vehicles, in terms of distance-based targets for the core European road Network, the Trans-European Transport network (TEN-T) [10], and compulsory national targets. The distance-based targets indicate the distances along the network at which charging or alternative fueling stations should be installed. On the national level, the regulation addresses the minimum availability of charging capacity, which is dependent on the number of registered battery-electric vehicles in each country.

The build-up of charging infrastructure is vital to enable road transport electrification and, moreover, to support cost-effective transport and travel [11]. Demand-oriented siting of charger capacities has been identified as crucial to overcome range anxiety among BEV drivers and to provide convenient charging experiences [12]. In the commercial sector, well-located infrastructure also enables more time-efficient—and therefore more cost-efficient—charging operations. Furthermore, siting charging stations at locations of high utilization supports cost-effective infrastructure investments [13]. However, the quantification and geographic allocation of required charging capacities remain non-trivial problems. Capacity sizing must be balanced against infrastructure utilization, the integration with the electricity system adds another layer of complexity, and limited empirical experienc- due to the currently low adoption numbers—constrains the understanding of how different factors in this problem interact [14].

1.2 Problem statement: Geographic allocation of future charging loads

The key challenge in determining charging demand for a defined geographic location is the *mobility* of vehicles, which, unlike for other energy consumers such as buildings or industrial sites, geographically extends the options for allocating energy loads. This geographic flexibility is what makes the planning for energy supply infrastructure, including charging infrastructure, fundamentally different from other consumer sectors.

This leads to the central problem statement addressed in this work, which is the spatial allocation problem of charging infrastructure that serves mobile consumers, i.e., vehicles embedded at a large geographic scope, i.e., beyond regions and countries.

This is practically urgent to two decision-making perspectives: First, transport policy makers and infrastructure planners who have to translate the regulations, such as the AFIR, into concrete investments in charging sites. These can include national, local authorities, or road network operators that are responsible for enabling, for example, by tendering or investing in local grid connection capacity, the build-up of the charging infrastructure. Second, operators of the transmission and electricity grid — of, both the transmission and distribution system — require long-term planning in the grid reinforcement to support increased peak loads through the charging of battery-electric vehicles and to integrate potential demand-side flexibilities for, for example, congestion management.

Therefore, this question of *where* charging capacities are needed is composed of different layers:

A Where is charging infrastructure *needed*?

B How does the spatial configuration *shape the demand and behavior*?

C How can the capacity be operated in an *electricity-system-friendly* way?

In addressing this group and all related questions, the applied analytical tools require the representation of spatial mobility in charging demand to capture where vehicles travel. Origin-destination data, coupled with network topology, provides exactly this. The use of origin-destination flow representation allows for consideration of flexibility in demand allocation for large fleets. Origin-destination data indicate the number of passengers or specific freight goods transported between two regions. From this, the traffic flow by location can be deduced, while also capturing the geographic extent of the movement of accumulated fleets.

Despite an extensive body of work in the scientific literature dedicated to answering questions around optimal charging capacity planning, several dimensions remain unexplored. These literature gaps primarily refer to the feedback between the planned infrastructure and charging behavior across different vehicle segments. We address different literature gaps. Through the representation of our analysis using origin-destination data and traffic flow, we integrate the spatial extent of vehicle fleet movement which leads to novel insights on all three subquestions that are mentioned above (**A**, **B** and **C**).

Motivation | Problem Statement		Research Question	Scientific publication
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1.3 Thesis' research questions

The thesis addressed four research questions that extend the state-of-the-art literature on geographic allocation of future charging capacity requirements. Each of the research questions is addressed within a scientific journal paper. Figure **??** displays an overview of the articles characterized by the addressed problem statement, research question, and specifications on the corresponding publication.

Figure **??** illustrates the contextualization of paper in the state-of-the-art literature. The papers' insights extend the state of the art in various directions, reflecting on the diversity of BEV application segments that are characterized by different requirements for the charging infrastructure allocation. The first and second contribution addresses the private passenger car segment, while the third and fourth, focus on commercial vehicles fleets. Moreover, the focus of contributions one and three lie on the charging infrastructure planning for long-distance applications. Contributions two and four address the charging of vehicle used for shorter distances. The key difference here lies in the charging activity allocated en route.

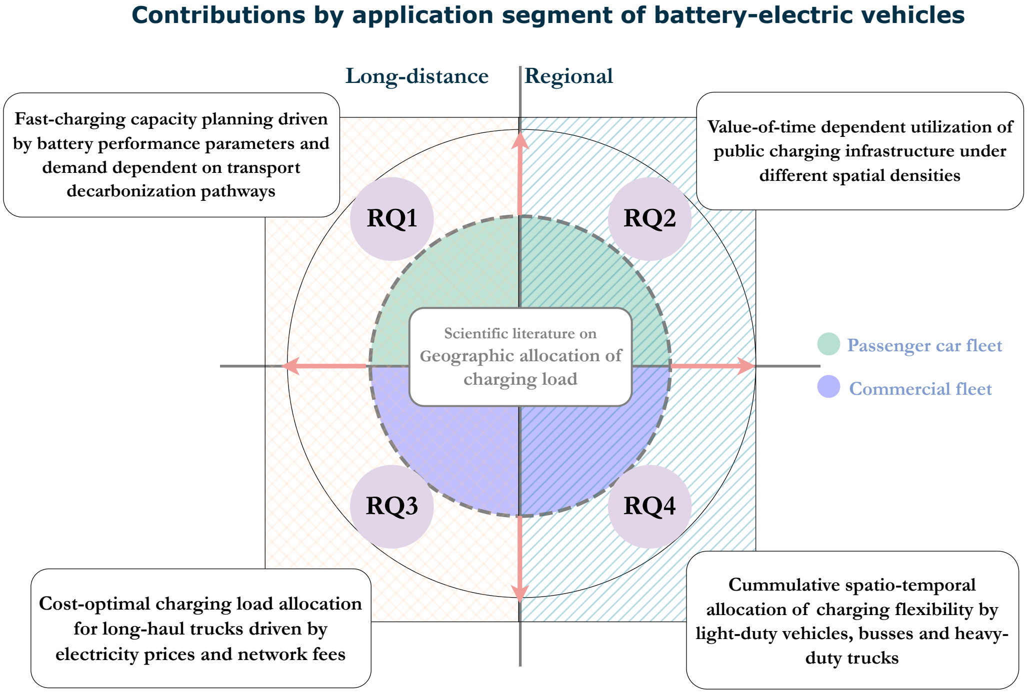


Figure 1.2: Contributions of Papers 1—4, each reflecting one core research question (RQ1—4): Each research question extends the scientific literature for a different application segment of battery-electric vehicles. The application segments differ in long-distance vs. regional transport as well as between passenger cars and commercial fleet applications. This figure illustrates the relative allocation of the research questions and therefore the scope of this thesis.

1.3.1 Research question 1 (RQ1)

The first contribution addresses the spatial allocation of fast-charging infrastructure for battery-electric passenger cars along highway networks. Long-distance travel by car depends on the availability of en-route charging, yet planning such infrastructure involves considerable uncertainty regarding future demand [14]. This demand is shaped by the technical characteristics of the electrified fleet (notably battery capacity and energy consumption), the share of battery-electric vehicles in the total fleet, and potential shifts in travel behaviour — including modal shift and overall demand reduction [15]. The challenge lies in ensuring sufficient geographic coverage to enable long-distance electric mobility while avoiding overcapacity that results from overly optimistic or misaligned assumptions. We apply a traffic flow-based optimization approach to the Austrian highway network to quantify fast-charging capacity requirements under a range of decarbonization scenarios for 2030, addressing the following research question:

Research question 1 (RQ1): What are the required fast-charging capacities along Austria's highway network for battery-electric passenger cars under different decarbonization scenarios, and where are these allocated?

In particular, this paper contributes to the understanding of the impact of technological advances on battery performance parameters, i.e., the charging efficiency and the driving range, of the traveling fleet along the highway network on the cost-optimal geographic allocation of charging stations. To analyze this, a mixed-integer linear program is proposed that considers the flexible allocation of charging demand under the consideration of local magnitudes of traffic flow, the network topology and parameters of the battery and charging stations. Fast-charging capacities are determined at high geographic resolution for explicit service areas. Based on energy system decarbonization scenarios and sensitivity analysis, understanding of these parameters on the fast-charger requirements is gained.

1.3.2 Research question 2 (RQ2)

Public charging infrastructure plays a key role in enabling the adoption of passenger BEVs at a large scale. Early adopters of BEVs are characterized by high income and homeownership, adopters of lower income are dependent on affordable and accessible public charging infrastructure. Empirical case studies have found that there is a disparity in the availability for potential adopters of different income classes [16]. In the long term, BEV adoption must extend across all socio-economic backgrounds [11]. This broader adoption will shift reliance from home charging—currently central to BEV use—toward public charging infrastructure. Such a shift is particularly relevant given that lower-income households are more likely to travel longer distances to reach affordable charging facilities [17].

Along with this large-scale adoption, the flexibility in the geographic allocation of the charging activity increases through the increasing driving range [18]. Empirical studies have shown cross-border impacts of local public charging infrastructure to neighboring regions and countries, which is likely to increase with the spatial flexibility [19], [20].

Bringing these drivers of these aspects together in the context of public charging infrastructure expansion at the regional level, the research question is as follows:

Research question 2: To what extent do the speed and spatial distribution of public charging infrastructure expansion influence BEV adoption rates among various income groups and across neighboring regions?

We introduce here intangible costs of consumers that vary by income class levels to a techno-economic optimization to reflect on tolerances of time consumption on detouring to re-charge as well as tolerance for the time consumption of charging. Impacts across regions are analysed with the consideration of commuter traffic and the potential to flexibly allocate the charging activity between origin and destination charging. This contribution particularly highlights income-class-dependent preferences for charger utilization and quantifies the cross-border impact.

1.3.3 Research question 3 (RQ3)

In the third contribution, the focus lies on long-haul international trucking. The variable costs of fueling or charging are an essential driver of transportation costs. For fossil-fueled trucks, the country-dependent regulations of diesel taxation have determined allocations of the fueling activity [15]. As there are country-dependent charging costs that are driven, by, next to taxation, local network fees and electricity-zone-dependent electricity prices [21], [22], this phenomenon will shift, with the adoption of battery-electric trucks, also to allocation of charging loads. This can lead to high concentrations of charging load in high-unfavorable locations in the electricity system. This leads to the following research question:

Research question 3: What magnitude of charging infrastructure capacities is affected by geographically varying network fees and electricity prices in the cost-optimal planning of charging infrastructure allocation for long-haul battery-electric trucks?

Addressing this question, we analyze the impact of geographically varying charging costs on the cost-optimal allocation and the route-dependent adoption of battery-electric trucks. International origin-destination truck flows are used as input for the cost optimization of fleet turnover, charging infrastructure development, and charging activities. In various electricity and technology pricing scenarios, we observe how local small charging costs along a corridor can lead to a high concentration of charging load, and, further, how local intervention in charging prices can prevent this.

1.3.4 Research question 4 (RQ 4)

With the electrification of the commercial fleet, large peak charging power levels are expected. The large-scale requirements in shifting charging loads in time to minimize required investments into grid capacity and balancing energy have been demonstrated by many studies [23]. For this, the spatio-temporal distribution of the future charging loads and flexibility potentials of different vehicle segments within an electricity market zone are required. The fourth contribution [24] addresses the modeling of charging loads across multiple vehicle segments, ingtegrating both, regional and interregional travel, for the case of Austria in 2040:

Research question 4 (RQ4): What is the expected charging demand of the commercial BEV fleet spatio-temporally distributed in Austria in 2040?

The methodology integrates both local and interregional transport patterns to estimate accumulated charging demands and flexibility potentials. The consideration of the interregional transport is hereby based on, again, traffic flow patterns that include national and transit transport going through Austria. This analysis showcases a bottom-up modeling of charging patterns implying the significant differences of charging flexibility by geographically varying transport demands by segments that are, moreover, dictated by transport flows along the highway network.

1.4 Outline of the thesis

TODO: at last

2 Review of State-of-the-Art & Progress Beyond

2.1 Electrification of passenger cars in the context of energy system decarbonization

2.1.1 Towards large-scale electrification of passenger car fleets

2.1.2 Role of charging infrastructure roll-out for passenger cars

2.2 Battery-electric vehicle adoption in commercial fleets

2.2.1 Electrification across commercial fleet segments

2.2.2 Charging infrastructure for battery-electric trucks

2.3 Modeling of charging demand, charging infrastructure capacities, and roll-out

2.3.1 Graph-based charging infrastructure allocation

2.3.2 Long-term optimal charging infrastructure deployment for different consumer segments for passenger car

2.3.3 Charging infrastructure planning for international long-haul road freight transport

2.3.4 Sub-annual modeling of charging demand for commercial fleets at large scales

2.4 Contribution to the progress beyond state-of-the-art

Kurz und knackig hinschreiben

3 Methods

3.1 Overview

Überblickstabelle/ ERklärung von Methodiken

3.2 *Static charging infrastructure planning*

MILP for fast-charging infrastructure sizing and allocation along highway networks (RQ1).

3.2.1 Problem description

new text: The model is designed to cost-optimally plan fast-charging infrastructure along highway networks. The panning encompasses the geographic allocation and the sizing of the charging capacities. The model aims to reflect optimal decisions from the perspective of an infrastructure planner seeking to determine a fast-charging infrastructure set-up for supporting long-distance travel with battery-electric passenger cars. This decision-making could, for example, apply to the highway network operator preparing tenders for charging service providers.

*new text:*The considered costs of charging infrastructure encompass two cost components: the onsite preparations to enable the support of large capacities provided by the charging points locally (c_X) and, on the other hand, the hardware and construction costs associated with the installation of a single charging point (c_Y). The planning refers exclusively to a defined network topology described by intersections, distances along highway segments, and positions of service areas. Potential sites for charging stations are exclusively service areas. *old text* The approach in this proposed methodology follows a node-based approach which has been reported to be mostly used in the allocation of charging infrastructure in urban areas where the demand at a node is defined through population density [25]. In this work, this model formulation is extended to the application to high-level road networks by reformulating the definition of demand at a node based on the energy consumed through BEVs driving along the road network, rather than population density, and further, regarding the traffic flow movement affecting the position of coverage of the demand.

new text In the following, the road connections between two junctions and between a junction and a network endpoint are referred to as *segments*, and the vertices are referred to as *nodes*. There are two types of nodes: some represent possible sites for charging station installation and lie along segments (*node type 1*), and others represent highway junctions or ending points of the network (*node type 2*). The nodes of type 1 can either be accessible from both driving directions

($k \in \{0,1\}$) or from only one direction ($k = 0 \vee k = 1$). At each node, a charging demand exists which can be covered at the node itself or at other nodes within a defined range, $dist_{max}$. First, we proceed with a detailed description of the main contribution of this work, which is the mixed-integer linear program formulation of a node-based highway allocation method. Based on the demand at the nodes, the program allocates sites to install charging stations and sizes them by determining the optimal number of charging points. Then, the demand calculation used in this work is outlined.

*new text:*The charging infrastructure is planned in the consideration of the traffic flow and technological parameters of the vehicle's battery. The following key assumptions related to the representation of charging demand are made here: *old text:*

- The BEV fleet traveling along the highway network is treated as a homogeneous quantity, allowing to consider accumulated charging demand and translating this into the optimal sizing of a charging station. Based on this assumption, the technical parameters of an *average* BEV are assumed, such as average driving range ($\overline{dist}_{range,BEV}$), energy consumption ($\overline{d}_{spec,BEV}$) and charging capacity ($\overline{P}_{charge,BEV}$).

- All charging demands, $\sum_{n,k} \hat{D}_{n_k}$, result from the energy consumption of BEVs driving along the highway and need to be compensated for in total by charging stations built along the highway network.

- Highway charging infrastructure is primarily used by long-distance drivers as BEV owners mostly charge at home or at work.

- A fast-charging infrastructure along a highway network is designed based on peak demands, including seasonal peak demand ($\hat{f}_{l_k}$) and hourly peak demand, during a day (γ_h).

3.2.2 Model features and assumptions

The underlying methodology of this work is presented in Figure **??**. It is based on a graph representation of the highway network. The approach in this proposed methodology follows a node-based approach which has been reported to be mostly used in the allocation of charging infrastructure in urban areas where the demand at a node is defined through population density [25]. In this work, this model formulation is extended to the application to high-level road networks by reformulating the definition of demand at a node based on the energy consumed through BEVs driving along the road network, rather than population density, and further, regarding traffic flow movement effecting the position of coverage of the demand.

3.2.3 Input-Output relations

TODO: insert the input-output relations here Figure ?? displays

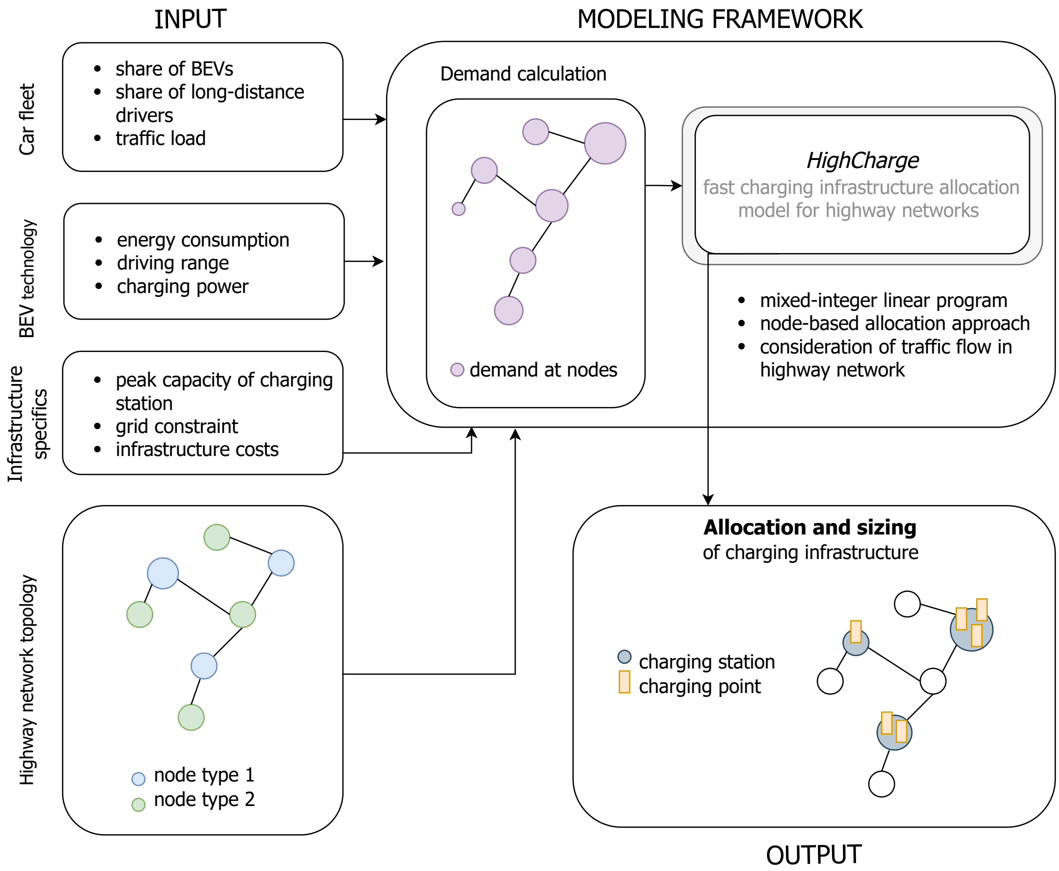


Figure 3.1: **Overview of methodology applied in this work.** Input parameters encompass demand calculation and optimization determining the allocation and sizing of charging infrastructure.

3.2.4 Mathematical formulation

The objective function of the optimization model is to minimize the total charging infrastructure investment costs:

$$\min_{X_l, Y_{l_k}, \hat{E}_{l_k}^{charged, n_k}, \hat{D}_{l_k}^{in, n_k}, \hat{D}_{l_k}^{out, n_k}} c_X * \sum_l X_l + c_Y * \sum_{l_k} Y_{l_k} \tag{3.1}$$

The charging infrastructure is designed in such a way that all demand $\sum_{n,k} \hat{D}_{n_k}$ in the network is covered. For each node the following energy balance is defined:

$$\hat{E}_{l_k}^{charged,n_k} - \hat{D}_{l_k}^{demand,n_k} = \hat{D}_{l_k}^{out,n_k} - \hat{D}_{l_k}^{in,n_k} \quad : \forall n_k, l_k \in A_{n_k} \tag{3.2}$$

Set A_{n_k} encompasses all nodes l_k which are within the distance of $dist_{max}$[1] to node n_k. Within this set radius around a node n_k, the energy demand stemming from node n_k, $\hat{D}_{n_k}$ has to be covered. Between the nodes l_k, which are part of A_{n_k}, the demand is shifted and for this, the following holds for adjacent nodes l_k and l'_k:

$$\hat{D}_{l_k}^{out,n_k} * r_{l_k,l'_k} = \hat{D}_{l'_k}^{in,n_k} \quad : \forall n_k, \{l_k, l'_k\} \in A_{n_k} \tag{3.3}$$

For parameter r_{l_k,l'_k}, the following applies:

$$r_{l_k,l'_k} = \begin{cases} 1, & \text{if } s_{l_k} == s_{l'_k} \\ < 1, & \text{otherwise} \end{cases} \tag{3.4}$$

$$\sum_{l_k} r_{l_k,l'_k} = 1 \tag{3.5}$$

This rationing parameter is, therefore, only lower than 1, if node l is a junction point and in this case, the $\hat{D}_{l_k}^{output,n_k}$ needs to be split to simulate traffic flow partitioning at a junction point. For example, if, e.g., three segments meet and it is assumed that traffic flow is split equally between these segments at the junction, then $r = 1/2$.

The demand coverage by a charging point and charging station is defined through:

$$\sum_{n_k} \hat{E}_{l_k}^{charged,n_k} \leq \sum_{k} Y_{l_k} * \overline{P}_{charge,BEV} \quad : \forall l_k \tag{3.6}$$

$$\frac{P_{max}}{\hat{P}_{CP}} * X_l \geq \sum_{k} Y_{l_k} \quad : \forall l \tag{3.7}$$

Equation **??** establishes the relation between the sizing of a charging station, i.e., the number of charging points, and the binary variable, whether a charging station is installed at node n_k.

[1] $dist_{max} = 4/5 * 0.6 * \overline{d}_{range,BEV}$: The factor 4/5 accounts for reduced driving range resulting from increased energy demand at highway speeds [26], [27]and 0.6 for charging processes starting at a state of charge of 20% up to 80% [28].

3.3 *Long-term charging infrastructure roll-out:* LP for charging infrastructure planning under consideration of multiple technologies and modes

3.3.1 Problem description and assumptions

new text The model represents the decision making from a social planner's perspective and determines the cost-optimal pathway for transitioning vehicle fleets and deploying supporting infrastructure. The costs for the vehicle fleet (purchase, maintenance, driver's costs), the costs for fueling, and the charging infrastructure (purchase, installement and OM) are minimized over multiple years.

*new text*Important features of the model are: *old text:*

- **Network design and transport demand coverage:** The geographic relation between multiple neighboring regions is conceptualized based on a graph representation. Nodes represent regions and edges represent the connections between neighboring regions. The modeling framework is designed based on origin-destination data. The travel demand is given exogenously by a set of trips that are defined by their origin-destination pair, purpose, distance, and consumer group on an annual level. These trips can be covered using different vehicle types, drivetrain technologies, and fuels. For trips that cross multiple geographic locations, i.e., for inter-regional trips that cross at least one other region, there can be a definition of multiple possible travel paths between the origin-destination pair.

- **Consumer groups by different income-class levels and level of service measure:** We introduce consumer-specific parameters that allow differentiation between income class levels in two dimensions: the value of time (VoT) and the monetary budget. The VoT relates to the monetary value of travel time as perceived by the consumer. The travel time is the level of service (LoS) that is provided by a drive-train technology, measured in hours. The value of time rises with the income level of a consumer. The monetary budget refers to the budget of a consumer that is spent on the purchase of a new vehicle and is defined together with a time horizon, reflecting the frequency of the purchase of a new vehicle.

- **Vehicle stock modeling:** The vehicle stock is modeled based on the numbers of different vehicle types and technologies. The *generation* of a vehicle is a particularly important dimension here. It defines the year in which a vehicle was purchased on the market. Each generation is associated with different technological attributes which allows to capture the technological improvements in the battery size and charging speed of BEVs while also modeling the presence of vehicles with variable technological attributes within the fleet.

- **Sizing of different types of fueling infrastructure:** Fueling infrastructure is sized based on the geographic allocation, and different types of fueling infrastructure, which may vary by the provided fueling power, maximum utilization rate, and availability. The expansion of fueling infrastructure capacity follows a defined set of investment periods.

- **Spatially flexible allocation of fueling activity:** For a given trip, there exists a set of different opportunities to fuel or charge, e.g., at work, at a public fueling station, or at home. The decision on whether the fueling demand is covered is endogenous and can change annually

3.3.2 Model features and assumptions

Figure **??** provides a conceptual overview of the most relevant input and output parameters as well as the core functionalities of the method. The basis of the methodology follows the classic formulation of the Network Design Problem [29]. Table **??** provides an overview of the state-of-the-art methods that are integrated here, together with corresponding extensions for the present work. The core model is formulated as a linear program with the objective of minimizing the total costs related to the vehicle stock, fueling, and fueling infrastructure[2], and other transportation costs, encompassing investments, operation and maintenance costs. This model is extended to a mixed-integer linear program to endogenously include the interaction between charging infrastructure expansion and the consumers' detouring fueling time.

The core features and functionalities of this model are:

- **Network design and transport demand coverage:** The geographic relation between multiple neighboring regions is conceptualized based on a graph representation. Nodes represent regions and edges represent the connections between neighboring regions. The modeling framework is designed based on origin-destination data. The travel demand is given exogenously by a set of trips that are defined by their origin-destination pair, purpose, distance, and consumer group on an annual level. These trips can be covered using different vehicle types, drivetrain technologies, and fuels. For trips that cross multiple geographic locations, i.e., for inter-regional trips that cross at least one other region, there can be a definition of multiple possible travel paths between the origin-destination pair.

- **Consumer groups by different income-class levels and level of service measure:** We introduce consumer-specific parameters that allow differentiation between income class levels in two dimensions: the value of time (VoT) and the monetary budget. The VoT relates to the monetary value of travel time as perceived by the consumer. The travel time is the level of service (LoS) that is provided by a drive-train technology, measured in hours. The value of time rises with the income level of a consumer. The monetary budget refers to the budget of a consumer that is spent on the purchase of a new vehicle and is

[2]To provide a general model formulation here in Sections **??** and **??**, the general terminology *fueling infrastructure* and *fuel* include also charging infrastructure and electricity as a fuel.

defined together with a time horizon, reflecting the frequency of the purchase of a new vehicle.

- **Vehicle stock modeling:** The vehicle stock is modeled based on the numbers of different vehicle types and technologies. The *generation* of a vehicle is a particularly important dimension here. It defines the year in which a vehicle was purchased on the market. Each generation is associated with different technological attributes which allows to capture the technological improvements in the battery size and charging speed of BEVs while also modeling the presence of vehicles with variable technological attributes within the fleet.

- **Sizing of different types of fueling infrastructure:** Fueling infrastructure is sized based on the geographic allocation, and different types of fueling infrastructure, which may vary by the provided fueling power, maximum utilization rate, and availability. The expansion of fueling infrastructure capacity follows a defined set of investment periods.

- **Spatially flexible allocation of fueling activity:** For a given trip, there exists a set of different opportunities to fuel or charge, e.g., at work, at a public fueling station, or at home. The decision on whether the fueling demand is covered is endogenous and can change annually.

- **Fueling detour time:** The detouring time that is needed to the closest fueling station is included as a decision variable that is tied to the expansion of the fueling infrastructure. This particular modeling aspect allows linking the investments in fueling infrastructure to an improved LoS.

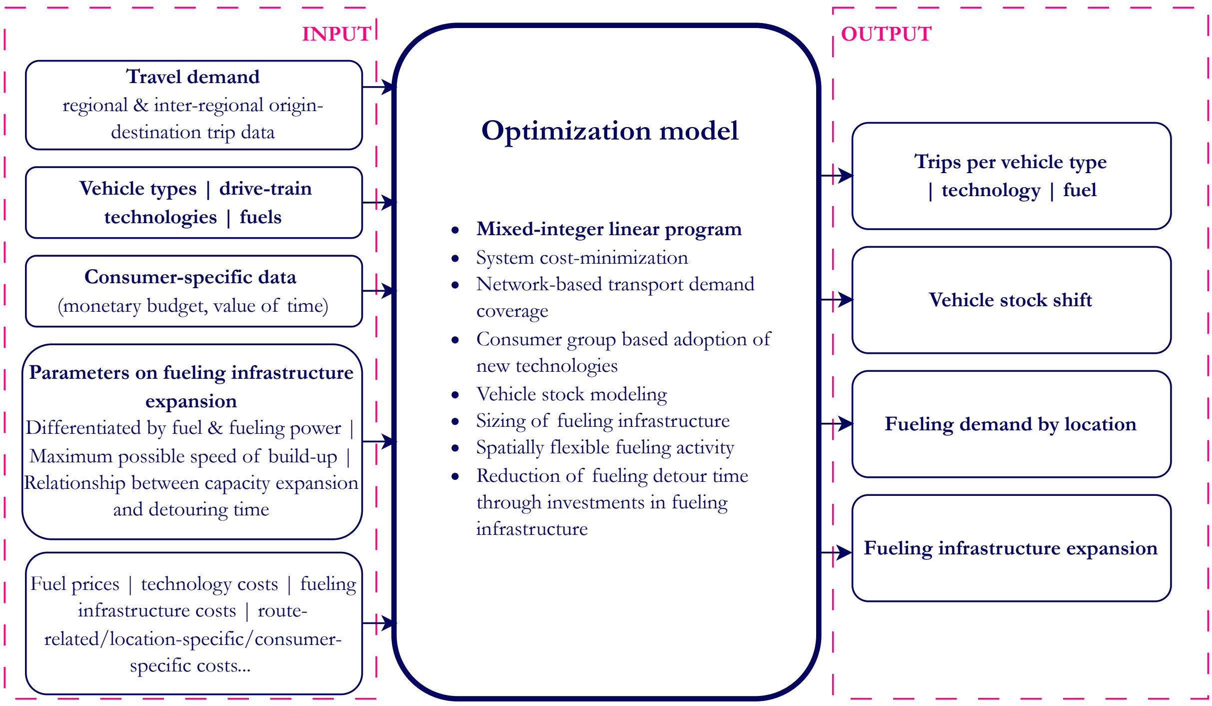


Figure 3.2: Overview on the input and output parameters of the optimization model and its core functionalities

Table 3.1: Overview of integrated model functionalities drawn from state-of-the-art methodology. *Fueling detour time* is written in cursive letters to imply that this model feature is not based in the existing state-of-the-art, and is, therefore, a novel extension. '-' implies that the included modeling feature is integrated without significant adaptations from the initial concepts. The listed sources are references to research papers that describe or apply these modeling approaches.

Modeling feature	State-of-the art references	Adoption/extension in this work
Network design and transport demand coverage	[29]	-
Consumer groups of different income-class levels and level of service measure	[17], [30]	-
Vehicle stock modeling	[31], [32]	-
Sizing of different types of fueling infrastructure	[33], [34]	-
Spatially flexible allocation of fueling activity	[35]	-
Fueling detour time		Consideration of the time required to reach closest charging station

3.3.3 Input-Output relations

3.3.4 Mathematical formulation

In the following, we elaborate on the mathematical formulation of the model functionalities that are extensions from state-of-the-art methodologies. The remaining constraints are to be found in the **??**. Table **??** contains the relevant nomenclature used in the following equations.

Table 3.2: Nomenclature (selection).

Sets and indices	Description
$y \in \mathcal{Y}$	year
$u \in \mathcal{U}$	consumer group
$p \in \mathcal{P}$	trip purpose
$r \in \mathcal{R}_p$	trip between origin-destination (OD) pair for a specified purpose
$k \in \mathcal{K}$	travel paths
$e \in \mathcal{E}$	geographic location
$v \in \mathcal{V}$	type of vehicle
$t \in \mathcal{T}_v$	drive-train technology fueled by a specific fuel
$g \in \mathcal{G}$	year that vehicle was introduced to market
$l \in \mathcal{L}$	types of fueling infrastructure (by capacity)
$i \in \mathcal{I}_l$	index for detour time reduction potential for type of fueling infrastructure l
$\mathcal{Y}^{exp}$	set of years of investment decisions
$\mathcal{K}_e$	set of paths that go through edge e
$\mathcal{L}^{nothome}$	fueling infrastructure that is not allocated at home of vehicle owner
$\mathcal{L}^{home}$	fueling infrastructure that is allocated at home of vehicle owner
$\mathcal{L}_{tk}$	types of infrastructure by drive-train technology and availability for travel path
$\mathcal{E}_{kl}$	geographic location along travel path and available fueling type
S^u_j	$= \{y_m \in Y \mid j \in [m, m + \tau_u - 1]\}, m = 1, ..., \lvert Y\rvert - \tau_u + 1$ subsets of time periods for which a monetary budget is defined by consumer group

Decision variables		Unit	
$f_{yurkvtg}$	number of person-trips	-	$[0, \infty[$
$h_{yurkvtg}$	number of vehicles	-	$[0, \infty[$
$h^+_{yurkvtg}$	newly purchased vehicles	-	$[0, \infty[$
$h^-_{yurkvtg}$	number of vehicles leaving the vehicle stock	-	$[0, \infty[$
$s_{yurkvtgle}$	energy fueled	kWh	$[0, \infty[$

$n_{yurkvtgle}$	number of fueling vehicles		$[0, \infty[$
$b_{yurkvtle}$	fueling detour time to reach closest available public charging infrastructure	h	$[0, \infty[$
w_{yeli}	binary decision variable indicating whether detour reduction i is active	-	$\{0, 1\}$
$z_{yrkvtle,i}$	decision variable substituting the multiplication $b * w$	h	$[0, \infty[$
$q_{yrte}^{+,\text{fuel\_infr,home}}$	added fueling infrastructure at home	kW	$[0, \infty[$
$q_{ytle}^{+,\text{fuel\_infr}}$	added fueling infrastructure	kW	$[0, \infty[$
$q_{ytle}^{\Delta+,\text{fuel\_infr}}$	relative difference of fueling capacity expansion to fixed capacity size values cap	kW	$[0, \infty[$
budget_{yur}^{+}	budget overrun	€	$[0, \infty[$
budget_{yur}^{-}	budget underrun	€	$[0, \infty[$
Parameters			
LoS	level of service	h	$[0, \infty[$
VoT	value of time	€/h	$[0, \infty[$
γ_l	factor between annual peak hour and total annual demand	%	$[0, 100]$
$Q_{urte}^{\text{fuel}_\text{i}\text{nfr,nothome}}$	Initial fueling infrastructure at home	kW	$[0, \infty[$
$Q_{urtle}^{\text{fuel}_\text{i}\text{nfr,home}}$	Initial fueling infrastructure	kW	$[0, \infty[$
α_{iel}	reduction $i = 1, \dots, I$ of detour time	%	$[0, 100]$
cap_{iel}	fixed lower bounds for capacity which tie to a reduction of detour time of α_i	kWh	$[0, \infty[$
τ^u	number of years between consecutive vehicle purchase decisions, representing the vehicle replacement period.	a	$[0, \infty[$
β	relative threshold for budget under- or overrun	%	$[0, 100]$
B_{el}^{init}	initial detour time	h	$[0, \infty[$
L_k	length of path	km	$[0, \infty[$
C_{yvtg}^{CAPEX}	expenditure costs for vehicles	-	$[0, \infty[$
Budget_u	monetary budget of consumer group	€/trip	$[0, \infty[$

Objective function

The objective function comprises costs for the vehicle stock ($C^{\text{vehicle\_stock,total}}$), required fueling ($C^{\text{fueling,total}}$), costs for fueling infrastructure ($C^{\text{infrastructure,total}}$), and intangible costs ($C^{\text{intangiblecosts,total}}$) as well as penalty costs ($C^{\text{penaltycosts,total}}$) that are introduced here to penalize the overrun or the underrun of monetary budgets of consumers. The objective function is defined as follows:

$$\begin{aligned} \underset{f,h,h^+,h^-,s,n,b,w,z,q^+,\text{budget}^+,\text{budget}^-}{minimize} \quad & z = C^{\text{vehicle\_stock,total}} + C^{\text{fueling,total}} \\ & + C^{\text{infrastructure,total}} + C^{\text{intangiblecosts,total}} + C^{\text{penaltycosts,total}} \end{aligned} \tag{3.8}$$

The vehicle stock is sized to cover all car trips and the required fueling activity is allocated among the visited geographic locations of a car trip and different fueling infrastructure types. The latter may imply, for example, fueling infrastructure installed at home or work, or public fueling infrastructure.

Sizing of different types of fueling infrastructure

Fueling infrastructure is expanded for each investment period, $y' \in \mathcal{Y}^{exp}$, and sized based on an assumed factor which represents the ratio between the annual demand peak and the annual total demand, γ_l. We differentiate here between fueling infrastructure of which the availability is independent from the particular trip ($\mathcal{L}^{\text{nothome}}$) and those that are dependent on it as this fueling infrastructure is installed at home ($\mathcal{L}^{\text{home}}$).

$$\begin{aligned} Q^{\text{fuel\_infr}}_{tle} + \sum_{y' \in \mathcal{Y}^{\text{exp}}_y} q^{+,\text{fuel\_infr}}_{y'tle} &\geq \gamma_l \sum_{r \in \mathcal{R}} \sum_{k \in \mathcal{K}_e} \sum_{u \in \mathcal{U}} \sum_{g \in \mathcal{G}} s_{yurkvtgle} : \forall y, t, e, l \in \mathcal{L}^{\text{not home}} \\ Q^{\text{fuel\_infr,home}}_{urtle} + \sum_{y' \in \mathcal{Y}^{\text{exp}}_y} q^{+,\text{fuel\_infr,home}}_{y'urtle} &\geq \gamma_l \sum_{k \in \mathcal{K}_e} \sum_{g \in \mathcal{G}} s_{yurkvtgle} : \forall y, u, t, r, e, l \in \mathcal{L}^{\text{home}} \end{aligned} \tag{3.9}$$

s refers to the annual fueling demand.

Table 3.3: Nomenclature (extended).

Sets and indices	Description
$y \in \mathcal{Y}$	year
$u \in \mathcal{U}$	consumer group
$p \in \mathcal{P}$	trip purpose
$r \in \mathcal{R}_p$	trip between origin-destination (OD) pair for a specified purpose
$k \in \mathcal{K}$	travel paths
$e \in \mathcal{E}$	geographic location
$v \in \mathcal{V}$	type of vehicle
$t \in \mathcal{T}_v$	drive-train technology fueled by a specific fuel
$g \in \mathcal{G}$	year that vehicle was introduced to market
$l \in \mathcal{L}$	types of fueling infrastructure (by capacity)
$i \in \mathcal{I}_l$	index for detour time reduction potential for type of fueling infrastructure l
$\mathcal{Y}^{exp}$	set of years of investment decisions
$\mathcal{K}_e$	set of paths that go through edge e
$\mathcal{L}^{nothome}$	fueling infrastructure that is not allocated at home of vehicle owner
$\mathcal{L}^{home}$	fueling infrastructure that is allocated at home of vehicle owner
$\mathcal{L}_{tk}$	types of infrastructure by drive-train technology and availability for travel path
$\mathcal{E}_{kl}$	geographic location along travel path and available fueling type
S^u_j	$= \{y_m \in Y \mid j \in [m, m + \tau_u - 1]\}, m = 1, ..., \lvert Y \rvert - \tau_u + 1$ subsets of time periods for which a monetary budget is defined by consumer group

Decision variables		Unit	
$f_{yurkvtg}$	number of person-trips	-	$[0, \infty[$
$h_{yurkvtg}$	number of vehicles	-	$[0, \infty[$
$h^+_{yurkvtg}$	newly purchased vehicles	-	$[0, \infty[$
$h^-_{yurkvtg}$	number of vehicles leaving the vehicle stock	-	$[0, \infty[$
$s_{yurkvtgle}$	energy fueled	kWh	$[0, \infty[$
$n_{yurkvtgle}$	number of fueling vehicles		$[0, \infty[$
$b_{yurkvtle}$	fueling detour time to reach closest available public charging infrastructure	h	$[0, \infty[$
w_{yeli}	binary decision variable indicating whether detour reduction i is active	-	$\{0, 1\}$
$z_{yrkvtle,i}$	decision variable substituting the multiplication $b * w$	h	$[0, \infty[$
$q^{+,\text{fuel\_infr,home}}_{yrte}$	added fueling infrastructure at home	kW	$[0, \infty[$
$q^{+,\text{fuel\_infr}}_{ytle}$	added fueling infrastructure	kW	$[0, \infty[$
$q^{\Delta+,\text{fuel\_infr}}_{ytle}$	relative difference of fueling capacity expansion to fixed capacity size values *cap*	kW	$[0, \infty[$
budget^+_{yur}	budget overrun	€	$[0, \infty[$
budget^-_{yur}	budget underrun	€	$[0, \infty[$

Parameters			
LoS	level of service	h	$[0, \infty[$
VoT	value of time	€/h	$[0, \infty[$
γ_l	factor between annual peak hour and total annual demand	%	$[0, 100]$
$Q^{\text{fuel}_\text{i}\text{nfr,nothome}}_{urte}$	Initial fueling infrastructure at home	kW	$[0, \infty[$
$Q^{\text{fuel}_\text{i}\text{nfr,home}}_{urtle}$	Initial fueling infrastructure	kW	$[0, \infty[$
$\hat{Q}^{\max}_{yule}$	upper limit for charging infrastructure capacity by consumer group	kW	$[0, \infty[$
$\hat{Q}^{\max}_{yle}$	upper limit for charging infrastructure capacity	kW	$[0, \infty[$
α_{iel}	reduction $i = 1, \ldots, I$ of detour time	%	$[0, 100]$
cap_{eli}	fixed lower bounds for capacity which tie to a reduction of detour time of α_i	kWh	$[0, \infty[$
τ^u	number of years between consecutive vehicle purchase decisions, representing the vehicle replacement period	a	$[0, \infty[$
β	relative threshold for budget under- or overrun	%	$[0, 100]$
B^{init}_{el}	initial detour time	h	$[0, \infty[$
D^{spec}_{vtg}	specific energy consumption	kWh/km	$[0, \infty[$
W_{vtg}	load factor	persons/vehicle	$[0, \infty[$
$\text{Cap}^{\text{tank}}_{vtg}$	tank capacity	kWh	$[0, \infty[$
L^{annual}_{vtg}	annual range	km	$[0, \infty[$
L_k	length of path	km	$[0, \infty[$
C^{CAPEX}_{yvtg}	expenditure costs for vehicles	-	$[0, \infty[$
Budget_u	monetary budget of consumer group	€/trip	$[0, \infty[$

appendix Decision variable f expresses the number of trips covered by a specific vehicle type and technology-fuel pair of a specific generation. The sum over all possible travel paths, vehicle types, technology-fuel pairs and vehicle generations equals the exogenously given travel demand:

$$\sum_{k \in \mathcal{K}_r} \sum_{v \in V} \sum_{t \in \mathcal{T}_v} \sum_{g \in \mathcal{G}} f_{yurkvtg} = F_{yur} \quad : \forall y, u, r \tag{3.10}$$

appendix The right side of the equation expresses the coverage of the demand by different vehicle types and drive-train technologies of different generations.

appendix Based on the trips covered by a vehicle type of a technology, the vehicle stock is sized as follows:

$$h_{yurvtg} \geq \sum_{k \in \mathcal{K}_r} \frac{L_k}{W_{yvtg} L^{\text{annual}}_{vtg}} f_{yurkvtg} \quad : \forall y, u, r, k, v, t, g \tag{3.11}$$

$$\sum_p h_{yurvtg} = \sum_p h_{(y-1)rvtg} + \sum_p h^+_{yurvtg} - \sum_p h^-_{yurvtg} \quad : \forall y \in \mathcal{Y} \setminus \{0\}, u, r, v, t, g \tag{3.12}$$

$$\sum_{p} h^{-}_{yurvt(g=y-\text{Lifetime}^{max}_{vtg})} = \sum_{p} h_{yrvt(g=y-\text{Lifetime}_{vtg})} \quad : \forall y,u,r,v,t \tag{3.13}$$

Equation ?? expresses the sizing of the vehicle stock via a vehicle's annual range L^{annual} and load factor W. With equations ?? and ??, the vehicle stock is aging. Vehicles exit the vehicle stock when a maximum lifetime is reached.

Fueling demand is derived from the number of trips f and via the specific demand D^{spec} of the vehicle:

$$\sum_{l\in\mathcal{L}_{tk}} \sum_{e\in\mathcal{E}_{kl}} s_{yurkvtgle} \geq \sum_{e\in\mathcal{E}_{k}} \gamma_l \frac{D^{\text{spec}}_{gvt}}{W_{gvt} L_k} f_{yurkvtg} : \forall y,u,r,k,v,t,g \tag{3.14}$$

n indicates the number of fueling vehicles and is deducted from the fueled energy:

$$\sum_{v,t} \frac{1}{\text{Cap}^{\text{tank}}_{vtg}} s_{yurkvtgle} = n_{yurklge} \quad : \forall y,u,r,k,g,e,l \in \mathcal{L}^{vt} \tag{3.15}$$

The geographic allocation of the fueling demand is given by the summation over all geographic elements that are traveled by the vehicle. The summation over all geographic locations along the travel path and different types of fueling infrastructures l ensures that the allocation of fueled energy along the path is an endogeneous decision. The expansion of fueling capacities are also limited in its expansion by maximum values:

$$\begin{aligned} Q^{\text{fuel\_infr}}_{tle} + \sum_{y'\in\mathcal{Y}^{\text{exp}}_{y}} q^{+,\text{fuel\_infr}}_{ytle} &\leq \hat{Q}^{\text{fuel\_infr}}_{tle} \quad : \forall y,t,l,e \\ \sum_{r\in\mathcal{R}_u} \left(Q^{\text{fuel\_infr,home}}_{urtle} + \sum_{y'\in\mathcal{Y}^{\text{exp}}_{y}} q^{+,\text{fuel\_infr,home}}_{yurtle} \right) &\leq \hat{Q}^{\text{fuel\_infr,home}}_{utle} : \forall y,u,t,l,e \end{aligned} \tag{3.16}$$

3.3.5 MILP extension for regional application (RQ2)

3.3.5.1 Extended problem description and model features

3.3.5.2 Extended mathematical formulation

Consumer groups by different income-class levels and level of service measure

The intangible costs ($C^{\text{intangiblecosts,total}}$) represent non-monetary costs that are monetized in the objective function by weighting them with the consumer-group-dependent VoT. The non-monetary costs refer to in particular the total travel time associated with different vehicle types and drivetrain technologies, i.e., the level of service:

$$C^{\text{intangiblecosts,total}} = \sum_{y,u,r,k,v,t,g} \text{VoT}_u * \left(\text{LoS}^f_{ykvt} * f_{yurkvtg} + \sum_l b_{yurkvtle} \right) \tag{3.17}$$

f is the number of person-trips. The parameter LoS is the level of service, i.e, total travel time, associated with a vehicle type and drivetrain technology for a trip:

$$\text{LoS}^f_{ykvt} = \frac{L_k}{\text{speed}_{vt}} + \text{fueling\_time}_{ykvt} \quad : \forall y, k, v, t \tag{3.18}$$

Decision variable b is the fueling detour time, i.e., the additional travel time.

Monetary budgets vary by consumer group. These are defined by the temporal frequency of car purchases, i.e., every τ years. The budget constrains expenditures for vehicles and fueling infrastructure installed at home, which is the left side of these constraints:

$$\begin{aligned} &\sum_{y \in \mathcal{S}^u_j} \left(\sum_{vtg} C^{\text{CAPEX}}_{yvtg} * h^+_{yurvtg} + \sum_{tl} \sum_{y' \in \mathcal{Y}^{\text{exp}}_{y'}} q^{+,\text{fuel\_infr,home}}_{yurtle} \right) \\ &\leq \beta * \tau_u * \text{Budget}_u * \sum_{kvtg} f_{yurkvtg} + \sum_{y \in \mathcal{S}^u_j} \text{budget}^+_{yur} \quad : \forall y, u, r, j \end{aligned} \tag{3.19}$$

$$
\sum_{y \in \mathcal{S}_j^u} \left(\sum_{vtg} C_{yvtg}^{\text{CAPEX}} * h_{yurvtg}^{+} + \sum_{tl} \sum_{y' \in \mathcal{Y}_{y'}^{\text{exp}}} q_{yurtle}^{+,\text{fuel\_infr,home}} \right)
\geq \beta * \tau_u * \text{Budget}_u * \sum_{kvtg} f_{yurkvtg} - \sum_{y \in \mathcal{S}_j^u} \text{budget}_{yur}^{-} \quad : \forall y, u, r, j \tag{3.20}
$$

Equation **??** expresses the lower limit for the expenditures, which relate to the investments in new vehicles (left hand-side of the equation). Equation **??** imposes an upper limit on these expenditures. A threshold for the budget is included with the factor β. Budget underrun and overrun, budget_{yur}^{-} and budget_{yur}^{+}, are decision variables that are penalized in the objective function and leveraged with a factor in the term $C^{\text{paneltycosts,total}}$ (Equation **??**).

We introduce lumpiness in the sizing of the infrastructure, which is expressed by:

$$
\begin{aligned}
Q_{tle}^{\text{fuel\_infr}} + \sum_{y' \in \mathcal{Y}_y^{\text{exp}}} q_{y'tle}^{+,\text{fuel\_infr}} = \sum_i w_{yiel} * cap_{iel} + q_{y'tle}^{\Delta+,\text{fuel\_infr}} &: \forall y, t, e, l \in \mathcal{L}^{\text{not home}} \\
\sum_i w_{yiel} = 1 \quad &: \forall y, e, l \in \mathcal{L}^{\text{not home}}
\end{aligned} \tag{3.21}
$$

$q_{y'tle}^{\Delta+,\text{fuel\_infr}}$ is a continuous variable that expresses the relative difference in capacity to the fixed capacity values cap_{iel}. The lumpiness is introduced via the binary variable w and ties fueling infrastructure expansion to the reduction of detour time.

The fueling detour time is explicitly defined only for fueling types not allocated at home, for $l \in \mathcal{L}^{\text{not home}}$. Based on an assumed fueling detour time B^{init} that is initially needed to reach the nearest fueling station for refueling, we model the relative reductions of the detour time that directly result from the expansion of the fueling infrastructure capacities. The decision variable b represents the total annual detour time of all vehicles by trip for this vehicle type, drivetrain technology fueling using the type of fueling infrastructure l at the geographic location e. We express this in the following way:

$$
b_{yiel} = \begin{cases} B^{init} * (1 - \alpha_{iel}) * \sum_{u,r,v,g} \sum_{k \in \mathcal{K}^e} \sum_{t \in \mathcal{F}^e} n_{yurkvtge} & \text{if } w_{yiel} = 1 \\ 0 & \text{if } w_{yiel} = 0 \end{cases} \tag{3.22}
$$

α_i^{-} represents the ith reduction of the detour time in percentage at fueling capacity cap_i. For better understanding of the computation of this equation, we provide the following example: At location e, there are 1000 vehicles charges (expressed by $\sum_{u,r,v,g} \sum_{k \in \mathcal{K}^e} \sum_{t \in \mathcal{F}^e} n_{yurkvtge}$). Due to the total installed public charging capacity at location e, the reduction $\alpha_{(i=7)e}$ is active which reduces the initial detouring time, B^{init} by 80%. B^{init} equals 60 minutes. Based on this, the total detouring time at this location is $b = 60\text{min} * (1 - 0.8) * 1000 = 120,000min$.

3.3.6 Extension for long-distance transport (RQ3)

add from paper 3

3.3.6.1 Extended problem description and model features

3.3.6.2 Extended mathematical formulation

Travel time

State of charge

3.4 *Bottom-up charging profile modeling:* Traffic-flow-data-based charging profile modeling and flexibility potential estimation (RQ4)

3.4.1 Problem description

demand and flexibility potential approximation for electricity market modeling inserting here the modeling steps ; also integrating the definition of flexibility potential (this one graph); refer here to the model of Loschan/EDISON The applied methodology consists of two distinct steps. The aim in the first step is the modeling of the future charging demand of the commercial BEV fleet together with an estimation of the demand-side flexibility potential. This flexibility option is then integrated into the electricity market model.To analyze the effect of commercial fleet charging on redispatch costs, we focus on the usage of flexibility in the dispatch market and redispatch measures.

Figure **??** gives an overview of these building blocks of the methodology and its most important features. In the modeling of charging profiles and the electricity market processes, the temporal resolution is hourly. The optimization of the day-ahead market clearing which has the objective of social welfare maximization, and the optimization of redispatch measures with the objective of minimizing the associated costs. Both models have the functionality of coordinating the aggregated charging processes of the commercial BEVfleet. Therefore, this modeling approach is capable of simulating the centrally aggregated coordination of charging processes and its participation in the dispatch market and using its flexibility for dispatch measures. It is important to note that, with this approach, the demand-response of charging is not modeled as the optimization of the charging processes is directly integrated in the dispatch and redispatch optimizations.

Throughout the methodology, different types of geographic information are referred to. We introduce here three graphs to support the description of the methodology ($\mathcal{G} = \{\mathcal{G}_1, \mathcal{G}_2, \mathcal{G}_3\}$; see Figure ??). These mirror the three models outlined in Figure ??. Graph $\mathcal{G}_1 = (\mathcal{N}_1, \mathcal{E}_1)$ represents a network of regions and route connections of the commercial vehicle fleet. At the visited nodes, different charging opportunities exist. $\mathcal{G}_2 = (\mathcal{N}_2, \mathcal{E}_2)$ functions as the basis for optimizing the dispatch, presenting market price zones. $\mathcal{G}_3$ is the representation of the transmission grid. These graphs overlap and values transferred between the layers are aggregated or disaggregated based on their geographic allocation.

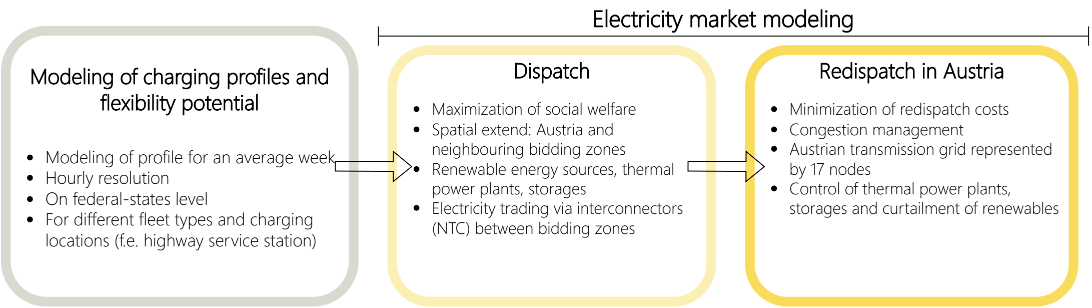


Figure 3.3: Overview of the steps of the methodology

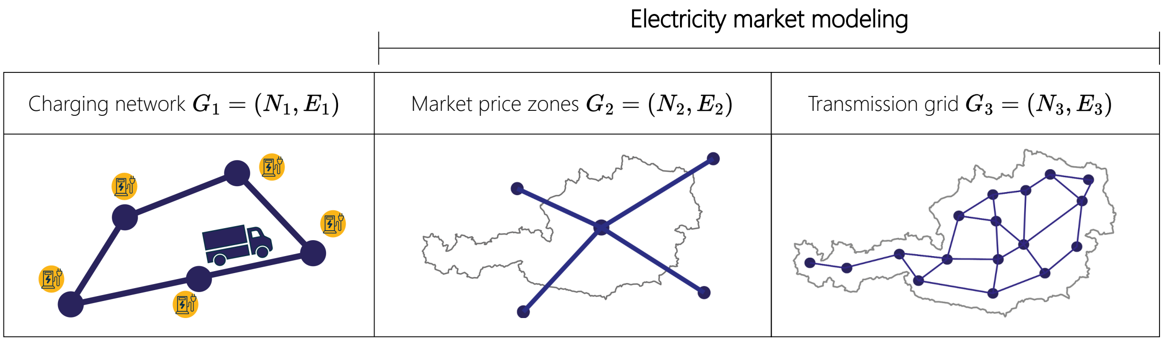


Figure 3.4: The three layers of geographic information used throughout the methodology.

3.4.1.1 Definition of the flexibility potential

Figure ?? describes the definition of the flexibility potential in the charging of vehicles graphically as a function of time and the state of charge: A vehicle is connected to a charging station for a defined period during which a certain amount of electricity must be charged. In the present example, the battery needs to be recharged until its maximum capacity, $\mathrm{SOC}^{\mathrm{BEVmax}}$. An initial charging profile is given based on an assumption of the charging strategy of the vehicle. In the illustrated case, this charging strategy is charging at the lowest possible continuous power level

($\mathrm{CAP}^{\mathrm{BEVconst}}$), distributing the charged energy evenly during the plug-in period (indicated with the dark red line). A maximum possible charging power, $\mathrm{CAP}^{\mathrm{BEVmax}}$, defines the inclination of the green lines and, therefore, the time span of the fastest possible charging process and the latest possible point in time at which the charging process must start in order to fully recharge. The orange line illustrates an example of a load curve with a variable power level, with the power level at the beginning and at the end being significantly higher than during the mid-part of the plug-in period. The area bounded by the green oblique lines indicates the extent of possible charging curves to reach $\mathrm{SOC}^{\mathrm{BEVmax}}$ during the plug-in time period, which translates to the flexibility potential of the charging process. For example, in fast-charging processes where the charging happens at $\mathrm{CAP}^{\mathrm{BEVmax}}$ and the plug-in period is closer to the point of "fastest achievable charging completion", flexibility is more limited.

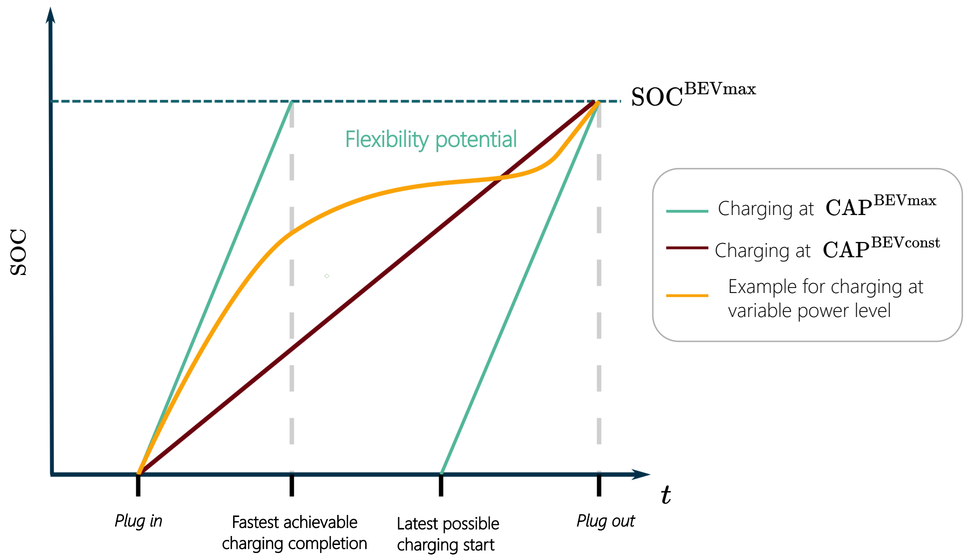


Figure 3.5: Graphic illustration of the flexibility of a charging process

3.4.2 Local transport

For the case of local transport, the charging demand of a vehicle is assigned to exclusively one node in $\mathcal{G}_1$. We aggregate all vehicles of a specific type to a fleet $f \in \mathcal{F}^{\mathrm{local}}$ and the energy demand for node n is estimated as follows:

$$D^{\mathrm{BEV}}_{f,n} = \overline{D^{\mathrm{spec,BEV}}_{f}} \cdot dist_f \cdot k_{f,n} \quad \forall f \in \mathcal{F}^{\mathrm{local}}, n \in \mathcal{N}_1 \tag{3.23}$$

$$\sum_{l \in \mathcal{L}^f} D^{\mathrm{BEV}}_{f,n,l} = D^{\mathrm{BEV}}_{f,n} \quad \forall f \in \mathcal{F}^{\mathrm{local}}, n \in \mathcal{N}_1 \tag{3.24}$$

The charging demand during the observed time period is deducted from the distance $dist_f$ that is driven by a vehicle of fleet f, its energy consumption $\overline{D^{spec,\mathrm{BEV}}_{f}}$ and the amount of the vehicles of fleet type f operating at node n $k_{f,n}$ is. The charging demand is assigned to different charging locations $\mathcal{L}^f$ that are available to the fleet. These are, for example, depots at node n. Each charging location type is characterized by an installed maximum charging power $\mathrm{CAP}^{\mathrm{BEVmax}}_{f,n,l}$.

The particular distribution of the charging demand to the charging location is conducted based on the assumed charging strategy for this fleet.

3.4.3 Interregional

For interregional transport, vehicles are assumed to travel between regions and charge at more than one node. In this case, a set of routes is given for the fleet $R^f = \{R_1, R_2, \dots R_I\}, i = 1, 2, \dots I$. The routes are all allocated in graph $\mathcal{G}_1$. The charging demand is determined and assigned to nodes $n \in \mathcal{N}_1$ for each route separately and later aggregated at each node for all considered types of charging locations. Each route R_i is traveled by a part of the fleet, $f_i \in \mathcal{F}^{\text{inter}}$. Charging locations are either allocated along the route $\mathcal{L}_f^{\text{enroute}}$ or at origin and destination nodes $\mathcal{L}^{f,\text{OD}}$. In accordance with this, the nodes contained in a route are categorized into two sets: $\mathcal{N}_i^{\text{enroute}}$ and $\mathcal{N}_i^{\text{OD}}$.

$$\begin{aligned} D_{f_i}^{\text{BEV}} &= dist_i \cdot \overline{D^{\text{spec,BEV}}}_f \cdot k_i \\ &= \sum_{n \in \mathcal{N}_i^{\text{enroute}}} \sum_{l \in \mathcal{L}_f^{\text{enroute}}} D_{f_i,n,l}^{\text{BEV}} + \sum_{n \in \mathcal{N}_i^{\text{OD}}} \sum_{l \in \mathcal{L}_f^{\text{OD}}} D_{f_i,n,l}^{\text{BEV}} \\ &\forall i = 1, 2, \dots I, f \in \mathcal{F}^{\text{inter}} \end{aligned} \tag{3.25}$$

k_i defines the number of vehicles traveling on the route R_i in the observed period. The charging demand for this route is distributed between the locations positioned along the route and at the origin or destination nodes. The particular assignment of the magnitude of charging demand to the nodes, $D_{f_i,n,l}^{BEV}$ depends further on the assumed charging strategy.

Nodal aggregation and temporal distribution We aggregate the charging demand for each fleet type and the respective locations on node-level:

$$D_{f,n,l}^{\text{BEV}} = \begin{cases} D_{f,n,l}^{\text{BEV}} & \text{if } f \in \mathcal{F}^{\text{local}} \\ \sum_i D_{f_i,n,l}^{\text{BEV}} & \text{if } f \in \mathcal{F}^{\text{inter}} \end{cases} \tag{3.26}$$

The plug-in periods are during periods of operational downtime of the vehicles, during operation times only when needed. Independently of obtaining the absolute magnitude for each fleet, the charging demand is assigned to timestep $t \in \mathcal{T}$:

$$D_{f,n,l,t}^{\text{BEV}} = g(D_{f,n,l}^{\text{BEV}}, t) \tag{3.27}$$

$g(\cdot)$ indicates here the function assigning the amount of charging load to each time, resulting in a charging demand defined for each time step, $D_{f,n,l,t}^{BEV}$.

3.4.4 Estimation of charging capacities

3.4.5 Integration to electricity system model

Hier die Implementierung mit dem EDISON

4 Results of case studies

4.1 Fast-charging infrastructure network capacities for passenger cars along Austria's highway network in 2030 (RQ1)

4.1.1 Case study: Austrian highway network 2030

The proposed modeling framework is applied to Austria‘s highway network by modeling a cost-optimal charging infrastructure expansion for 2030 under different future scenarios. In this study, year 2030 has been chosen here mainly due to the two following reasons: first is that the aim of the analysis of this paper is to illustrate short-term infrastructure requirements (short term in terms of infrastructure planning), and second is that it is a significant year in decarbonization plans for the transport sector as the Paris Agreement explicitly states a 20% electrification of global road transport by 2030 [36].

To extrapolate future scenarios, model input parameters were set, which describe the current status of Austria in 2021. Table **??** presents the selected values. Until the end of December 2021, $76,539$ electric vehicles have been registered in Austria [37], which make up for 1.5 % of all the registered passenger cars in Austria. In order to determine traffic load on highways during peak hour and the share of long-distance drivers, the most recently acquired data (Austrian-wide) on mobility patterns was used [38]. Similar to the work of Jochem et al. [39], it was assumed that all car trips taking longer than 45 min and are longer than $25km$ or car trips longer than $50km$ are most probable to include driving on highways or motorways. Furthermore, trips were classified as long-distance if the drive was at least $100km$ long, following the common definition of *long-distance* travel [40]. Based on the starting times of these trips, it was evaluated that during the hour of peak demand on Austrian highways 12% of the daily traffic takes place and 24% of the traffic are long-distance travelers.

Traffic counts were obtained from ASFINAG [41], which provide averaged weekly traffic counts for up to 276 positions along Austrian‘s highways and motorways. Their data encompasses counts for vehicles of two categories, namely: vehicles weighing up to 3.5 tons and those weighing greater than 3.5 tons. As no differentiation is made between light-duty vehicles and passenger cars in the category of $<$ 3.5 tons, it was assumed that all vehicles of this category are passenger cars, as light-duty transport will also be transitioned to electromobility [42]. Data for the year 2019 was chosen to be representative for 2021 as the complete data set for 2021 has not been published as of the time of the conduction of this analysis, and the 2020 dataset cannot be used due to being effected by the month-long lockdowns during the COVID pandemic.

The technical parameters $\overline{d}_{spec,BEV}$, $\overline{dist}_{range,BEV}$, and $\overline{P}_{charge,BEV}$ were set in such a way that they would represent an average Austrian BEV. For this, the technological attributes of the respective top 10 sold cars during the years 2019, 2020 and 2021 were used to evaluate the average values (see Appendix **??** for details on this).

Infrastructure cost component c_X is particularly difficult to set here as these onsite preparation costs may significantly vary based on the location of the site. Indications for the approximation of this value were drawn from [39], [43] and [44]. The installation costs of one charging point, c_Y, was assumed to be €60,000 for the hardware of a charging pole with $\hat{P}_{CP} = 150kW$ — which currently enables the fastest charging of passenger cars; an added construction costs to be €7,000 [44, 45]. Furthermore, it was assumed that the maximum installed capacity at a charging station is $12MW$.

The shape of the Austrian highway and motorway network was mapped based on geographic data by OpenStreetMap contributors [46]. The positions of the service areas were gathered based on the information drawn from ASFINAG [47] and complemented with geographic information from OpenStreetMap contributors [46]. The retrieved highway network used throughout the analysis has an overall length of $220km$ and consists of 55 segments. Moreover, there are 249 nodes in total, 139 of which represent service areas and 110 junctions. Further details on data preparation are found in the Appendix **??**.

Table 4.1: Model input parameters reflecting the status quo in Austria.

Base case	
Input parameter	Value
BEV share ϵ	1.5%
Share of traffic load during peak hour γ_h	12%
Share of long-distance drivers μ	24%
Share of overall traffic load compared with the survey year of traffic counts α	100%
traffic count data $\hat{f}_{ik}$	maximum recorded daily traffic counts 2019
energy consumption of an average BEV in the car fleet $\overline{d}_{spec,BEV}$	$0.24kWh/km$
driving range of an average BEV in the car fleet $\overline{dist}_{range,BEV}$	$340km$
charging capacity of an average BEV $\overline{P}_{charge,BEV}$	$81kW$
peak capacity of a charging point $\hat{P}_{CP}$	$150kW$
maximum installed charging capacity at a charging station P_{max}	$12MW$
investment costs for installation a charging station c_X	€ 40,000
investment costs for installation of one charging point $c_{Y,150kW}$	€ 67,000

4.1.1.1 Future scenarios

Four quantitative scenarios for Austrian highway charging infrastructure expansion are outlined. These were developed in the course of the Horizon 2020 research project openEntrance [48]. The scenarios outline pathways to climate change mitigation by reaching the $1.5°C$ or $2.0°C$ targets and are referred to as the *Societal Commitment* (SC), *Techno-Friendly* (TF), *Directed Transition* (DT) and *Gradual Development* (GD) scenarios. The former three pathways aim to mitigate climate change by keeping the temperature rise to a maximum of $1.5°C$ as specified in the Paris Agreement, the latter to $2.0°C$. Within these scenarios, the extent of societal engagement, implementations of technological novelties and the strong presence of political interventions in climate change mitigation vary [see also 49, 50]. These scenarios were developed to outline mitigation paths for different economic sectors in Europe and are used here to align the analysis described in this paper into the large-scale context of decarbonization. Based on this, different developments of the transport sector relevant to the present work are projected:

- **Societal Commitment (*SC*):** Within this scenario, politics are strongly intervening which is met by wide-spread societal acceptance, triggering behavioral changes in the face of awareness of the necessity of climate change mitigation. While this scenario is characterized by a reduction in energy demand due to behavioral changes, societal engagement supporting circular economy, and new market solutions, it is assumed that no significant technological breakthroughs appear. This translates in the transport sector to an increased modal shift to sharing concepts and public transport, which causes a significant decrease in individual passenger road transport.

- **Techno-Friendly (*TF*):** This setting combines the appearance of major technological breakthroughs and strong societal engagement, which results in an increased top down push effect in the application of new technologies that improve energy efficiency. Simultaneously, similarly as in the SC scenario, there is a strong social commitment driving an increased modal shift away from individual passenger car transport.

- **Directed Transition (*DT*):** Similarly as in the TF scenario, there is a strong active policy push supporting new technology options. While there are major technological developments, the social commitment to adopting such developments is missing. This results in the moderate growth of BEV share throughout the years and a decreased modal shift, but registered BEVs of the Austrian car fleet still show similar technological improvements as in the TF scenario.

- **Gradual Development (*GD*):** This scenario represents the projection of less ambitious climate change mitigation goals. It embodies the exertion of all three dimensions, namely, social engagement, technological breakthroughs, and significant political interventions, only a weaker extent of each. Therefore, while BEV penetration will grow to some degree, and technological improvements will appear, no changes in mobility patterns are expected for this pathway.

Based on these scenario descriptions, we embed projections on changes in the modal split and developments in the BEV technology in European climate mitigation pathways for 2030. Parameters ϵ and α are specified based on the climate change mitigation goals for Austria‘s passenger transport sector described in the governmental document “Austria’s Mobility Master Plan 2030” (*AMMP*) [42]. One of these key goals is to reduce motorized private transport by 31% between the years 2018 and 2040 to meet the $1.5°C$ target set by the Paris Agreement. In the SC scenario where strong societal and political engagement act together, this goal will be met by 2030. The AMMP further specifies that by 2030, 100% of newly registered passenger vehicles must be exclusively powered by an electric engine. In the SC and TF scenarios, it is assumed that the share of new registrations of electric vehicles will gradually increase until 100% in 2030 due to the strong awareness of the necessity of electromobility by the society. For the DT and GD scenarios, the steady growth rate as experienced in 2020-2021 is projected until 2030, which will result in an EV share of 27%[1].

Table **??** presents the projected values. The presence of major technological breakthroughs is expressed by a significant development in the driving range of BEVs and increasing charging power, which is in line with the current major focus in BEV technology research on battery technology with the goal of allowing faster charging and longer trips [51, 52]. According to the study by Thielmann et al. [52], there is a great potential in battery storage research suggesting that technological breakthroughs in the next years could lead to the sale of BEVs with a driving range of up to $1000km$. Based on this, the sale of BEVs with an average driving range of up to $800km$ is projected for 2030 in the TF and DT scenarios, whereas in the SC scenario, this range is assumed to be $450km$, being slightly larger than the ranges of BEVs currently on the market (see Table **??** in Appendix **??**). To reflect a weak extent of technical developments in the GD scenario, the increase in the average driving range of up to $600km$ is projected for 2030.

To compare the results of the scenarios, a similar peak power for charging points is assumed for all four scenarios. The study by Andersen et al. [51] projected $\hat{P}_{CP} = 350kW$ to be the predominant peak charging power by 2030. The costs for the hardware of a charging pole are estimated to be €120,000, as well as an additional construction cost of €7,000 [53, 54]. To reflect different improvements in charging efficiency, technological breakthroughs are assumed to lead to charging power levels of up to $\overline{P}_{charge,BEV} = 315kW$, given that the efficiency will increase up to 90%, as for charging poles with peak capacity of $50kW$ nowadays [55]. Today, one of the passenger car models with the highest charging power is Porsche Taycan with $\overline{P}_{charge,BEV} = 197kW$. For the SC and GD scenarios, this is assumed to be adopted by all BEV vehicles in 2030.

Other model input parameters are assumed to be similar as in 2021, using the values from Table **??**. Table **??** summarizes the overall projected values describing the average Austrian car fleet in 2030 which were extrapolated based on the assumption that these parameters would gradually change in a linear way until 2030 on the basis of the values for 2021 (see also Appendix **??**).

[1]This was calculated under the assumption that the size of the Austrian car fleet will not grow further from today.

Table 4.2: Car fleet parameters and average technical parameters of an average BEV on the market in 2030 for different scenarios (BEV share ϵ, share in road traffic α, average driving range $\overline{dist}_{range,BEV}$, average charging power $\overline{P}_{charge,BEV}$).

	Projections for 2030 under different scenarios			
Model parameters	*Social Commitment*	*Techno-Friendly*	*Directed Transition*	*Gradual Development*
$\epsilon(\%)$	33	33	27	27
$\alpha(\%)$	69	83	83	100
$\overline{dist}_{range,BEV}(km)$	450	800	600	800
$\overline{P}_{charge,BEV}(kW)$	200	315	315	200

Table 4.3: Model parameter values projected for the scenarios of climate change mitigation, set for year 2030 (BEV share ϵ, share in road traffic α, average driving range $\overline{dist}_{range,BEV}$, average charging power $\overline{P}_{charge,BEV}$, peak charging power of a charging point $\hat{P}_{CP}$, costs of installment of one charging point c_Y).

	Input parameters for scenarios 2030			
Model parameters	*Societal Commitment*	*Techno-Friendly*	*Directed Transition*	*Gradual Development*
ϵ (%)	33	33	27	27
α (%)	69	83	83	100
$\overline{dist}_{range,BEV}$ (km)	420	670	660	520
$\overline{P}_{charge,BEV}(kW)$	166	248	243	164
$\hat{P}_{CP}(kW)$	350	350	350	350
$c_{Y,350kW}$ (€)	127,000	127,000	127,000	127,000

4.1.2 Expansion of Fast-Charging Infrastructure along Austrian Highway Network under Different Scenarios

In this section, the most relevant results are presented. It is divided into two parts: First, we elaborate on the expansion requirements for the existing fast-charging infrastructure along Austria's highway network under different future scenarios for 2030. Details on the results obtained for the DT scenario, for which the costs of fast-charging infrastructure expansion are the lowest, are presented. Subsequently, the results of the modeled expansion given four different scenarios, SC, TF, DT and GD, are compared based on parameters describing the costs and the required charging infrastructure expansion. To gain better insight into how the observed differences between the scenarios come to place, selected input parameters of the scenario result with the highest infrastructure expansion costs for 2030, which is the GD scenario, are altered. In the second part of this section, the focus shifts from the required infrastructure expansion for 2030 to the analysis of changing infrastructure requirements in the face of technological development and increasing demand. First, the effect of change in the driving range of an average BEV is observed and, second, that of increasing demand by the rising share of BEVs in the Austrian car fleet.

4.1.3 Expansion of fast-charging infrastructure along Austrian highway network under different scenarios for 2030

Under the consideration of existing charging points with the peak capacity of $\hat{P}_{CP} = 350kW$, which is assumed to be the predominant charging capacity of fast-charging infrastructure for 2030, and the assumption that the investment of on-site preparation (c_X) has been made for all existing charging stations with charging points allowing fast-charging, the expansion of the current charging infrastructure along the Austrian highway network was modeled under different climate mitigation scenarios.

4.1.3.1 Austria‘s fast-charging infrastructure for 2030 under the Directed Transition scenario

Table **??** and Figure **??** display the modeling results for the expansion of the current $350kW$ charging infrastructure along highways in Austria for 2030 under the DT scenario. In Figure **??**, the charging infrastructure expansion is expressed through additionally needed capacities. The expansions at existing charging points are indicated in dark green, and required capacities at newly installed charging points are indicated in orange . The charging stations in the lighter shades of green and orange indicate the required expansion of $350-4900kW$, i.e., by 1-14 charging points, and charging stations in the darker shades installations of additional $5200 - 10500kW$, i.e., 15 - 28 additional charging points. The total infrastructure expansion costs are estimated to be €54 Mio., which are translated to €/kW 369 and €39 per registered BEV in the Austrian car fleet in 2030. While currently, 40 charging points with $\hat{P}_{CP} = 350kW$, i.e., $14MW$, are installed along Austrian highways, an additional $+146MW$ of charging capacity are required until 2030. Further, additional 24 charging stations are needed, of which 10 are positioned within the dense part of the highway network in the East of Austria, in the vicinity of Vienna. The results also indicate the need for the installation of new charging stations near the Austrian border in order to cover all demand within the boarders, which mostly results from the model formulation enforcing all coverage of demand within the network as described in Section **??**. Aside from this, there exist three charging stations that do not need any infrastructure expansion.

Table 4.4: Cost parameters and charging infrastructure attributes resulting from the expansion of the existing $\hat{P}_{CP} = 350kW$ charging infrastructure under the *Directed Transition* (DT) scenario.

	Nb. of charging stations	Total capacity	Specific capacity costs	Specific costs per BEV	Total expansion costs
DT scenario 2030	54	$160MW$	€/kW 369	€/BEV 39	€ 54 Mio.

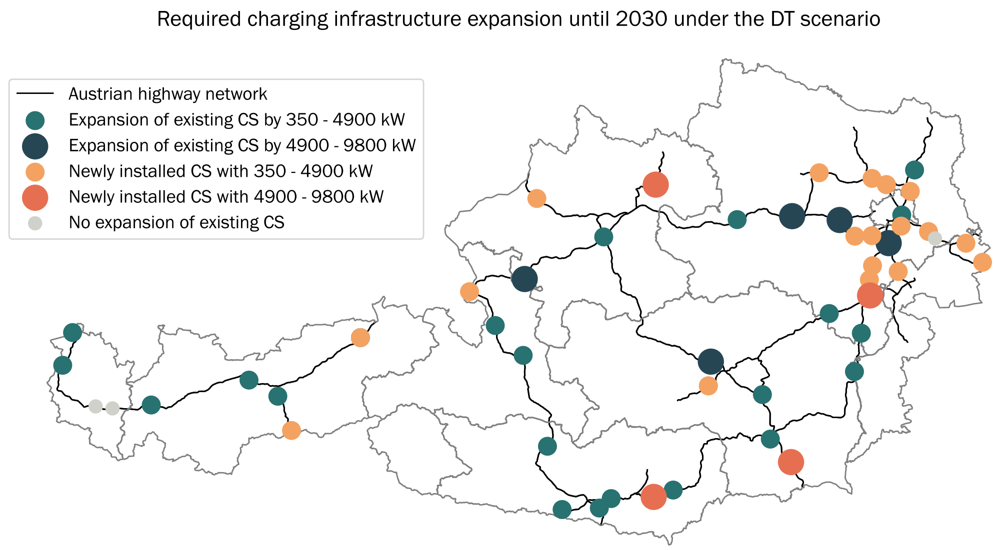


Figure 4.1: **Required expansion of fast-charging infrastructure along Austrian highways in 2030.** Sizing of capacities that need to be added at currently existing and nonexisting charging stations (CS) given the *Directed Transition* (DT) scenario.

4.1.3.2 Comparison of the results from different future scenarios

Table **??** presents a comparison of key parameters describing the required infrastructure expansion under different future scenarios for Austria in 2030. The following observations are made:

- The expansion under the DT scenario ,for which the input parameters were set based on the assumption of a strong presence of political incentives pushing technological developments, results in the lowest costs of charging infrastructure expansion (€54 Mio.).

- There is a relative difference of up to +84% between the scenario causing the minimum expansion costs (DT) and the highest costs arising in the GD scenario, within which weaker climate change mitigation measures are assumed.

- The number of charging stations remains in a similar range for all scenarios, varying between 54 and 57. The specific infrastructure expansion costs per kW remain also very stable at around €/kW 368.

- The specific costs per BEV range between 39 and 72 and are the lowest in the TF and DT scenarios. The common trait of these two scenarios is the presence of technological breakthroughs leading to higher driving ranges and charging capacity of BEVs.

Table 4.5: Comparison of the results for expansion of fast-charging infrastructure expansion along Austrian highways under different scenarios for 2030. The lowest specific costs per BEV and lowest total infrastructure expansion costs are highlighted.

Model output	Scenarios 2030			
	Societal Commitment	*Techno-Friendly*	*Directed Transition*	*Gradual Development*
Nb. charging stations	54	53	54	56
Total capacity (MW)	238	192	160	285
Specific capacity costs (€/kW)	368	368	369	367
Specific costs per BEV (€/BEV)	49	39	39	72
Total infrastructure expansion costs (€)	85 Mio.	68 Mio.	54 Mio.	100 Mio.
Rel. change of costs to DT scenario	+57%	+26%	-	+85%

4.1.3.3 Cost-reduction potentials in the Gradual Development scenario

To shed light into why the infrastructure expansion costs in the GD scenario are up to +85% higher than in the other scenarios and how the high specific costs per BEV of €/BEV 72 come to place, selected input parameters are altered and the effects on the costs are observed. These alterations reflect developments which are absent in the GD scenario but present in the others and which essentially lead to a cost reduction in charging infrastructure expansion investments. The following projections are drawn from the other scenarios and based on these, input parameters are altered in the GD scenario: a medium decrease in road traffic by -17% until 2030 as in the TF and DT scenarios, a major decrease by -31% as in the SC scenario, technological breakthroughs as in the TF and DT scenarios altering the driving range of an average BEV sold in 2030 to be $800km$, and having an average charging capacity of $315kW$ at a charging point with $\overline{P}_{CP} = 350kW$. Further details on these alterations are displayed in Table **??**.

Figure **??** and Table **??** display the resulting cost reductions and changes in the required fast-charging infrastructure in response to the respective parameter changes. The lowest infrastructure expansion costs are achieved through the increase of BEV charging power which causes a large decrease in the required capacity as the efficiency of charging increases. Similarly, high cost reduction is accomplished by decreasing the overall traffic load which essentially reduces the demand for charging infrastructure. No cost reduction results from the increase in BEV driving range. Figure **??** illustrates these changes in costs in response to the specific parameter alterations visually.

Table 4.6: Description of input parameter alterations reducing costs in the *Gradual Development* (GD) scenario. The parameter alterations are based on the other three scenarios: *Societal Commitment* (SC), *Techno-Friendly* (TF), *Directed Transition* (DT).

Parameter change	**Description (reference scenario)**	**Altered input parameter**	**Value in GD scenar**
Medium decrease in road traffic	The overall road traffic load is subject to a reduction of -17% (DT, TF).	α	100%
Major decrease in road traffic	The overall road traffic load is subject to a reduction of -31% (SC).	α	100%
Increase in driving range	The driving range of BEVs being sold in 2030 is increased to $1000km$ (DT, TF).	$\overline{dist}_{range,BEV}$	$520km$
Increase in charging power	The average charging capacity of BEVs sold in 2030 is projected to be $315kW$ (DT, TF).	$\overline{P}_{charge,BEV}$	$164kW$

Table 4.7: Changes in fast-charging infrastructure and associated investment costs in the face of different cost-reduction measures as described in Table **??**. The highest cost reductions are highlighted.

		Cost-reduction measures			
	GD scenario 2030	Medium decrease in road traffic	Major decrease in road traffic	Increase in driving range	Increase in charging pow
Nb. of charging stations	54	54	54	55	54
Total capacity (MW)	285	238	197	286	139
Total expansion costs (€)	100 Mio.	82 Mio.	68 Mio.	100 Mio.	66 Mio.
Rel. change	-	-18%	-32%	-0%	-34%

4.1.4 Sensitivity Analyses on the Requirements for Fast-Charging Infrastructure

In the following, the mere infrastructure requirements in 2030 without regards to the charging infrastructure currently in place are analyzed. This is done to better understand how requirements for the fast-charging infrastructure change as a function of technological BEV parameters and in response to growing demand. First, the effect of the average driving range of an average BEV in the Austrian car fleet is observed in the context of the TF scenario during which major developments in battery technology are expected. Second, the change in modeled charging infrastructure depending on the BEV share in the car fleet within the SC scenario, which reflects high societal commitment to BEV uptake, is demonstrated.

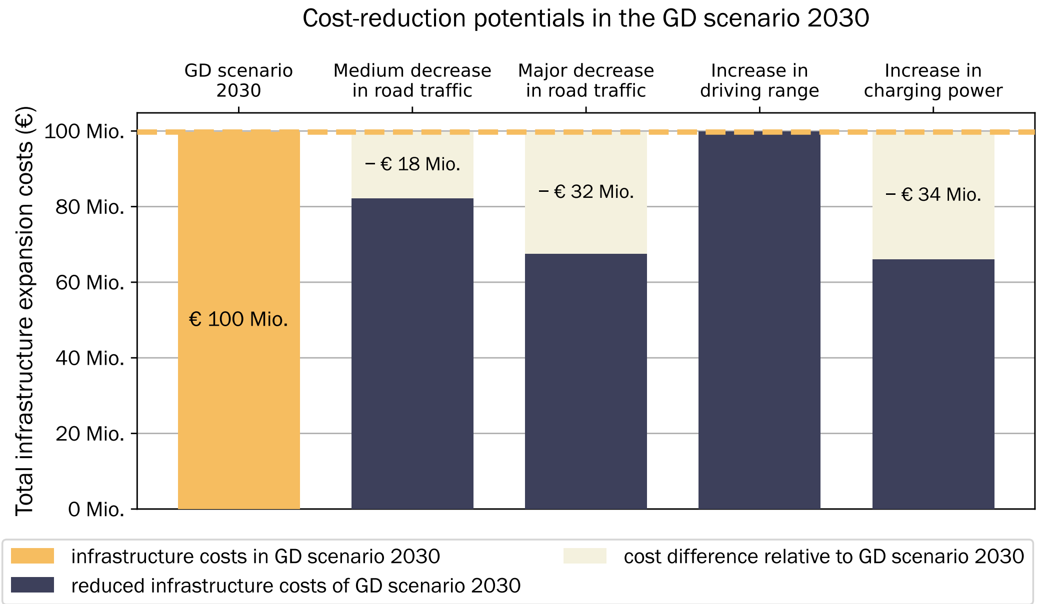


Figure 4.2: **Cost reduction potentials in the *Directed Transition* (*DT*) scenario.** (Detailed descriptions of the measures are in Table **??**.)

4.1.4.1 Increasing driving range in the Techno-Friendly scenario

The driving range is altered between 200 and 1400km. Figure **??** presents the changing distribution of the numbers of the charging points at the charging stations and total number of charging stations in response to gradually increasing driving range in the TF scenario. In this figure, the blue boxplots display the distribution of charging points (CP) along the charging stations (CS). The gray dashed line indicates the maximum possible number of charging points at a charging station which is 34. This is given by the maximum installed capacity of 12MW at a charging station. The dark red connected points indicate the total number of charging stations in the modeled charging infrastructure. Table **??** presents the change in the key parameters for the driving ranges of 200, 800 and 1400km and gives an impression on how the key parameters of the modeled fast-charging infrastructure change in the course of the conducted sensitivity analysis. Given the assumed development in the TF scenario, the average driving range of BEVs in the Austrian car fleet is projected to be 670km by 2030 and reach approximately 1000km by around 2040.

With the increasing range, energy demand can be shifted further away from the node where it originates, which results in wider solution space during the optimization. Overall, the infrastructure costs stay stable between €71 Mio. and €72 Mio. throughout this parameter alteration. The total number of charging stations decreases from 55 at 200km to a minimum of 38 at 1100km. The installed capacity stays constant. Starting at the range of 300km, fully occupied charging stations occur throughout the sensitivity analysis. Overall the highest costs of investments are at 200km and drop to €71 Mio at the range of 500km.

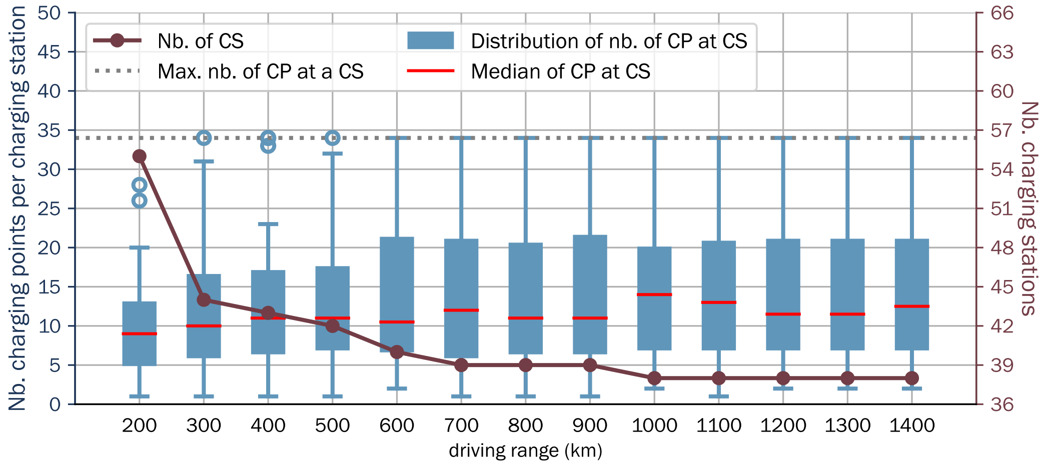
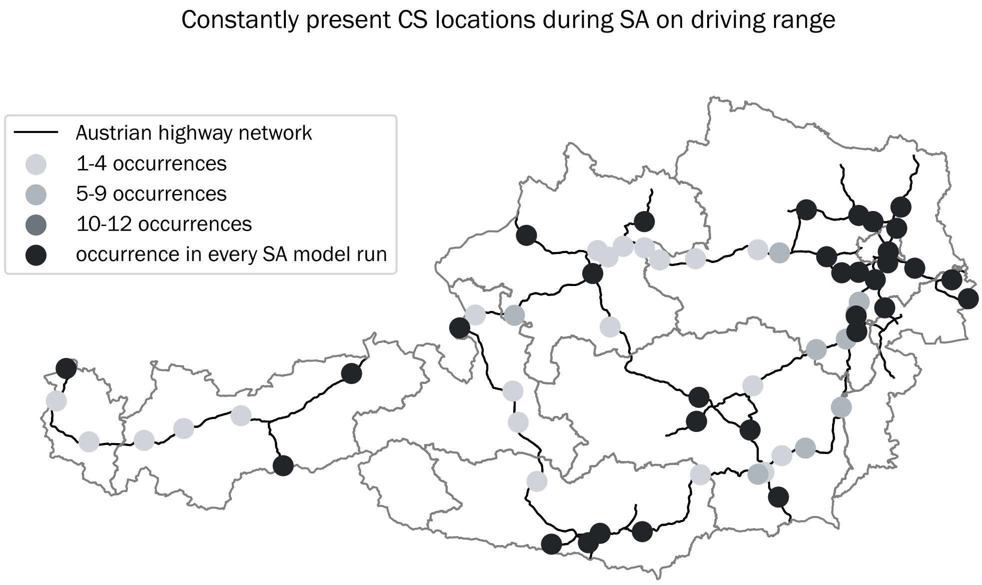


Figure 4.3: **Sensitivity analysis on driving range.** Impact of the increase of the driving range of BEVs on the distribution of the number of charging points (CP) at charging stations and the total amount of charging stations (CS).

During this analysis, the model was run for each of the ranges between 200 and 1400km every 100km and, therefore, in total, for 13 times. During all of these model runs, at 34 of all service areas, charging station installations occurred in each of the model runs. The top sub-figure in Figure **??** illustrates these charging stations in black. The bottom illustration shows which of these are currently existing charging stations (in bright green) and which are not (in red). Overall, 11 of these 34 permanent charging stations are existing charging stations.



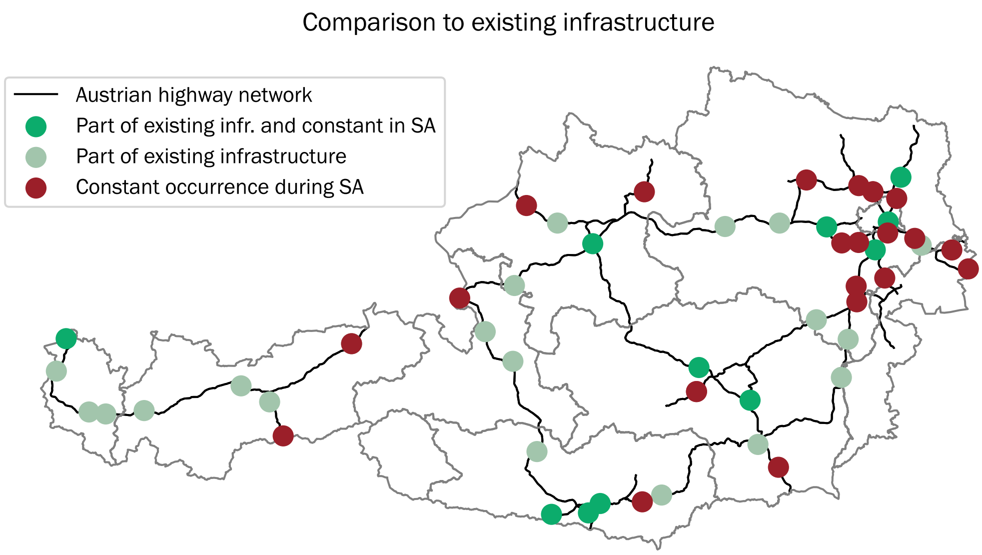


Figure 4.4: **Frequent charging point allocations. Top:** Visualization of charging stations (CS) which occur during the model runs of the sensitivity analysis (SA) on BEV driving range. **Bottom:** Visualization of CS which are constantly present during the SA and are part of the existing infrastructure.

4.1.4.2 Increasing share of BEVs in the Societal Commitment scenario

Figure **??** presents the results of the sensitivity analysis on the share of BEVs in the Austrian car fleet under the SC scenario for 2030. The top-left sub-figure presents the total installed capacity of the fast-charging infrastructure as a function of rising share of BEVs. The top-right sub-figure displays the change in the number of charging stations. Boxplots illustrating the distribution of the number of charging points at charging stations are presented in the bottom-left sub-figure. The timeline in this figure is projected based on the assumption that as of 2030, all registered cars will be BEVs and a BEV has a lifetime of 10 years which would lead to an Austrian car fleet that is 100 % electric by 2040. Table **??** presents the values of parameters describing the key features of modeled infrastructure for the different shares of BEVs, 10%, 50% and 100%.

The required capacity for fast-charging is rising linearly with the share of BEVs. The number of charging stations is significantly increasing between 40% to 100%, indicating the requirement for a densification of the fast-charging infrastructure. This effect of densification can be attributed to the increasing amount of fully occupied charging stations which is visible in the bottom left sub-figure of Figure **??**. The overall cost increase by a factor of about 10 between 10% and 100% share of BEVs, so does the required capacity.

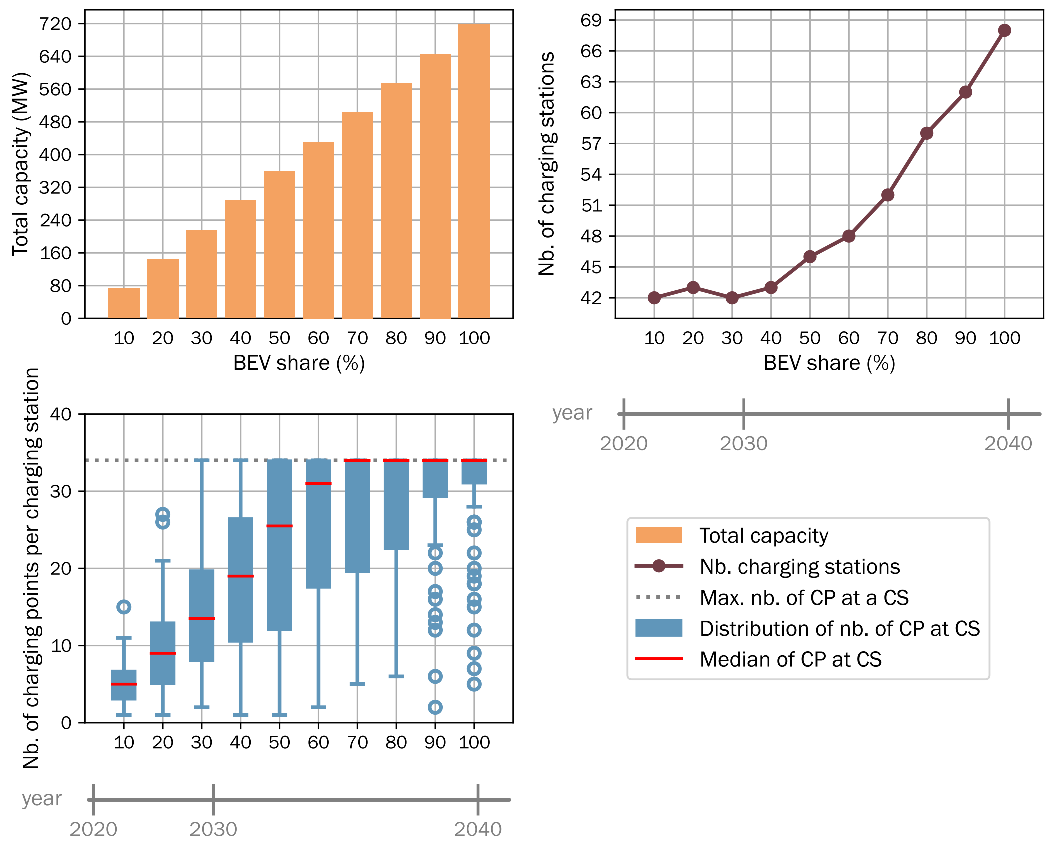


Figure 4.5: **Sensitivity analysis of the increasing BEV share. Top-left:** Total required capacity of the fast-charging stations of required charging infrastructure. **Top-right:** Number of charging stations (CS). **Bottom-left:** Distribution of the number of charging points (CP) at the charging stations.

Table 4.8: Key parameters describing the results of the sensitivity analyses on the driving range in the *Techno-Friendly* (TF) scenario and share of BEVs in the *Societal Commitment* (SC) scenario.

	driving range $\overline{dist}_{range,BEV}$ (TF)			**share of BEV ϵ (SC)**		
	$200km$	$800km$	$1400km$	10%	50%	100%
Nb. of charging stations	55	39	38	42	46	68
Total capacity (MW)	192	192	192	73	360	718
Total investment costs (€)	72 Mio.	71 Mio.	71 Mio.	28 Mio.	132 Mio.	263 Mio.

4.2 Impact of charging infrastructure roll-out strategies on BEV adoption in the Basque Community, Spain in the long-term (RQ2)

4.2.1 Case study: Passenger car fleet of the Basque Country, Spain

4.2.1.1 Basque Country

The geographic extent of this analysis of this paper is the autonomous community Basque Country (in Spanish: *País Vasco*, NUTS code: ES21). This region is located in the North of Spain. The current passenger car vehicle stock is in the magnitude of 1.08 Mio. (2022) [56]. In 2023, the electrification rate of the passenger car fleet was at 0.05% [57]. The Basque Country is classified as a NUTS-2 region in the EV NUTS classification scheme [58] and consists of three NUTS-3 regions: Araba/Álava[2] (ES211), Guipuzcoa (ES212), Bizkaia (ES213). Figure **??** displays the relative geographic allocation of the regions and of the capital cities. For RQ1, we represent the NUTS-2 region as one node. For RQ2, we derive a graph-based conceptualization with three nodes representing each of the NUTS-3 regions and three edges representing the transport connections between neighboring regions.

Origin-destination data We use the modeled passenger car trips by ETISplus database [59] which holds information about: origin, destination zones (NUTS-3 level [58]), trip purposes, as well as route lengths and shortest-path route information for trips between all regions. A subset including NUTS-3 regions of the Basque Country is extracted. We further exclude all trips that go beyond the border of the case study area. This corresponds to the selection of 99% of all trips originating from there. Based on this, we set the system boundaries of the analysis equal to the boundaries of the Basque Country.

The ETISplus data were calibrated for transportation demand in 2010. To consider the growth in passenger car trips since then, we use the relative growth of the passenger car fleet since then [60]. The subsequent growth of the travel demand until 2050 is extrapolated based on historic GDP growth since 2020 [61].

Trips are categorized by the following purposes: *Business*, *Private*, *Vacation*, and *Commuting*. Trip purposes of the category *Business* are taken into account in the sizing of fueling infrastructure, but are not assigned to explicit consumer groups of different income levels. *Private* trips are defined as non-business trips with a duration of up to four days, while *Vacation* refers to trips that take more than four days. *Commuting* includes daily trips for working and studying purposes. Figure **??** displays the initial data trip count by purpose for local trips, i.e. within a NUTS-3 region, and inter-regional trips between NUTS-3 regions within the Basque Country.

[2]For the readability of the article, we refer to the region by its Basque language, Araba.

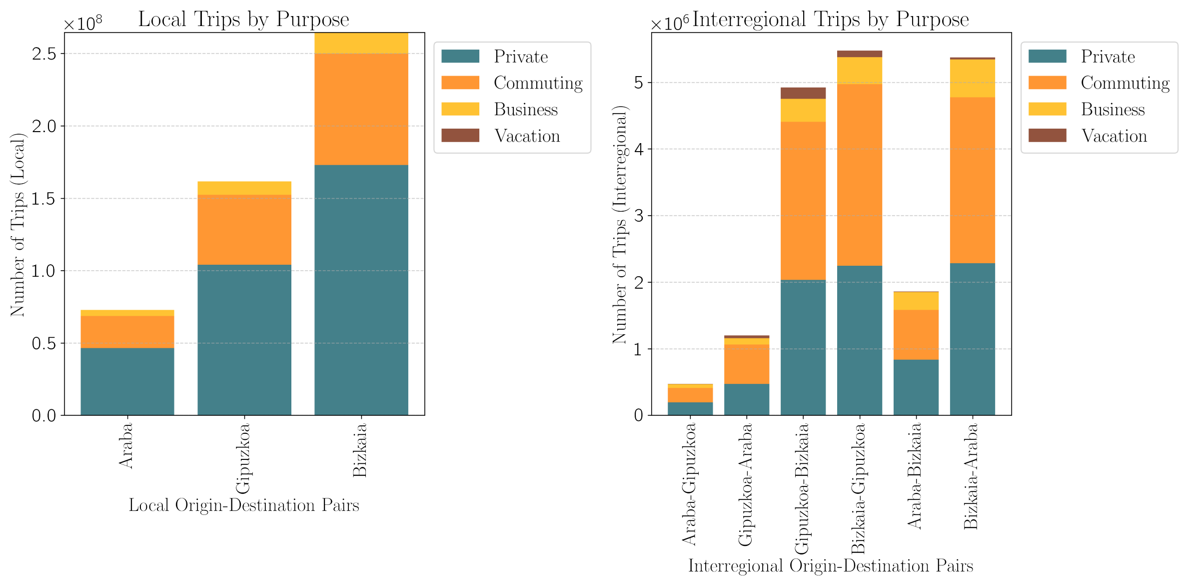


Figure 4.6: Passenger car trips by purpose: Within a NUTS-3 region (*left*) and between NUTS-3 regions (*right*)

In the underlying data set by ETISplus, route lengths are given for the connections between NUTS-3 regions but not for trips within a region. To compensate for this missing information, we perform the assignment of route lengths (see Table **??**). More details on the assumptions made in this process are in the Appendix of the manuscript (see Appendix **??**).

Table 4.9: Path lengths assigned to trips within a region (same origin and destination on NUTS-3 level)

		Average trip length (km)		
Region type	Share of total trips within a region	Private	Commuting	Business
Urban	21%	7.4	10.4	13.0
Rural	79%	9.7	17.1	23.2

Introduction of income-class specific parameters The key assumptions in the introduction of the income-class specific parameters is that the central difference in travel patterns by income class is the motorization rate, by monetary budget and home ownership [62, 63]. The income classes are characterized by having different monetary budgets for the purchase of vehicles and different VoT values. We consider five different income classes: *Very high income*, *High income*, *Medium low income*, *Low income* and *Very low income* class, mirroring the income class classification of EUROSTAT via five quintiles [64]. The most important preprocessing steps related to the income classes include the distribution of trips among them, the determination of monetary budgets and limitations for home-based charging infrastructure. We, therefore, characterize the five consumer groups by the motorization rate, VoT, average monetary budgets for new vehicles, the frequency of vehicle purchase, and the share of home ownership. Assumptions for these are summarized in Table **??**.

Mattioli et al. [65] define a relation between motorization rate and purchasing power on NUTS-2 region level, derived from EUROSTAT data. We use this as a proxy to determine a relationship between the purchasing power standard (PPS) of the income class and the motorization rate, together with the average motorization rate in the Basque Country. This relationship is: Motorization rate $= 0.02 \times \text{PPS} + 79$. The VoT parameter is reported to vary significantly based on the monetary budgets. We use the value used in the case study by Tattini et al. [17] who apply these values in the context of a Danish case study. Due to the lack of published data for VoT values calibrated for different income classes in Spain or the Basque Country, we assume similar values for the present case study as found for Denmark and adapt these based on relative purchase power numbers, applying the factor $\times(92/139)$ [66].

Table 4.10: Overview on assumptions between the income classes

Income class	*Purchase Power Standard*	*Motorization rate (nb. of veh/1000)*	*Value of Time (€/h)*	*Average monetary budget over 10 years (€)*	*Purchase frequency (a)*	*Assumed home ownership*
Very low	10081	338	6.60	4160	10	30%
Low	19685	425	12.77	9282	8	55%
Medium low	27932	500	18.93	13910	6	85%
High	37910	599	25.10	18824	4	100%
Very high	61086	800	31.27	26545	2	100%

A statistic for the UK details expenditures for purchases [67] [68], displaying an approximately linear relationship between level of income and expenditure for purchases, among with how much is spend on the primary market. Based on this, we determine the monetary budgets for a new vehicle from the primary market for the *Very high*, *High* and *Medium High* income class, while we use the vehicle purchase price from the secondary market for the budget quantification of income class levels *Low* and *Very low.* Home ownership is extrapolated from the average Spanish home ownership rate reported in [69].

4.2.1.2 Drivetrain technologies and fuels

When it comes to the selection of the drivetrain technologies, we simplify it to two options: fossil-fueled vehicles and plug-in battery-electric vehicles. In contrast to this choice, studies in the literature have included larger technology portfolios by considering different electric car technologies, such as hydrogen fuel-cell or hybrid plug-in electric. The reason for the limitation to two technologies is twofold: Plug-in battery-electric vehicles have been largely proven to be cost-wise and environmentally the most viable, with a promising outlook on further cost decreases [70]. Therefore, most policies focus on supporting this technology. We reduce the fuels used to *fossil fuel*, including diesel and petrol, and electricity. Cost parameters for electricity are drawn from marginal costs for the energy system optimization for Spain performed with GENeSYS-MOD [71]. The average fuel price is based on [72]. Costs of the drive-train technologies are drawn from a detailed modeling of the manufacturing of all components by [70]. We reduce the complexity of different car sizes to one representative vehicle type as related parameters to the choice of the car size - for example, household size, housing type [73] - are not part of the modeling. Therefore, different sizes are excluded to avoid introducing a modeling bias due to

Table 4.11: Overview of a selection of assumed parametrization for passenger cars of battery-electric vehicles (BEV) and fossil-fueled internal-combustion engine vehicles (ICEV).

	2025	2035	2045	Reference
BEV (first-hand market)				
CAPEX (€)	18,000	16,100	15,200	[70]
fuel costs (€/kWh)	0.05	0.03	0.03	[71]
Specific consumption (kWh/100km)	16.9	13.4	12.7	[70]
Battery capacity (kWh)	56	69	70	[70]
ICEV (first-hand market)				
CAPEX (€)	12,000	12,800	13,200	[70]
fuel costs (€/kWh)*	0.08	0.12	0.18	[70]
Specific consumption (kWh/100km)	58.1	44.9	36.9	[70]
carbon price (€/tCO2)	52	113	250	[75]
Charging infrastructure				
Level II: CAPEX (€/kW)		108		[21]
DCFC: CAPEX (€/kW)		350		[21]
OPEX		30% of CAPEX		

*without carbon pricing

insufficient complexity of the model. Table **??** summarizes all assumptions on cost parameters and sources. The cost assumptions are based on the work by Grube et al. [70] who have evaluated a wide range of different drive-train technologies for passenger cars and different passenger car sizes, including small, medium, and SUV. Here, we derive the costs for an *average*-sized vehicle by averaging the costs using weights that correspond to the magnitudes of the sizes in the current vehicle stock, assuming that this distribution would be constant throughout the optimization horizon. The data on different vehicle sizes represented in the statistic for different engine sizes in the Spanish vehicle stock are retrieved from [74]. The costs for the maintenance are increased at a rate of 3% per year for the first three years, and then by 10% per year.

To also allow for purchases from the second-hand vehicle market, purchasing options for vehicles of older generation are allowed for. For each technology, we introduce three groups of older vehicles with decreased investment costs but higher costs for maintenance and operation. The technological performance of vehicles available on the second-hand market is a function of their counterpart on the first-hand market and their average age. These three age-groups are: *1-5*, *6-10* and *11+ years*. The maximum lifetime of a vehicle is set to 25 years. An initial vehicle stock with vehicles of different ages is assumed based on data from [74]. The cost for vehicles on the second-hand market are calculated assuming a 65% drop in resale price after the first year and after this, an annual 10% cost decrease. The maintenance costs follow the annual increase in number as described above.

4.2.1.3 Types of charging infrastructure

For fossil-fueled vehicles, we assume that the fueling infrastructure with sufficient capacities has been established. Therefore, for combustion-engine passenger cars, no expansion of the fueling infrastructure is required.

For charging infrastructure, we introduce four different types: Home (Level II), Workplace (Level II), Public slow (Level II), and Public fast (DCFC) (based on [76]). Tables **??** and **??** summarize relevant assumptions. The reduction in fueling detour time is relevant for public infrastructure. In the case of fast charging (DCFC), the fueling time is considered in addition to the level of service (similar as in the work by Luh et al. [30]), while for the other types of infrastructure, we assume that there the charging is during typical down times of the vehicle and therefore does not impact the level of service. Initial home charging capacity (40 MW in 2020) reflects the early adopter profile of BEV owners, who were predominantly homeowners with dedicated parking and charging infrastructure. This assumption is consistent with empirical findings that early BEV adopters had home charging access rates exceeding 90% [77].

Table 4.12: Overview on the introduced types of charging infrastructure and most important assumptions.

Type of charging infrastructure	Peak power level	Location	Max. utilization rate	Fueling detour time	Extra fueling time
Home (Level II)	11 kW	home	2%		
Workplace (Level II)	11 kW	workplace	20%		
Public slow (Level II)	22 kW	public	25%	×	
Public fast (DCFC)	50 kW +	public	25%	×	×

Table 4.13: Assumptions for the sizing of initial capacities and upper limits for the expansion of charging infrastructure.

Type of charging infrastructure	Sizing of initial charging infrastructure	Limitation for capacity installation
Home (Level II)	based on current observations in the share of charging processes at home chargers (88%, [77])	Home charging infrastructure can be installed in 30% of owned homes.
Workplace (Level II)	based on current observations in the share of charging processes at workplace chargers (8.8%, [77])	based on today's charging demand coverage at work and scaled by current total number of passenger cars in the given region.
Public slow (Level II)	current BEV-to-charging point ratio for public slow chargers [78, 79]	No upper limit
Public fast (DCFC)	current BEV-to-charging point ratio for public fast chargers [78, 79]	No upper limit

. The maximum expansion speed of charging infrastructure is assumed to be 30% which is in line with reported expansion speed by [4].

To ensure that next to public slow charging, capacities for fast charging are installed to reduce range anxiety and enable recharge in cases of emergency (f.e. battery not sufficiently charged), we introduce a constraint imposing a minimum requirement for fast charging depending on the capacity installed for slow charging, which is set at the proportion of 2. This number is derived from the relative difference of the peak power level (the current value in Spain is 4.6 [78]) .

4.2.2 Charging infrastructure roll-out scenarios

Figure ?? illustrates the setup for analyzing different scenarios of the roll-out of public charging infrastructure. Illustrations 1 and 2 address the setup to answer RQ1: two expansion strategies are compared, the *Concentrated* and the *Distributed expansion*. For this, the case study area is considered as one NUTS-2 node, while for addressing RQ2, the area is modeled on NUTS-3 level with three nodes.

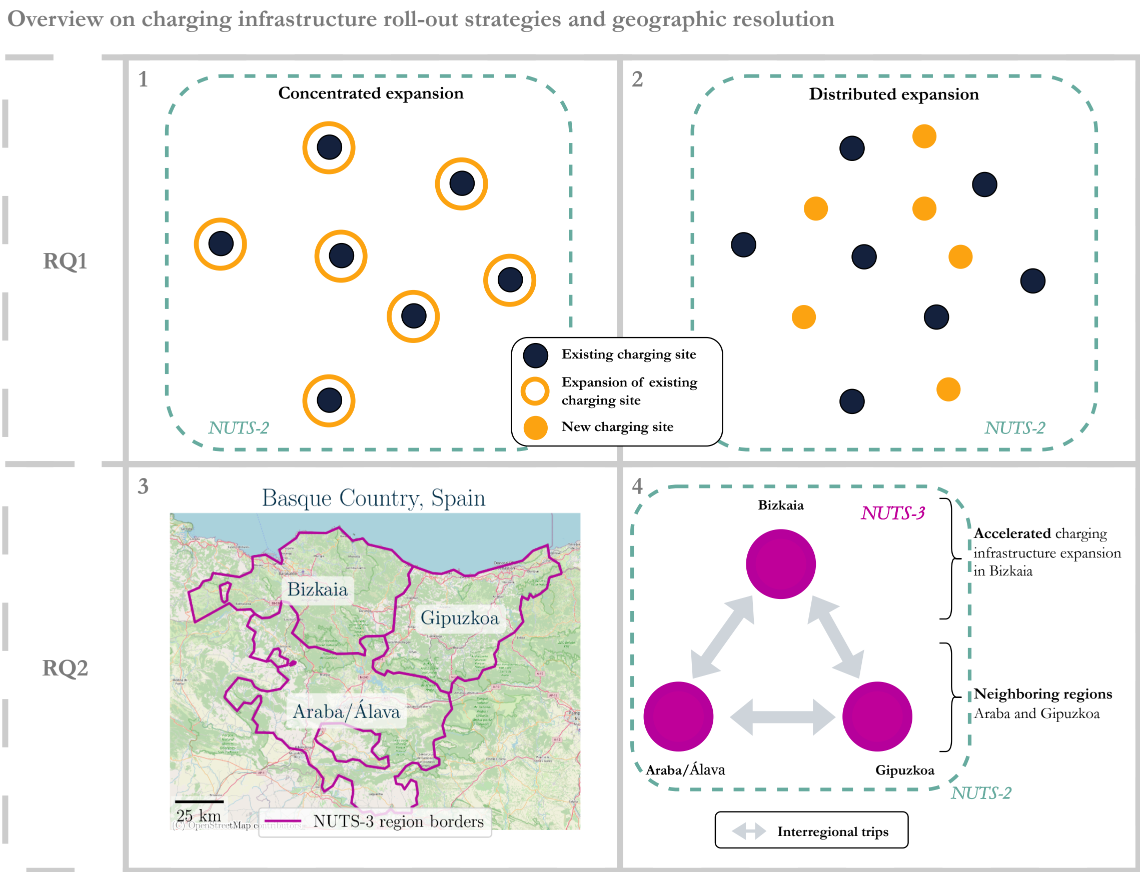


Figure 4.7: Overview of the scenario setups for the analysis. The top row (illustrations 1 and 2) displays the contrasting approaches to the densification of public charging infrastructure, addressing research question 1 (RQ1). In the bottom row, illustration 3 displays a map of the geographic area of Basque Country by its three NUTS-3 regions, together with the corresponding capitals. In illustration 4, it is implied which pace of charging infrastructure roll-out is assumed for the NUTS-3 regions — addressing research question 2 (RQ2).

Spatial densification (RQ1)

The spatial densification of charging infrastructure is addressed using the mixed-integer extension of the optimization model. For this, the trip data is accumulated to the NUTS-2 level.

To quantify the interaction between charging infrastructure investments and the detouring time required to reach the closest public charging station, a function between the average detouring time and installed charging capacities needs to be defined:

$$\alpha = g\left(q^{fuel\_infr,+}\right) \tag{4.1}$$

α is the factor for the relative decrease of the fueling detour time and is a function of additionally built capacities. By formulating this function, we directly assume that the chargers are spatially evenly distributed throughout the regions' road network. By doing this, we neglect the different degrees of urbanization and the option of allocating charging sites at points of interest, which would decrease detour time in reality. We do this with the premise that for a share of 100% BEV penetration of the passenger car fleet, a spatially even distribution of charger availability is a necessity, to be equally accessible for all. Further, this assumption indicates that there are no malfunctions of charging points which could lead to extended detouring times. The function $g()$ represents this relationship and varies for different charging infrastructure expansion strategies, which are explained in the following:

- *Distributed expansion:* Charging sites with singular charging stations are installed with the aim of achieving a dense charging network. Only when a maximum number of charging sites is reached, the number of charging points at the charging stations is expanded.
- *Concentrated expansion:* The focus lies on expanding the number of stations at charging sites. A maximum is set for the average number of charging stations at charging sites. New stations are only installed when existing sites are expanded to their maximum.

Figure **??** illustrates these strategies (Illustrations 1 & 2): Filled circles of dark blue color indicate initial charging infrastructure sites; orange color indicates the allocation of the installation of new charging points. The two strategies are contrasting as the *Concentrated expansion* leads to significantly lower increases in the density of charging stations versus *Distributed expansion* rapidly leads to a dense charging infrastructure. This boils down to the installed charging points ($n^{\text{points per site}}$) per charging site:

$$n^{\text{sites}} = \left\lfloor \frac{\text{installed capacity}}{n^{\text{points per site}}} \right\rfloor \tag{4.2}$$

We simplify the shape of an area using the rectangular form and translate the detour distance to a closest available charging station using the following definition:

$$\begin{aligned} d^{\text{arieal}} &= \frac{1}{2}\sqrt{\frac{\text{area}}{n^{\text{sites}}}} \\ \text{detour distance} &= \mu \times d^{\text{arieal}} \end{aligned} \tag{4.3}$$

Factors μ is a value ≥ 1 and translated the areal distance to the driving distance in the street network. Finally, this is translated to detouring time, B:

$$B = \text{detour distance} \times \frac{1}{\text{driving speed}} \tag{4.4}$$

Three scenarios are defined for the analysis of spatial densification via different values for the parameter $n^{\text{points per site}}$, reflecting the *Distributed* roll-out scenario ($n^{\text{points per site}} = 2$), the *Concentrated* roll-out scenario ($n^{\text{points per site}} = 40$), and one between these two extreme cases with a balanced ten charging points per site ($n^{\text{points per site}} = 10$).

For the definition of suitable ranges in charging infrastructure expansion, we define a minimum detour time that is possible. This is set to five minutes[3]. No greater reductions of the initial detour time are possible. Figure **??** displays reduction curves for different cases of $n^{\text{points per site}}$ for both, fast and slow public charging.

[3]The five minute threshold is based on an educated guess by the authors. This is based on the assumption that lower times for detouring (time required to reach the charging station **and** back from the charging station) are unrealistic. Further, a lower limit is set to avoid very small values in the optimization which could lead to increased computational complexity in the solution of the MILP.

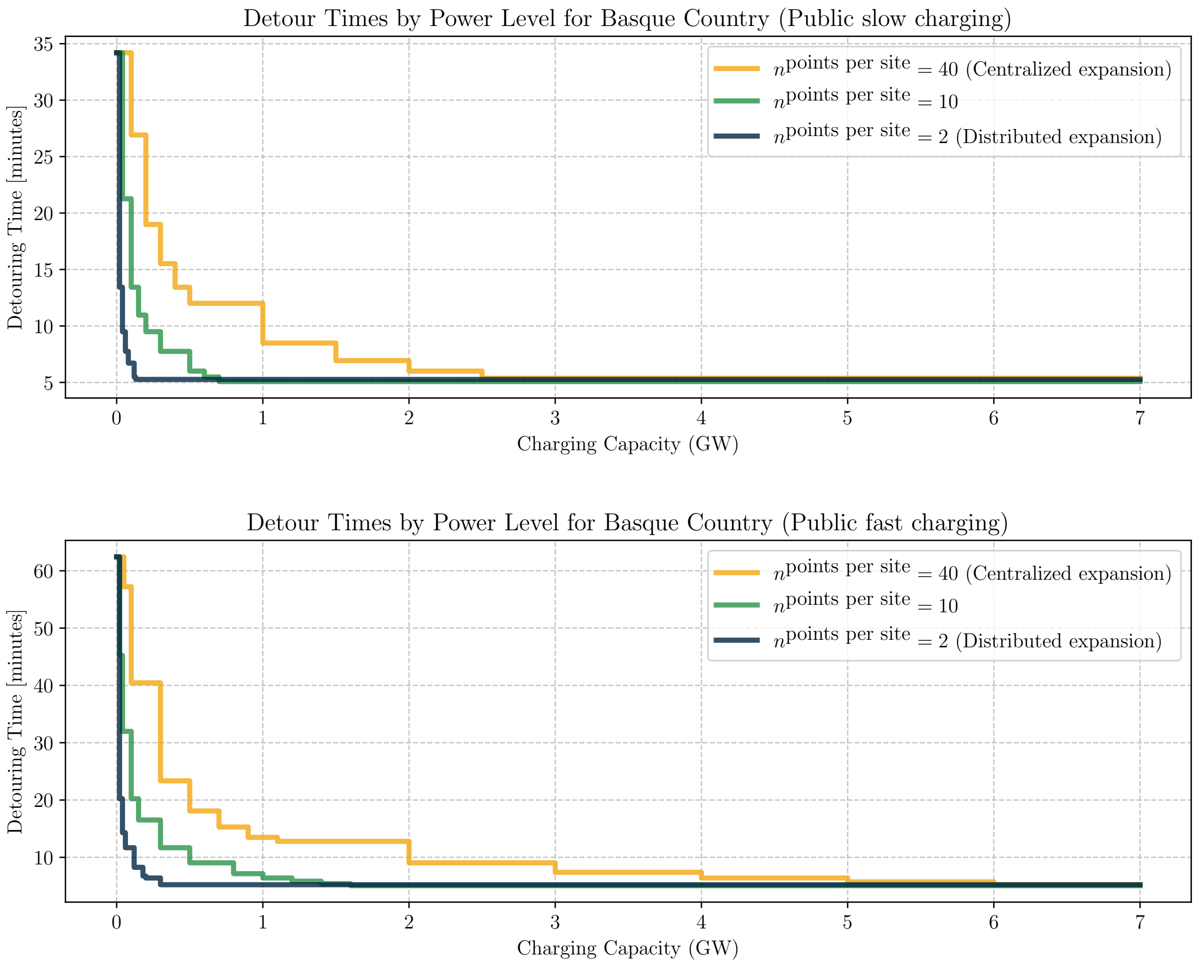


Figure 4.8: Comparison of two vertically aligned figures.

4.2.2.1 Speed of roll-out (RQ2).

The setup for the analysis of RQ2 is displayed in the bottom row of Figure **??**: We consider BEV adoptions in the three NUTS-3 level regions of the Basque Country and focus on the accelerated charging infrastructure expansion in Bizkaia, while observing the neighboring regions, Araba and Gipuzkoa. For this analysis, we assume the charging infrastructure capacities exogenously by including hard constraints for the infrastructure capacities. Table **??** displays an overview of the designed scenarios for the analysis. *Baseline Roll-out* defines a reference scenario based on the disaggregated expansion pathway to the region. The *Central Acc. Roll-out* is designed to analyse the relative changes in electrification compared to this reference scenario caused by an increase of charging infrastructure by 30%. In the scenarios *Neighbor Slower Roll-out* and *Central Acc. + Neighbor Slowed Roll-out*, the neighboring regions have slower expansion than the reference, and the charging capacity roll-out pathway is reduced by 30%. These two scenarios differ again by first assuming the reference expansion pathway and in the second, the accelerated expansion with a charging capacity increased by 30% to the reference.

Table 4.14: Scenarios for analysing RQ2. The cross indicates the assumed expansion pathway for the regions in each scenario.

		Expansion pathway		
Scenario name (RQ2)	**Region name**	-30%	Reference	+30%
Baseline Roll-out	Bizkaia		×	
	Gipuzkoa		×	
	Araba		×	
Central Acc. Roll-out	Bizkaia			×
	Gipuzkoa		×	
	Araba		×	
Neighbor Slowed Roll-out	Bizkaia		×	
	Gipuzkoa	×		
	Araba	×		
Central Acc. + Neighbor Slowed Roll-out	Bizkaia			×
	Gipuzkoa	×		
	Araba	×		

The reference expansion pathway is determined based on a model run, during which the constraint of 100% decarbonized passenger car fleet is imposed. The resulting total charging capacity values for the investment periods between 2020 and 2050 are included as hard constraints for the charging capacity expansion. Figure **??** displays the reference values by region.

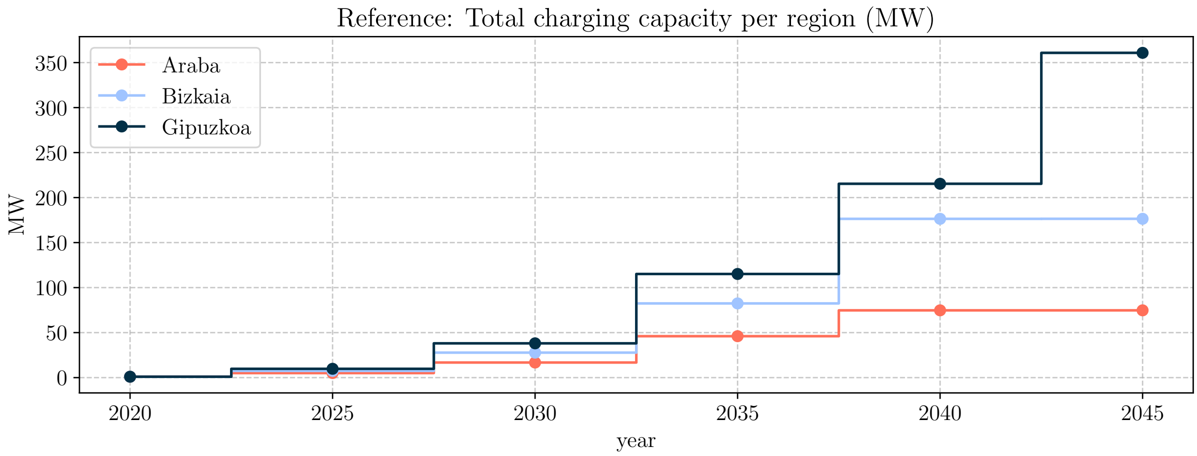


Figure 4.9: Reference expansion pathway for scenario design of different charging capacity build-up scenarios.

4.2.3 Income-class dependent impact of spatial densification of public charging infrastructure

Figure **??** displays two snapshots of the development of the share of electrification in the passenger car fleet by consumer group: years 2030 and 2040. $n^{\text{points per site}}$ indicates how many charging points are installed in newly built charging stations as of 2020, implying the degree of spatial densification of the public charging infrastructure network. The development of technology turnover is different among the consumer groups. In 2030, the electrification in the vehicle fleet belonging to the *Very high income* and *High income* consumer groups is significantly higher, at the level of around 48.9-65.1%, than that of the vehicle fleet belonging to the other consumer groups. By 2040, the share of BEVs rises in all consumer groups to the level of 9.6-69.0%. It is important to note here that in absolute numbers, the BEVs in the fleet owned by the consumer group *High income* do not exceed the *Very high income* consumer group.

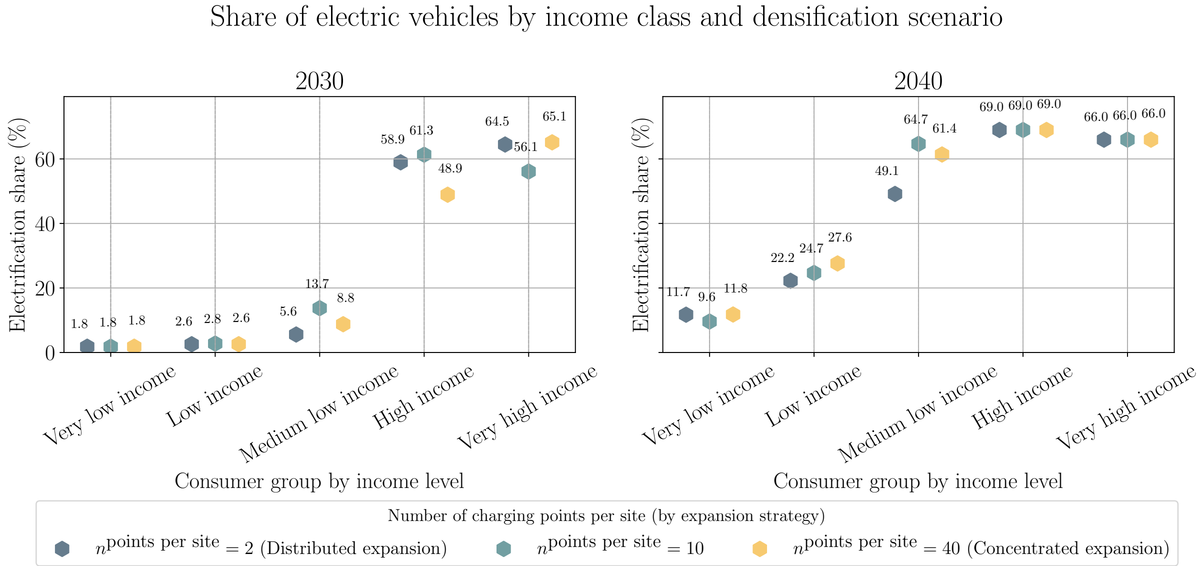


Figure 4.10: Share of battery-electric vehicles in the passenger car fleet in 2030 and 2040 in consumer groups of different income levels for roll-out strategies of public charging infrastructure defined via the number of charging points per site ($n^{\text{points per site}}$).

The relative order of the number of BEVs in the fleet by consumer groups is not changed by the different roll-out strategies. However, significant differences in the adoption are visible between the different densification strategies: While the *Concentrated expansion* leads to a gap of 6.2% between the electrification share of the *Very high income* consumer group and the *High income* consumer group, this gap is lower in the scenario *Distributed expansion*. The electrification of the *Medium low income* group is accelerated in the more balanced scenario of ten points per site. Income groups *Very low income* and *Low income* are not significantly affected by 2030. By 2040, a significant gap of 5.4% between the *Distributed* and *Concentrated* expansion scenario arises. Overall, there is no visible correlation to be deduced between the number of points per site and the development of the electrification share in the fleets owned by the consumer groups of different income levels. Figure **??** displays differences in the development of the gap in the share of electrification between the *Distributed* and *Concentrated* scenarios. It shows that the highest overall impacts are on *High income* and *Medium low income*. By the end of the horizon, differences converge towards 0.0%, indicating that the $n^{\text{points per site}}$ parameter affects the speed of electrification but is not decisive for the resulting size of the decarbonized passenger car fleet.

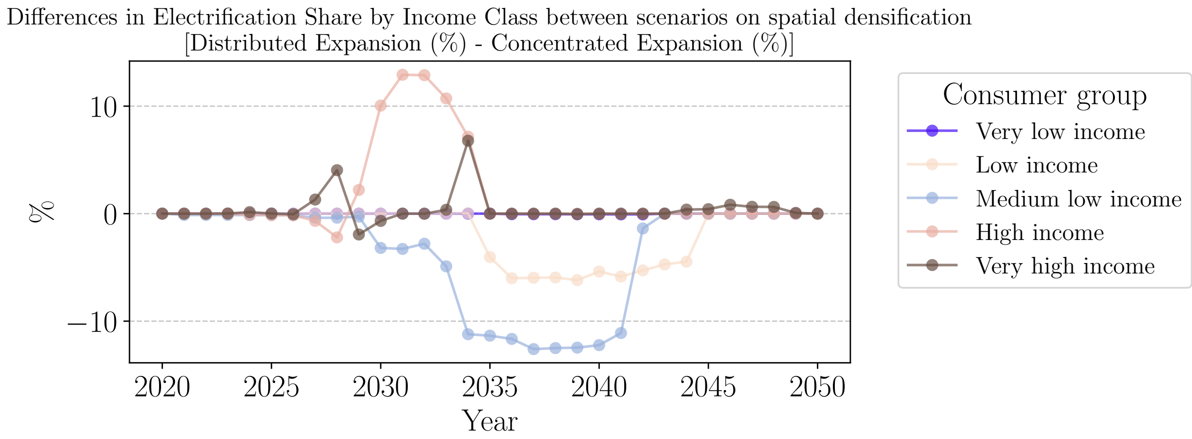


Figure 4.11: Maximum differences in the electrification share between scenario $n^{\text{points per site}} = 2$ *(Distributed expansion)* and $n^{\text{points per site}} = 40$ *(Concentrated expansion)* by consumer groups over time.

To gain a better understanding of the variation in the electrification across consumer groups, we take a look at the three key output parameters that describe the charging infrastructure expansion decisions and their utilization by scenario. Figure **??** displays expanded charging infrastructure capacities together with the development of the utilization rates of public infrastructure for all scenarios. Figure **??** shows how the average detour time of public charging infrastructure is reduced by these capacity expansions. Figure **??** illustrates the charger utilization by income class, showing how much energy is charged by charger type and income class in years 2030, 2040, and 2050.

The following observations are the most relevant here:

- With an increase of the value for the parameter $n^{\text{points per site}}$, higher investments in public charging infrastructure are made earlier. In the scenario $n^{\text{points per site}} = 10$, public charging infrastructure capacity expands more rapidly in the investment periods 2030-2040 compared to the scenario $n^{\text{points per site}} = 2$ (*Distributed expansion*). In the scenario $n^{\text{points per site}} = 40$ (*Concentrated expansion*), the capacity of the public charging network in 2035 equals that of the 2040 level under lower values of the $n^{\text{points per site}}$ parameter (see Figure **??**). In scenario $n^{\text{points per site}} = 2$ (*Distributed expansion*), substantial increases in the public charging infrastructure network occur during later years, 2040 and 2045. In all scenarios, these investment periods of substantial expansion coincide with decreases in detouring times for public charging infrastructure (see Figure **??**).

- The accelerated expansion in the scenario $n^{\text{points per site}} = 10$, the increased scenarios in 2030 coincide with the sharp increase in adoption in the consumer group *Medium low income* (as displayed in Figure **??**), indicating that the increased charging capacities particularly accelerate the electrification of the passenger car fleet owned by consumers of medium level income.

- Home and work charging capacities are consistent across all scenarios. While work charging is expanded early on to its maximum possible capacity values, home charging capacities are not further expanded, though they are used consistently by the consumer groups *Very high income* and *High income* as shown in Figure **??**.

- The utilization rates of public charging infrastructure diverge substantially between the slow and fast charging types. For both charger types, maximum utilization — indicated by the red dashed line in graphs of the right column in Figure **??** — is not reached. In particular, the utilization rate of fast charging is very low (maxima are at 6-11%), indicating substantial investments in overcapacities.

- While, in all scenarios, the absolute numbers of BEVs and total energy consumption are similar by 2050, installed charging capacities and their utilization by income groups are different. Looking at the right column in Figure **??**, there is a significant difference between the charged energy by income class and type between the scenario of $n^{\text{points per site}} = 2$ and the other two with charging sites of higher concentration. Particularly, there is a significant difference in the usage of fast charging by the consumer groups *Very low income* and *Low income*[4]. In the *Distributed expansion* scenario, higher amounts of public charging are available and used, while, in the *Very low income* group, fast charging is the dominating charging technology, leading to higher total utilization of fast charging.

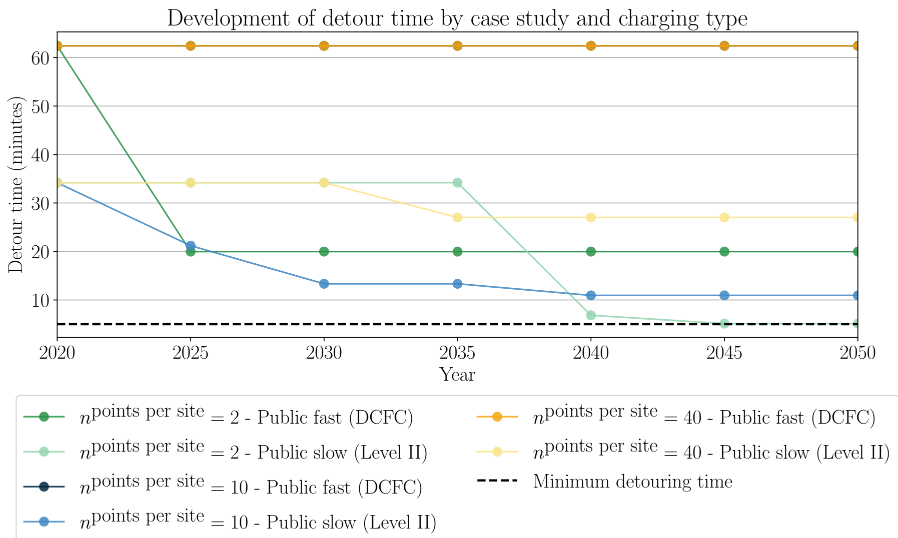


Figure 4.12: Development of average detouring times for public fast and slow charging in Basque Country for different scenarios of spatial densification.

[4]We want to emphasize here for the interpretation of the results that we do not consider the different *pricing* of charging types here.

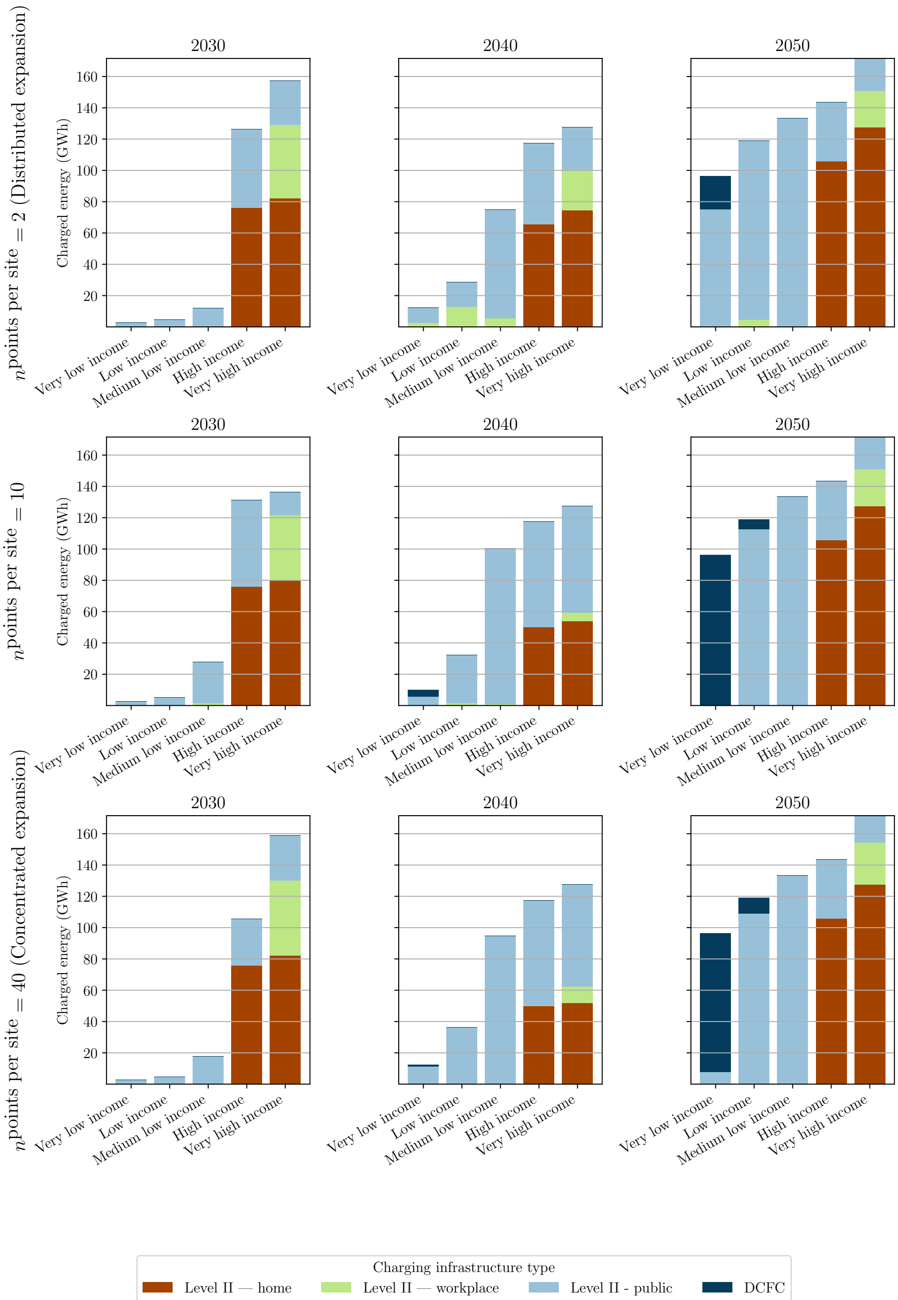


Figure 4.13: Charged energy in 2030, 2040 and 2050 at different infrastructures

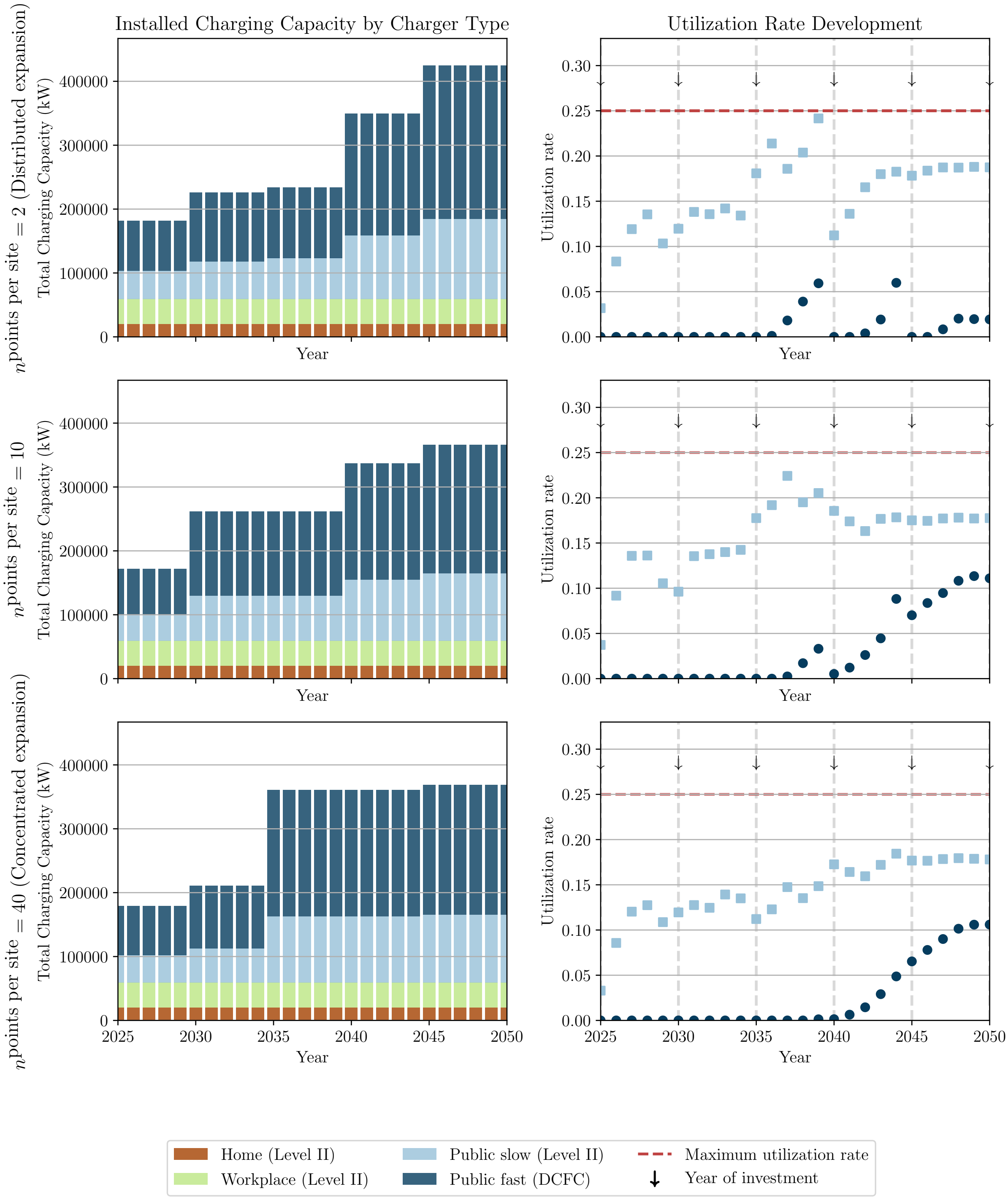


Figure 4.14: Charging infrastructure expansion for Basque Country region in the scenario of *Concentrated expansion* ($n^{\text{points per site}} = 40$).

4.2.4 Spill-over effect of charging infrastructure planning for destination charging

Figure **??** displays the development of the adoption of BEVs by years 2030 and 2040. In particular, this is shown for the NUTS-3 regions Bizkaia, Araba, and Gipuzkoa, under the different scenarios in the speed of charging infrastructure expansion. In the *Baseline Roll-out* case, in 2030, the range of the electrification rate varies by region within 2.6-6.0%. By 2040, the region-dependent range becomes wider, 35.5-42.8%, with Araba having the highest rate of electrification and Bizkaia the lowest. With increased charging capacities built in Bizkaia (case *Central Acc. Roll-out*), the electrification share in Bizkaia increases slightly (0.9 % by 2030 and 3.3% by 2040), while the electrification rates of Araba and Gipuzkoa are also positively affected (increase by 0.6-1.3%). When the charging infrastructure capacity in Araba and Gipuzkoa (scenarios *Neighbor Slowed Roll-out* and *Central Acc. + Neighbor Slowed Roll-out*) are reduced, the values for the share of electrification in Araba and Gipuzkoa in 2040 are significantly lower than in *Baseline Roll-out*. Figure **??** displays the temporal development of the difference in electric vehicle numbers between the*Central Acc. Roll-out* and the *Baseline Roll-out*. A peak in the positive absolute differences occurs in 2045. The maximum relative difference is in 2044 and is 2.1% for Araba and 1.1% for Gipuzkoa. For some time periods, we observe negative spillover. In particular, there is a distinctive decrease in the BEV numbers in 2049.

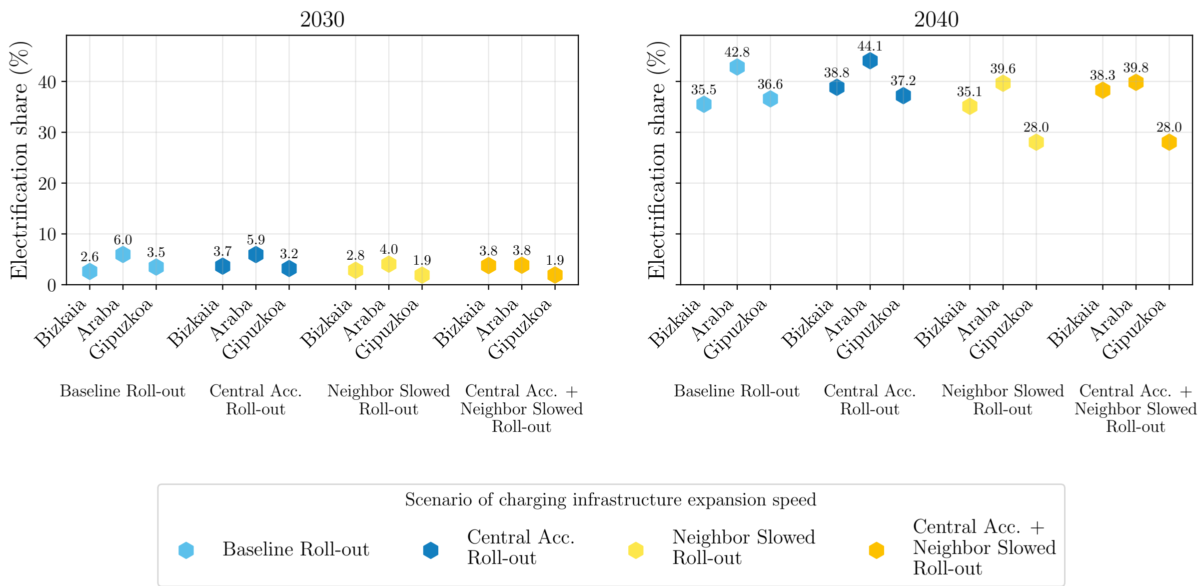


Figure 4.15: Share of electrification of the passenger car fleet in the regions Bizkaia, Araba, and Gipuzkoa under different scenarios referring to the speed of charging infrastructure roll-out, for years 2030 and 2040.

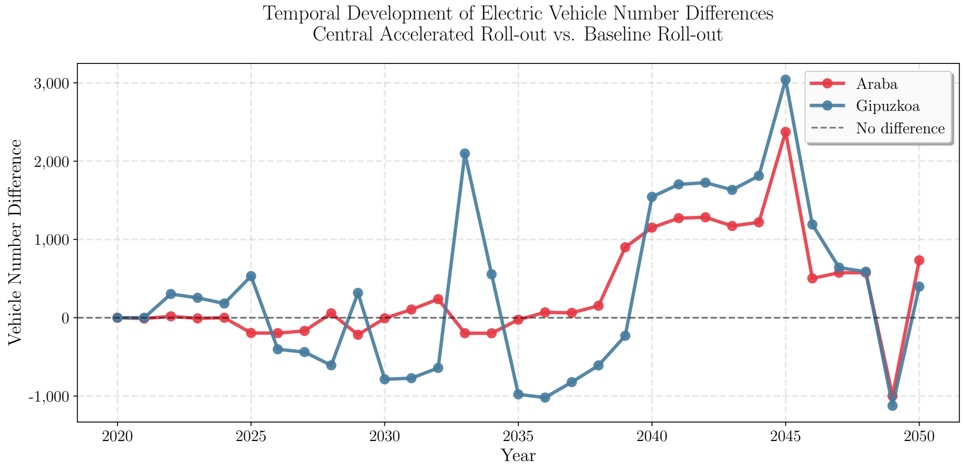


Figure 4.16: Temporal development of the difference of adopted battery electric vehicles numbers in Araba and Gipuzkoa between the *Basic Roll-out* and *Central Acc. Roll-out*.

With higher expansion in Bizkaia in *Central Acc. + Neighbor Slowed Roll-out*, the electrification share in Bizkaia is increased by 2.1% by 2040. The BEV adoption shares in Araba and Gipuzkoa are here impacted significantly less, i.e., than in the reference capacity expansion. In 2030, a slight negative impact is observed.

Figure **??** gives an insight into the effect of increased charging capacity in Bizkaia on the electrification of the commuting traffic. The plots display the absolute numbers of BEVs used for commuting trips originating in Araba or Gipuzkoa and traveling to Bizkaia. We zoom in on three years: 2030, 2040, and 2050. The text in blue indicates the relative differences to the *Baseline Roll-out* scenario. The gray text indicates the relative difference to *Neighbor Slowed Roll-out*. The following four key observations are made here:

- The slowed roll-out in Araba and Gipuzkoa has little impact on the BEV adoption in the commuting fleet. Some negative impact is observed during 2040-2050 which is partly compensated with increased capacities in Bizkaia.
- In Araba, the electrification of the commuting fleet is mainly positively accelerated during the years 2030 and 2040 by the increased charging infrastructure deployment in Bizkaia. By 2050, this positive impact is limited to +0.6%.
- In Gipuzkoa, the impact of increased infrastructure expansion in Bizkaia remains not significant.
- In the case of reduction of charging infrastructure in Araba and Gipuzkoa, the increased charging infrastructure in Bizkaia does not fully compensate for the reduced capacities.

In Figure **??**, we examine the allocation of charging processes for commuting trips between the origin and destination regions. We generally observe a high share of destination charging across all cases, years, and both regions. These shares increase under the accelerated rollout in Bizkaia. One exception is the development in Gipuzkoa between 2030 and 2040, during which there is a 43% increase in charging processes at the origin (between the Central Acc. Roll-out and Baseline Roll-out scenarios).

Figure **??** displays utilization rates for the public charging infrastructure in the Baseline Roll-out across all three regions. Here again, utilization rates of public slow charging are consistently higher than those of public fast charging. Overall, utilization rates are significantly higher when spatial density is not considered.

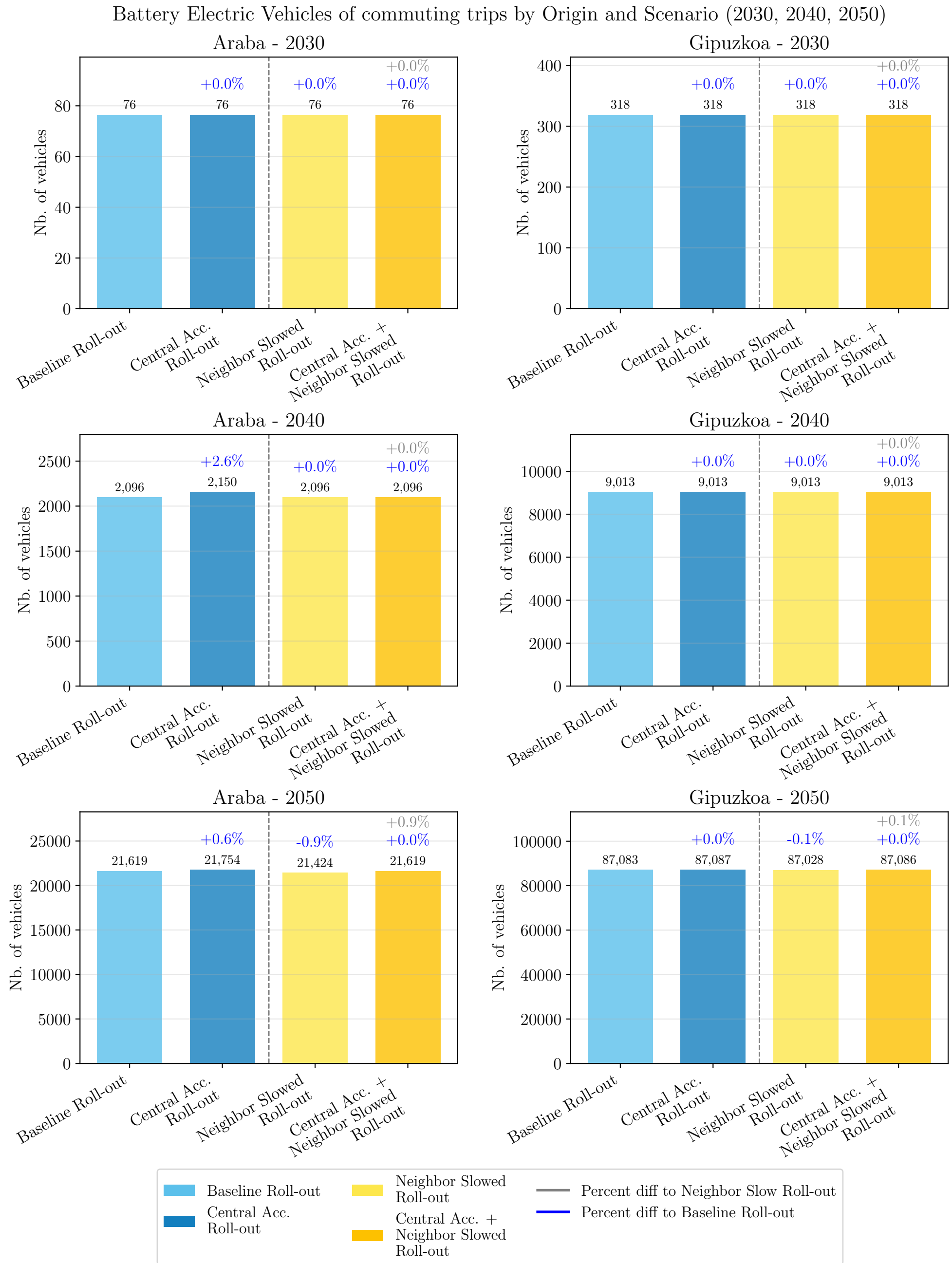


Figure 4.17: Numbers of BEVs in the commuting trips between Araba or Gipuzkoa and Bizkaia under different scenarios of charging infrastructure roll-out scenarios for years 2030, 2040 and 2050.

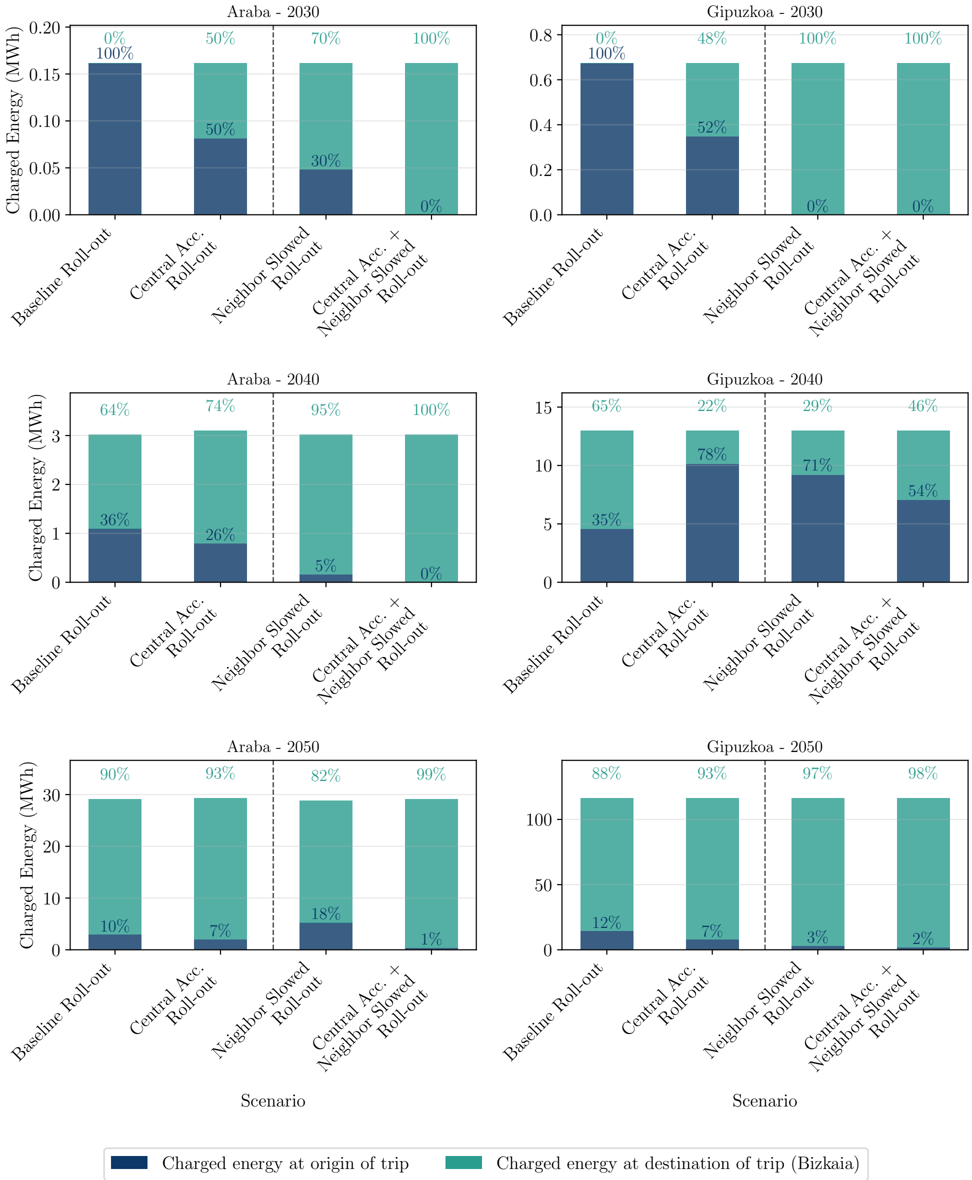


Figure 4.18: Snapshots for 2030, 2040 and 2050: Allocation of charging processes between origin and destination of commuting trips originating in Araba or Gipuzkoa and going to Bizkaia with text indicating relative percentages of charging processes.

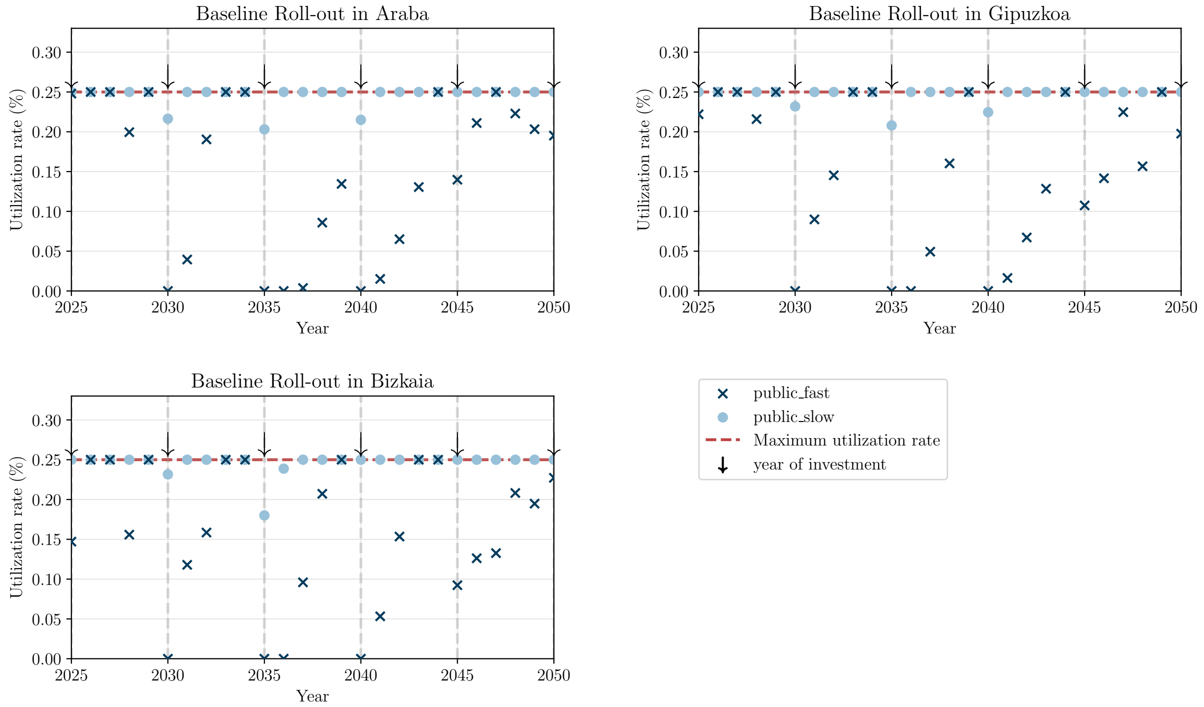


Figure 4.19: Development of utilization rates for public charging infrastructure network in Bizkaia, Araba and Gipuzkoa.

4.3 Charging infrastructure for long-haul battery-electric trucks among the Scandinavian-Mediterranean corridor in the TEN-T (RQ3)

4.3.1 Case study: Road freight along Scandinavian-Mediterranean corridor

4.3.2 Cost-optimal adoption of battery-electric trucks and charging activity

4.3.3 Role of modal shift towards rail freight

4.4 Hourly charging demand profiles of the commercial fleet in Austria in 2040 (RQ4)

4.4.1 Case study: Austria's commercial fleet at Federal State level

The representation of the commercial fleet is focused on three fleet types: LDT, HDT, and buses. These are chosen based on their substantial fleet size and transport activity. Their electrification is therefore expected to play a significant role in the electricity system. Based on the mobility patterns of the different fleet types and expected charging strategies, future charging profiles are generated together with plug-in times and installed charging power. The charging profiles are generated for an average week in 2040, i.e. representing seven days in hourly resolution. The theoretical framework presented in Section **??** is the starting point for the estimation of future charging profiles. In the geographic aggregation of charging profiles, Austria is represented by nine nodes ($|\mathcal{N}_1| = 9$) mirroring the nine federal states of Austria.

Light-duty trucks TheLDT fleet classified as vehicles that have a maximum total weight of 3.5 tons **usp_nutzfahrzeuge**. The Austrian vehicle fleet of this type amounted to a size of around 510,000 vehicles by the end of 2023 and is expected to be 535,000 by 2040 in decarbonization scenarios by **umweltbundesamt_rep0808**. According to **SCORRANO2021101022**, the average daily range of a light-duty vehicle operated in Germany is 70km on average. We adopted this value for Austria. Further assumptions for the vehicle are summarized in Table **??**. Based on this, we assume the routes of vehicles of this fleet type to only within one Federal State and, therefore, the charging profile of the LDT fleet is modeled based on the operational pattern of *local transport*.

The core assumptions for the modeling of a charging profile of light-duty vehicles are the following:

- **Charging strategy:** Vehicles are charged during nighttime and weekends. Recharging is done at depots. During weekends, the vehicles have a substantially higher flexibility in the recharging processes. The charging process is performed at the lowest possible power level and is evenly distributed during the plug-in period. Departure times are evenly distributed between 7 am and 9 am, and arrival times are between 16 pm and 18 pm.

- **Geographic scaling:** The expected amount ofLDT is distributed proportionally to the population size.

- **Sizing of charging infrastructure:** The aggregated charging infrastructure for all depots within a federal state region is sized based on assuming that the charging power of 11kW and charging the vehicle every sixth night is sufficient.

Heavy-duty truck TheHDT has a total weight greater than 3.5 tons. Technical assumptions for this fleet are summarized in Table **??**. Origin-destination flow data on the European level is used here to capture charging demand from national as well as transit transport. The ETISplus dataset provides estimations of the annual tons transported by trucks in the year 2030 **speth2021synthetic**. We apply the charging profile generation for *interregional transport* here under the following considerations:

- **Charging strategy:** For this we consider that the European regulation dictates a maximum driving shift of 4.5 hours.HDTs are charged at depots and highway service areas **ec_driving_time_2023**. Further, in Austria, a regulation prohibits driving between 10 pm and 5 am for multiple transport segments **usp_lkw_fahrverbote**. During Saturdays and Sundays, the operation of heavy-duty transport is also restricted. For trips that take longer than 4.5 hours, the 45-minute break takes place at a highway service area, and during this time, theHDT is connected to a megawatt charging station and is fully charging. The remaining energy demand is covered at the origin and the destination depots during nighttime. For trips shorter than 4.5 hours, charging is fully compensated at depots. Recharging happens also at depots during the day if the driving range is not sufficient to be covered with one charged battery. During trips that take multiple days, charging demand is also compensated at service areas during nighttime.

- **Sizing of charging infrastructure:** Charging in depots is assumed to be conducted at 100kW of peak power and megawatt charging is available at charging stations. As a reference point for the sizing of charging infrastructure, the goals for the installment of 5MW of grid connection at each charging station until 2035/2040 along the Austrian highway network by the highway infrastructure operator ASFINAG **ioebenergiespeicher**[5]. This is assumed to be available for the electrification rate of a heavy-duty fleet of 30%. A relative factor to the charging demand is deducted for each region based on the amount of

[5] The exact number of 5MW was stated by a representative of ASFINAG in the course of a stakeholder interview.

Table 4.15: Parameter settings for modeling the charging demand of light-duty vehicles

Parameter	Value	Reference
Fleet size (Austria 2040)	535,000	**umweltbundesamt_rep0808**
Battery capacity	145 kWh	**irena2019smart_charging**
Specific energy consumption	27 kWh/100km	**umweltbundesamt_rep0808**
Daily range	70 km/day	**SCORRANO2021101022**
Charging power at charging station depot	11 kW	**SCORRANO2021101022**

existing service areas and applied to all charging location demands within the respective region.

- **Flexibility in the fast-charging along highway service areas:** Due to the short time frame of the break of 45 minutes and the used temporal resolution of the modeling being one hour, there is no flexibility given for highway charging processes. It may be foreseeable that the operational times and the timing of the break and, therefore, the charging process would be adapted to charge for lower expenses in the future. Therefore, to introduce some flexibility here, we created three distinct plug-in time frames of two hours each, which are allocated around noon.

Busses For the bus fleet, we consider the application case for public transport in both cities and rural regions. Similar to the modeling of light-duty vehicles, the routes of buses do not go through multiple regions. Table **??** comprises technical assumptions for an average bus in public transport.

The charging profiles for busses are estimated based on the following:

- **Charging strategy:** Most charging demand is covered during night time at the bus depot. If required, busses enter the depot for fast charging during daytime. The operation is assumed to be similar during each day of the week.

- **Geographic scaling:** City busses are considered for Austrian cities that surpass the population size of 100,000. For each city, the size of the bus fleet is scaled using the population size. The bus fleet in rural areas is sized using the total area of the rural region within a federal state.

- **Sizing of charging infrastructure:** During night time, each bus is connected to a 100kW charging station. The power connection of the depot is limited to two-thirds of the summed peak power of the charging stations which is sufficient to cover the charging demand during down times at night and is in line with the peak power achieved with coordinated and, therefore, cost-efficient charging **Borlaug2021**.

Table 4.16: Parameter settings for modeling of charging profile of heavy-duty vehicles

Parameter	**Value**	**Reference**
Battery capacity	350 kWh	**teoh2022**
Specific energy consumption	1.3 kWh/km	**umweltbundesamt2024**
Average load	10.63 tons	**umweltbundesamt2024**
Average driving speed	50 km/h	**9543135**
Peak charging power at highway/depot charging station (fast charging during daytime)	1000 kW	
Peak charging power at highway/depot charging station (slow charging during nighttime)	100 kW	

Table 4.17: Parameter settings for the modeling of charging profile by busses in the application in the city and rural areas

Parameter	**Value**	**Reference**
Fleet size (Austria 2040)	12,900	extrapolated based on **wienerlinien2024**, **vmobil2023**
Battery capacity	350 kWh	**ag2022flexibility**
Specific energy consumption	1.3 kWh/km	**umweltbundesamt2024**
Daily range - city	236 km	**wienerlinien2024**
Daily range - rural	138 km	**vmobil2023**
Peak charging power at depot charging station (fast charging during daytime)	1000 kW	
Peak charging power at depot charging station (slow charging during nighttime)	100 kW	

Table 4.18: Electrification scenarios considered in the analysis

	Share of electrification in fleet		
Scenario	Light-duty vehicles	Heavy-duty vehicles	Busses
LOW	100%	30%	100%
MEDIUM	100%	50%	100%
HIGH	100%	100%	100%

4.4.1.1 Scenarios and case studies

In the application to the Austrian electricity system in 2040, we explore two different dimensions: On the one side, the variation in the share of electrification of the commercial fleet in 2040, and, on the other side, the role of the commercial BEV fleet in the electricity market. Table **??** displays the shares of electrification for the three considered electrification scenarios, *LOW*, *MEDIUM*, and *HIGH*. The three case studies for market participation describe:

4.4.1.2 Electricity market 2040

All 13 countries (Austria, Germany, Netherlands, Belgium, Luxembourg, Czech Republic, Slovenia, Switzerland, Poland, Slovakia, Hungary, Italy, and France) within the optimized area are expected to fulfill the European national energy and climate plans **NECP2022** by 2030 and continue to compensate for the rising electricity demand by expanding generation capacities in 2040. According to Austria's national energy and climate plans, RESE compensates for 100% of the yearly electricity demand. The used *National Trends* dataset, provided by the European Network of Transmission System Operators for Electricity is based on the fulfillment of these plans **TYNDP2022**. It includes a power plant fleet with RESE, fossil fuel-fired power plants (coal, oil, lignite, and combined-cycle gas turbines, and other types of thermal power plants that do not emit CO_2 (nuclear, biogas, biomass, and fuel cells).

- **Baseline:** The charging demand of the commercial BEV fleet is inflexible.
- **Dispatch:** The flexibility of the charging of the commercial BEV fleet is optimized in the dispatch.
- **Redispatch:** The flexibility of the commercial BEV fleet charging is utilized in redispatch measures.

4.4.2 Spatio-temporal demand distribution

Table **??** summarizes the total values for annual load estimates for the commercialBEV fleet under different electrification scenarios in Austria for 2040. The annual charging demands are 7.4 TWh / 9.6 TWh / 15.2 TWh. This makes up for 8 % / 11 % / 16.9% of the estimated total electricity load in 2040. The highest charging load stems from the charging of heavy-duty trucks (HDT) which is mostly allocated to depot locations. In the electrification scenarios *MEDIUM* and *HIGH* which indicate a respective electrification rate of 50% and 100% of the HDT fleet, the fleet is the clear dominant demand segment with 5.6 TWh/ 11.2 TWh of annual charging demand.

Figure **??** displays peak power levels along the highway for the *HIGH* scenario. Positions of service areas along the Austrian highway network are shown together with the coloring indicating approximated peak power levels. The peak power level at a service area is deducted from the estimated accumulated load within the Federal state which is then equally distributed among all existing service areas. It is important to note here that this image is an estimation of the peak power distribution aimed to illustrate geographical variations and an estimate for peak power levels at service areas in 2040. The figure indicates a wide range in required power levels at highway service areas, between 7 and 29 MW. The illustration suggests distinctly higher power levels at the service areas located in the Northeast than in the Western regions of Austria.

The accumulated demand profile for the charging of the commercial BEV fleet is visible in Figure **??** for the whole of Austria. The figure displays an average week of charging load. During daytime time, most charging at highway service areas by the HDT fleet around noon is conducted. The load peaks at night time around midnight due to accumulated night charging of the LDT fleet, city, and regional busses, and the HDT fleet. During weekend days, the charging demand is substantially lower than during work days as vehicle operation is mostly performed during workdays. Fleet operators of vehicles that are not operated during the weekend recharge the vehicle for the next operation between Friday night and Monday morning and have, therefore, also higher flexibility in the recharging process while still having similar charging infrastructure as used during a workday available.

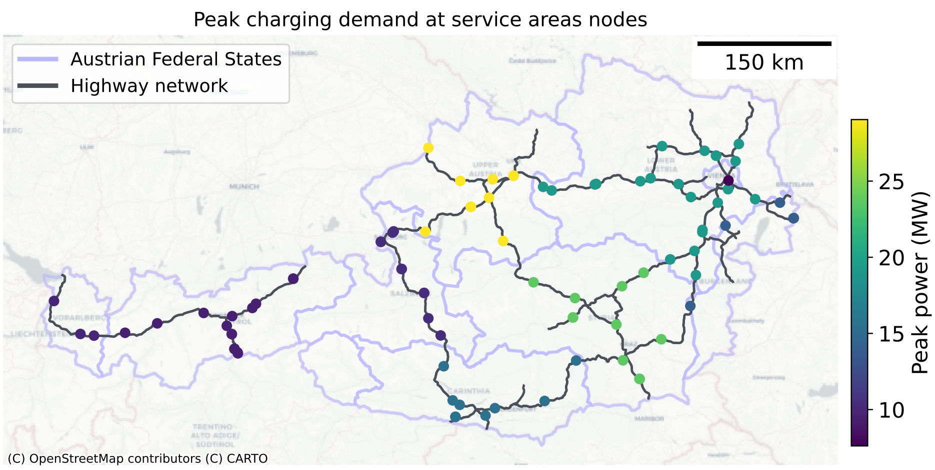


Figure 4.20: Approximation of charging peaks at Austrian resting areas for an 100% electrified commercial vehicle fleet (positions retrieved from **ASFINAG**)

Table 4.19: Annual charging demand of three different considered fleet types under different assumptions on electrification rate for the commercial vehicle fleet in Austria in 2040.

		Total annual demand of fleet types 2040 (TWh)					
	Total	LDV	Bus	HDV			
				Charging location			
Scenario				Depot	Highway (day time)	Highway (night time)	Total
LOW	**7.4**	2.7	1.3	1.8	1.1	0.5	3.4
MEDIUM	**9.6**	2.7	1.3	3.1	1.7	0.8	5.6
HIGH	**15.2**	2.7	1.3	6.2	3.5	1.5	11.2

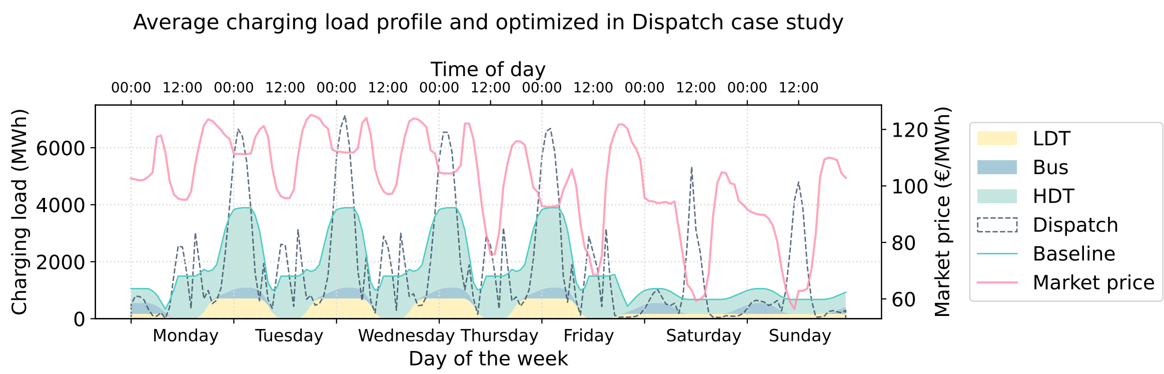


Figure 4.21: Aggregated charging demand profile of the commercialBEV fleet in the *Baseline* and *Dispatch* case study with the average day-ahead market price.

4.4.3 The value of charging flexibility to congestion management

todo:discuss here with hans what makes sense to include?; vielleicht nur 4.4. hier aus paper reinnehmen

5 Discussion & Synthesis of Results

5.1 Contextualizing findings in existing literature

5.2 Synthesis

does it make sense to look at these seperately? Overarching question: where are future charging loads? 2 aspects: utilization a

6 Conclusion & Future Work

Modal shift potential mehr reinbringen (HA)

.1 Model validation

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