38th International Electric Vehicle Symposium and Exhibition (EVS38) Göteborg, Sweden, June 15-18, 2025

Assessment of Charging Infrastructure Needs for Electric Vehicles Long-Distance Trips in Sweden

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Executive Summary

This study uses a dynamic, agent-based simulation framework (MATSim) to analyze charging infrastructure needs for electric vehicles (EVs) on long-distance trips in Sweden. A novel methodology identifies candidate ultra-fast charging station (UFCS) locations based on user charging behavior and unserved charging needs (UCNs), while also integrating Electric Road Systems (ERSs) as dynamic charging options along the Trans-European Transport Network (TEN-T) core network in Sweden. Results show that only 400 UFCSs, with 29287 chargers, can handle almost all trips, while combined with partial ERS deployment required chargers significantly drops to 7505. These findings provide actionable insights into strategic infrastructure deployment, supporting the transition to a sustainable and efficient electric mobility system.

Keywords: electric vehicles, modelling & simulation, consumer behavior, fast & megawatt charging infrastructure, optimal charging locations

1 Introduction

Electric vehicles (EVs) have gained significant attention as an effective strategy to reduce greenhouse gas emissions and decrease the environmental impact of the transportation sector. Despite their potential benefits, widespread adoption of EVs remains limited due to challenges such as restricted driving ranges and inadequate charging infrastructure, especially on long-distance trips [1].

To make long-distance EV travel feasible, there is a need for carefully planned, strategically located, and adequately sized charging infrastructure that balances user needs, operational efficiency, and investment costs. While many countries and stakeholders are actively working to expand EV infrastructure, the complexity of EV users' charging behaviors, real-world traffic patterns, and evolving user demands calls for more sophisticated planning approaches.

Previous studies have provided important insights into EV charging infrastructure development for long-distance trips. However, much of the existing research either focuses on macro-level assessments, cost-optimization strategies under static conditions, or theoretical sitting models based on simplified assumptions [2].

High-level system assessments provide valuable insights into overall system costs and energy demands but lack the spatial granularity needed to identify candidate ultra-fast charging station (UFCS) locations based on dynamic, real-world EV behaviors [3]. Similarly, sitting frameworks that are informed by user patterns and aggregated criteria are proposed in [4], however, they do not adequately capture the evolving, real-time charging behaviors characteristic of long-distance travel.

Cost-optimization studies emphasized static network designs or technological enhancements but fell short of modeling the stochastic and heterogeneous nature of EV operations across large and diverse travel networks [5]. Likewise, theoretical models contributed to important infrastructure planning concepts but often rely on idealized assumptions, such as uniform driving ranges, static departure times, or simplified behavioral models, that limit their applicability under real-world conditions [6].

Furthermore, localized or deterministic approaches focused on specific highway corridors or fixed travel patterns, which restrict their scalability and reduce their relevance to broader, interconnected transport networks required for national or continental EV adoption [7].

On the other hand, while Electric Road Systems (ERS) offer significant potential as a dynamic charging solution for long-distance electric vehicle travel [3], most existing research remains largely empirical, relying on real-world measurements rather than comprehensive simulations. Few studies have rigorously modeled the dynamic interaction between EVs and ERS under realistic, large-scale conditions. This underscores a critical need for detailed, simulation-based investigations capable of evaluating the large-scale deployment, operational performance, and seamless integration of ERS networks within broader charging infrastructures. Similarly, ERS benefits using real-world global positioning system data are assessed and emphasize how ERS can reduce EV battery sizes and peak charging loads, though their analysis remains largely static and scenario-based [8]. The agent-based simulations compared various ERS deployment scenarios for Sweden's long-distance transport but mainly evaluated system-level impacts without a fine-grained modeling of charging behaviors [3].

A dynamic adaptive planning framework and a spatial decision support system for EV charging infrastructure under deep uncertainties, emphasizing route-based demand estimation and dynamic network planning, is proposed [9]. The approach captures critical factors like evolving charging behaviors, grid access constraints, and infrastructure competition, providing a significant advancement over static planning models. However, while the system effectively models stationary fast-charging infrastructure and long-distance transport routes, it does not explicitly simulate ERS as dynamic charging options within trips or model consumer behavior balancing ERS and stationary charging usage. This leaves a research gap in the integrated planning of ERS and UFCS for long-distance EV travel, which this study addresses by combining ERS deployment with behavior-driven UFCS planning strategies.

Despite these advancements, most studies still abstract from fully modeling the dynamic charging decision processes during trips, the spatial heterogeneity of ERS deployment, and the integration of ERS with complementary ultra-fast charging infrastructure. This paper addresses these gaps by combining dynamic agent-based modeling, detailed UFCSs placement, ERS on the Swedish TEN-T core network, and a behaviorally realistic charging logic that minimizes ERS dependency while ensuring trip feasibility based on our previous work [10], which was developed in detail using the multi-agent transportation simulation framework (MATSim) that models dynamic EV-ERS-UFCS interactions under real-world travel conditions, focusing on destination-oriented charging strategy. The main contributions of this study are as follows:

- Developing a dynamic, agent-based simulation framework that models long-distance EV travel and real-world charging behaviors across Sweden's road network.
- Proposing a behaviorally informed, location-specific method for identifying candidate UFCS sites based on unserved charging needs and minimizing detours.
- Integrating ERS into the simulation, introducing a consumer behavior model that prioritizes ERS usage only when necessary to reach a target final state-of-charge, thereby minimizing ERS dependency and cost.
- Providing a spatially detailed, operationally grounded infrastructure planning strategy that bridges the gap between macro-level planning models and the stochastic, dynamic nature of real-world EV travel.

Through this approach, the paper contributes to more realistic and practical infrastructure deployment strategies that can better support the large-scale adoption of EVs for long-distance transport.

2 Methodology

An agent-based modeling approach is adopted for modeling EV trips and their charging behavior in the MATSim simulation framework because it provides a flexible, detailed, and dynamic framework for simulating the complex behaviors and interactions of EV owners with the charging infrastructure and the road network [11]. In this section, first, a methodology to find candidate locations and the size of ultra-fast charging stations is introduced. Second, an evaluation based on charging behavior on ERS deployment for pre-defined high-traffic roads is presented. Finally, a combination of these two methods is proposed to establish an efficient charging infrastructure network of ERS and ultra-fast charging stations for long-distance trips. This comprehensive approach aims to ensure the applicability and effectiveness of the proposed solutions in meeting the charging demands of EV users across the Swedish road network.

2.1 Trip and EV Modelling

SAMPERS is a Swedish national travel demand model that simulates the average daily flows of passengers for both business and leisure trips using different transportation modes, cars, airplanes, buses, and trains. In this study, only car flows are used. The model takes aggregated data and breaks it down into individual trips using detailed origin–destination information and land cover data [12].

This study evaluates the requirements for the charging infrastructure capable of supporting all long-distance trips made by fully electric passenger vehicles. The research develops a robust, agent-based model that characterizes long-distance travel behavior and charging patterns of EV users using MATSim. This model serves as the foundation for identifying candidate locations and determining the number of chargers needed at each site. Given that the success of the EV transition hinges on the availability and accessibility of charging facilities, our novel methodology maps the spatial distribution of charging demands along major travel routes. Focusing exclusively on trips exceeding 150 km, where the need for recharging is most critical, ensures that the analysis directly addresses the energy delivery challenges associated with long-distance travel.

Fig. 1 presents a histogram of passenger-car trips exceeding 150 km, based on SAMPERS data. A total of 109,038 trips are included, representing an aggregate travel distance of 92.60 million km. The bulk of these trips fall between 150 and 300 km, with the highest frequency observed in the 150–200 km range. Beyond approximately 400 km, trips decline markedly, although a long tail extends to nearly 2,000 km, indicating the occurrence of a small number of very long-distance trips.

In order to model electric vehicle (EV) long-distance trips in MATSim, departure times must be assigned to all activities. However, the SAMPERS dataset does not include departure times for long-distance trips. Therefore, assumptions were made based on trip length and trip type.

For very long trips (greater than 1000 km), departures are assumed to occur early in the morning, between 6:00 and 10:00 a.m. For shorter trips, departure times are differentiated by trip purpose. Private trips are distributed as follows: 70% are assumed to depart between 5:00 a.m. and 12:00 p.m., 20% between 12:00 p.m. and 4:00 p.m., and the remaining 10% after 4:00 p.m. Business trips are assumed to follow typical working hours, with 80% departing between 5:00 a.m. and 10:00 a.m., and the remaining 20% after 10:00 a.m.

The study considers a 100% EV penetration scenario with a mixed fleet characterized by different battery capacities. The fleet is categorized into three groups: small vehicles with 60 kWh batteries (15% of the fleet), medium vehicles with 80 kWh batteries (50%), and SUVs with 100 kWh batteries (35%). Each trip is randomly assigned to an EV type.

It is further assumed that all EVs begin their long-distance trips with an initial state of charge (SOC) distributed as follows: 50% of vehicles have an initial SOC between 90% and 100%, 30% between 70% and 90%, and 20% between 50% and 70%, with assignment performed randomly.

To model realistic end-of-trip conditions, a desired final state of charge (SOC) of 20% is assumed. Furthermore, the study assumes that electric vehicle (EV) energy consumption depends on both vehicle speed and road slope. A detailed description of the development and calibration of the EV energy consumption map can be found in [3].

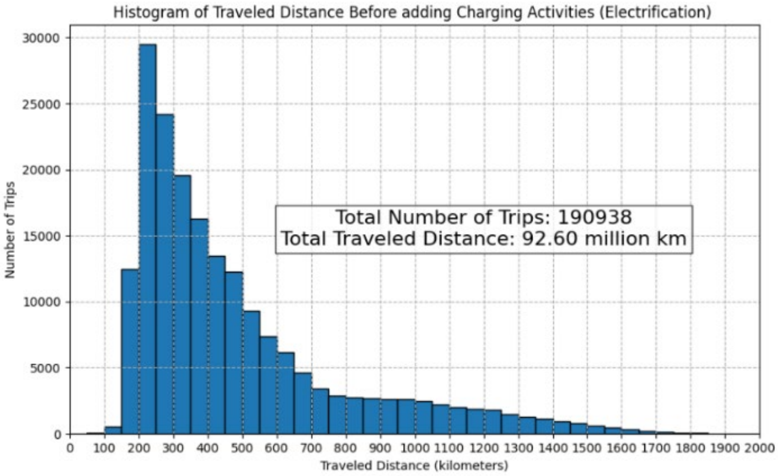


Figure 1: Distribution of long-distance trips from SAMPERS

2.2 Finding candidate locations for UFCSs

Finding good candidate locations for ultra-fast charging stations supporting EV long-distance trips is a crucial step toward promoting sustainable and efficient transportation. The proposed algorithm is based on the low-energy event (LEE) and missing energy event (MEE) concepts in MATSim and is based on our previous work [13]. An EV will generate a LEE and/or MEE at the locations where its SOC reaches a predefined low value (typically 20%) and/or zero, respectively. Additionally, those LEEs that result in MEEs are called Unserved Charging Needs (UCNs). Essentially, LEEs act as warnings that the EV battery SOC is approaching a critical energy level, and if not addressed, they lead to an MEE and UCNs.

The algorithm utilizes the locations where UCNs occur to identify potential sites for UFCSs. It categorizes SOC thresholds into two groups: safe (UCNsafe) and critical (UCNcrit). The UCNsafe thresholds are set at SOC levels of 40%, 35%, and 30%, representing locations where drivers might opt to charge if a convenient station is available along their route. In contrast, the UCNcrit thresholds are set at 25%, 20%, and 15%, representing SOC levels critical for the continuation of a trip.

As EVs travel, the algorithm tracks each vehicle's SOC and logs potential charging station locations based on where UCNs are triggered. By aggregating all UCN trails from multiple EVs, the algorithm identifies the most strategic and suitable locations for placing UFCSs. In this aggregation, critical thresholds (UCNcrit) are given double weight when calculating the total UCNs to emphasize their importance. This approach ensures that charging infrastructure is efficiently located to meet the needs of EV drivers, particularly in areas where the risk of battery depletion is highest.

In the first step, it is assumed that no ultra-fast charging infrastructure exists along the route for any of the EVs, and that all EVs embark on long-distance trips with a predetermined initial state of charge (SOC). Then the UCN identification described above is applied in order to find the locations where the charging demands of the EVs are not served. These locations are aggregated in a hexagonal network with a 30km radius, and the areas are ranked based on the frequency of UCNs. Finally, a predetermined number of ultra-fast charging stations are placed in those areas with the highest UCN frequency.

The flowchart of the proposed methodology for finding candidate locations for ultra-fast charging infrastructure is shown in Fig. 2. The proposed approach ensures that the deployment of ultra-fast charging stations balances the interests of private and public stakeholders. Charging station companies can install stations in locations where they expect high utilization, while government agencies can ensure that charging infrastructures are available on all roads and adequately spaced. Moreover, the approach considers the behavior of EV drivers, who are more likely to start a long-distance trip with a high SOC, reducing the need for charging stations in certain areas. By considering multiple factors, the proposed approach can effectively identify the optimal locations for ultra-fast charging stations to support the growth of the EV market.

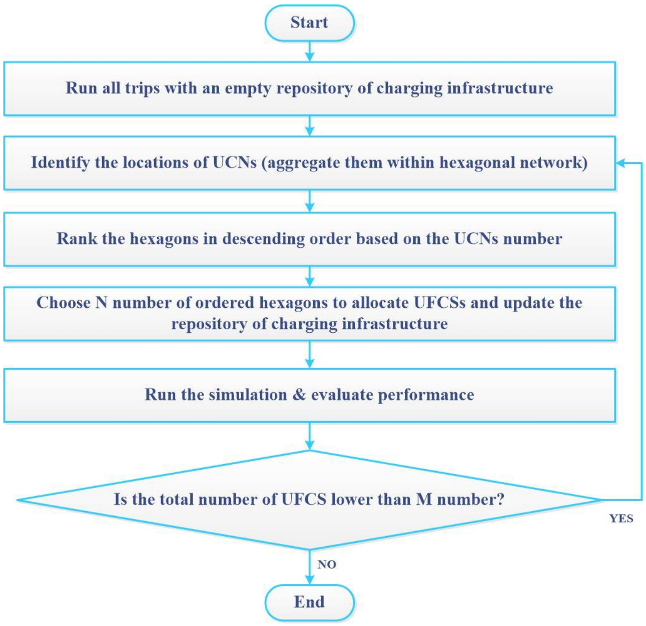


Figure 2: Flowchart of the methodology for identifying ultra-fast charging infrastructure candidate locations. N= {25,25,50,100,200} is a set of numbers that defines the number of new added UFCSs to the charging infrastructure repository, and M is set to 400 UFCSs

2.3 Combine UFCS with the electric road systems

In this study, a scenario was developed to assess the charging infrastructure needs for electric vehicles EVs undertaking long-distance trips by combining the deployment of ERS with UFCSs. The focus is on the Trans-European Transport Network (TEN-T) core network in Sweden, covering approximately 3270 km, complemented by a network of fast-charging stations.

To model the ERS, it is necessary to define both the location of roads equipped with dynamic charging technology and key technical parameters, such as the rated charging power and the proportion of each road segment that is actually electrified. Since complete road electrification is extremely challenging and definitely not economically attractive [14], only selected portions are assumed to provide dynamic charging. So it is assumed that the 50% TEN-T core corridors are equipped by ERS with 150kW rated power. Based on these parameters, the available energy from the ERS for each electrified segment can be estimated. In addition, charging behavior must be modeled, including a decision-making logic for EVs interacting with ERS and UFCS infrastructure.

For each trip, a target state of charge (SOC) at the destination is assumed. It is presumed that charging at home or at the destination point is preferred over charging from the ERS. However, charging from the ERS is preferred over UFCS when charging is needed en-route. This would be the case if, e.g., charging from the ERS and UFCS implied a similar energy price (with ERS offering a time advantage), and charging at home or at the destination point could be done at a lower energy price. Therefore, a charging strategy is implemented where EV users aim to minimize their use of ERS and UFCS while ensuring that the target SOC at the destination is achieved, as introduced in [10].

When combining ERS with UFCS, the ERS is prioritized. If a trip can be completed using ERS without requiring additional stops for using UFCS, the EV will avoid using UFCSs entirely. Thus, UFCSs act as a supplementary option, serving trips where ERS charging alone is insufficient. This combined approach enables more efficient use of ERS infrastructure while ensuring trip completion and reducing the need for frequent fast-charging stops, thus enhancing the feasibility of long-distance electric travel.

3 Results

The study is conducted using input data and assumptions to compare two scenarios for deploying EV long-distance charging infrastructure. The first scenario considers deploying only UFCSs, while the second combines UFCS deployment with the integration of ERSs.

3.1 Scenario 1: Only Ultra-Fast Charging Stations

Following the methodology described in the previous section, the first simulation is conducted assuming there is no charging infrastructure available. Based on the resulting aggregated UCN distribution, UFCS are added at 25 locations in the first step. A new simulation is conducted, resulting in a new UCN distribution which serves as a basis for deploying charging infrastructure at an additional 25 locations (to a total of 50 locations). In subsequent steps, UFCS are added at 50, 100, and 200 additional locations, adding up to 400 locations in total, as shown in Fig. 3 and Fig. 4.

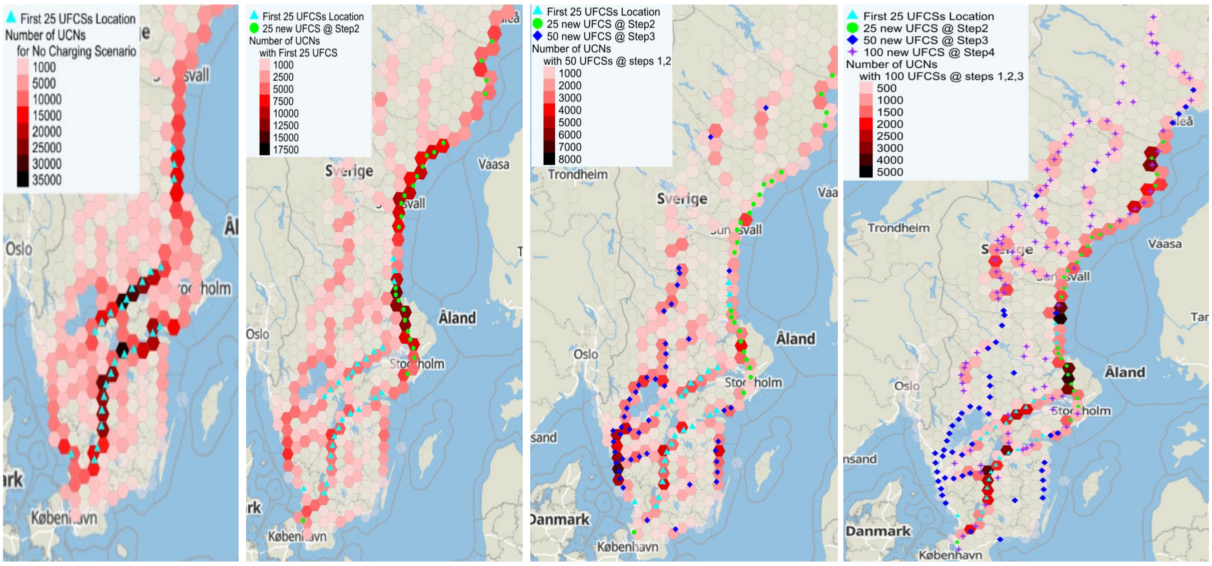


Figure 3: From left to right: UCN distribution assuming there is no charging infrastructure installed as well as the location for the first set of UFCS (25 locations, represented by cyan triangles); UCN distribution assuming there are 25 UFCs installed as well as the location for the second set of UFCS (additional 25 locations at the green circles); UCN distribution assuming there are 50 UFCs installed as well as the location for the third set of UFCS (additional 50 locations at the blue diamonds); UCN distribution assuming there are 100 UFCs installed as well as the location for the fourth set of UFCS (additional 100 locations at the lilac stars)

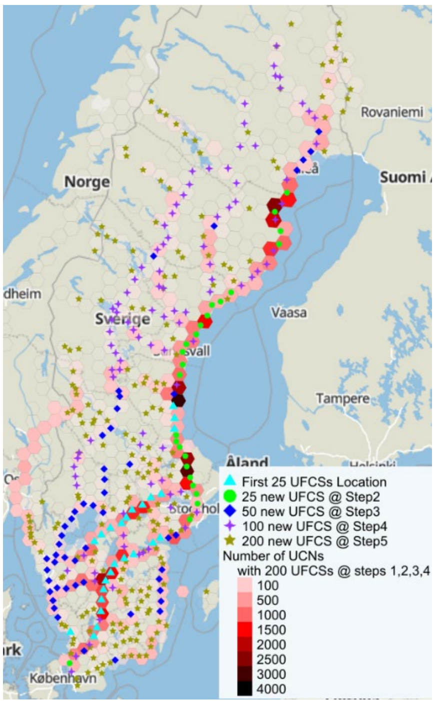


Figure 4: UCN distribution, assuming there are 200 UFCs installed as well as the location for the last 200 UCNs (represented by the golden stars, for a total of 400 charging stations)

Fig. 5(a) illustrates the charger distribution for 200 ultra-fast charging stations, totaling 27,744 chargers to satisfy peak demand for long-distance electric passenger car travel. The histogram shows a right-skewed distribution, indicating that while most stations require a moderate number of chargers, a few high-traffic locations demand substantially more. Fig. 5(b) presents a comparable scenario with 400 stations and 29,287 total chargers. Although distributing stations more widely lowers the average chargers per station, the overall total increases due to broader coverage. Both configurations sufficiently meet projected charging needs but reveal a key trade-off: fewer, higher-capacity stations concentrate resources and may simplify management, while a greater number of smaller stations can enhance coverage and potentially reduce waiting times. The optimal choice depends on policy objectives, geographic factors, and expected travel patterns.

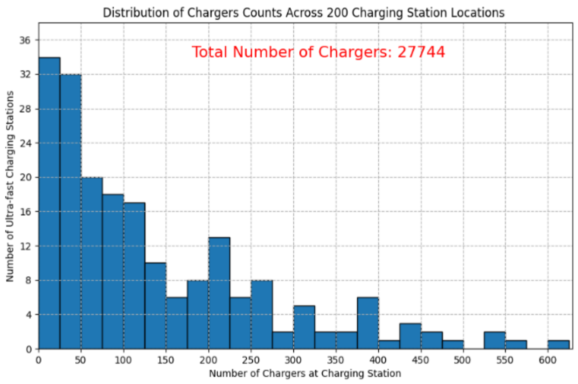


Figure 5(a): Distribution of chargers across 200 UFCS locations

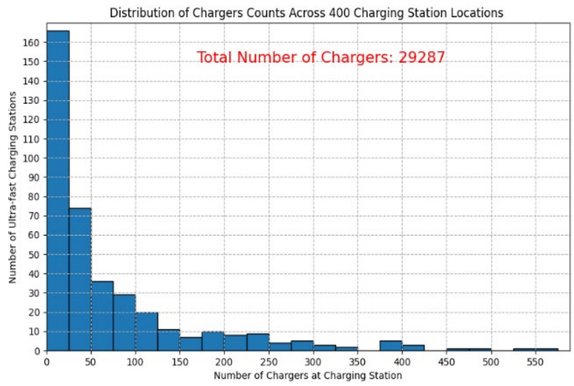


Figure 5(b): Distribution of chargers across 400 UFCS locations

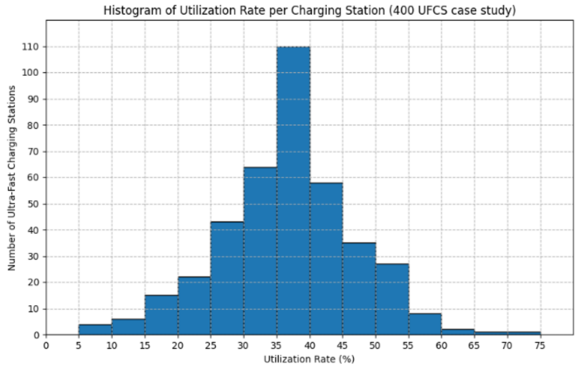
Figure 5: Comparison of the distribution of chargers across 200 and 400 UFCS locations

Fig. 6(a) shows the distribution of utilization rates for all 400 UFCSs. The results reveal a near-normal distribution centered around 35% to 40% utilization, with most stations operating between 25% and 50%. This suggests that the majority of stations achieve a balanced usage level, supporting efficient investment without widespread overcapacity. Very few UFCSs experience extreme underutilization (<15%) or overutilization (>55%), indicating that the overall network design is reasonably effective in matching infrastructure supply to long-distance EV travel demand. However, the presence of some low-utilization stations suggests opportunities for optimization in site selection and network expansion strategies.

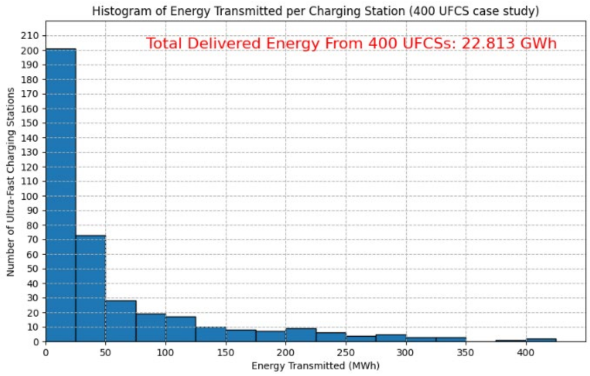
Figure 6(b) shows the distribution of total energy delivered per UFCS across the 400 stations. The total transmitted energy amounts to 22.813 GWh, with the majority of stations delivering less than 25 MWh and only a small number exceeding 100 MWh. The distribution is highly right-skewed, indicating that a few UFCSs located along major highways handle a disproportionately large share of the energy demand, while many stations installed primarily for network coverage serve relatively low volumes. It is important to note that we limit the deployment to one station per hexagon with a radius of 30 km, thus, these very large stations may, in practice, represent multiple smaller stations clustered within the same area. This pattern emphasizes the importance of strategically reinforcing high-demand locations and optimizing low-usage sites to balance infrastructure investments with operational efficiency.

Figure 6(c) shows the hourly variation in energy demand across UFCSs, presented as a boxplot. The results indicate that energy demand remains very low during nighttime hours and rises sharply from early morning, peaking between 11:00 and 13:00. During peak hours, the median hourly energy demand per station reaches approximately 5–7 MWh, with some stations delivering more than 30–40 MWh, as indicated by outliers. The widespread demand across stations at any given hour underscores significant spatial variability, driven by differences in trip patterns and station locations. These findings show the importance of accounting for temporal peaks and station-specific variations in the design and operation of fast-charging networks. Moreover, they open up opportunities for future work on the design of such stations, particularly the integration of local electricity generation and storage solutions to alleviate high power peaks.

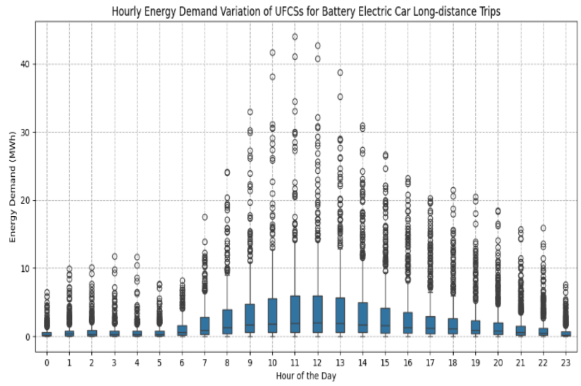
Figure 6(d) shows the total hourly energy demand across all UFCSs, effectively representing the aggregation of the station-level data presented in Figure 6(c). The results reveal a clear diurnal pattern that mirrors long-distance travel behavior. Energy demand remains low during nighttime hours, begins rising sharply after 06:00, and peaks between 11:00 and 13:00, reaching a maximum of over 1,750 MWh — a pattern that aligns well with typical solar production profiles. After midday, demand steadily declines into the evening, dropping significantly after 21:00. The sharp midday peak clearly demonstrates the need to ensure sufficient UFCS capacity during late morning and early afternoon hours to avoid congestion, making peak load management a key consideration in infrastructure planning.



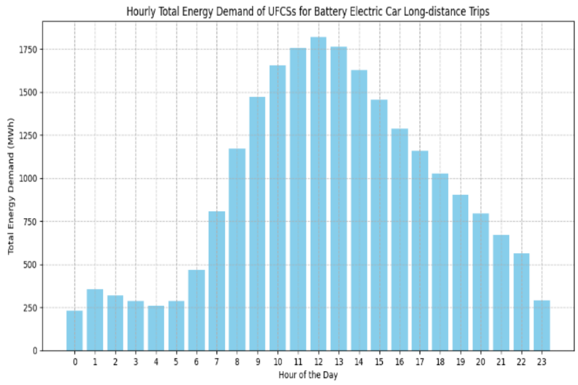
(a) Distribution of the UFCSs' utilization ratio



(b) Distribution of UFCSs' energy consumption



(c) Hourly distribution of energy demand of UFCSs.



(d) Hourly Total Energy Demand of UFCSs

Figure 6: Simulation results with 400 UFCSs

Since the model imposes no limits on the number of chargers available at each location, some of these become too large. The number of chargers represented in Fig. 6(a) corresponds to the maximum number of EVs that have been charging simultaneously at any point in time during the simulated period. Looking at that histogram, around 300 stations comprise less than 100 chargers (actually, 165 stations feature between 1 and 25 chargers), but there are 6 stations in the country with over 400 chargers. To understand where these large stations are located in the country, the same results have been plotted on a map in the left plot of Fig. 7. The largest stations are located on the road E4 around Jönköping, on the E18 between Örebro and Västerås, and on the E4 again, along the east coast between Gävle and Sundsvall.

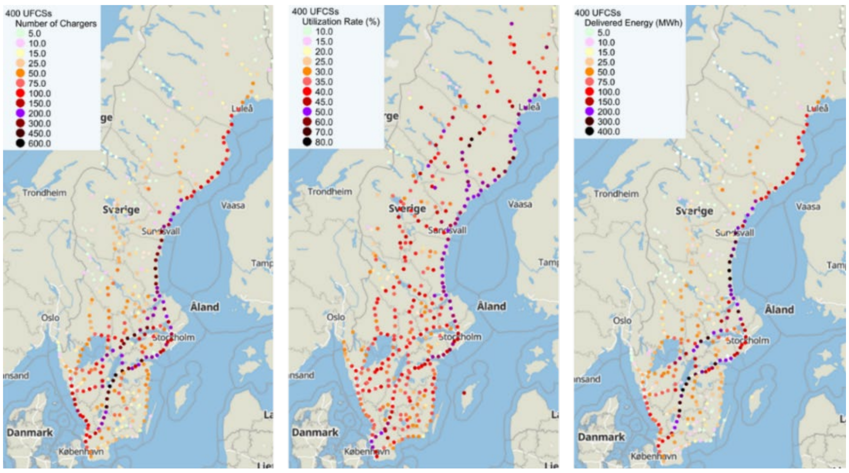


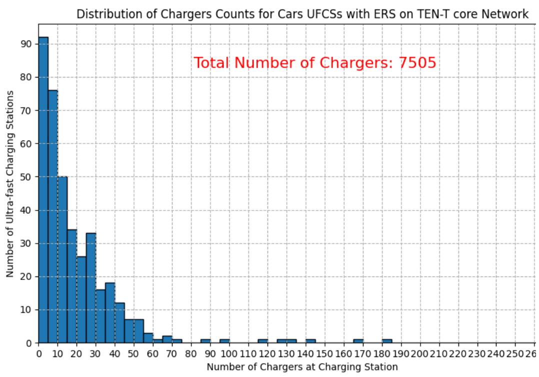
Figure 7: Geographical representation of the final 400 UCFSs in Scenario 1, indicating the size of the stations (number of chargers), their utilization rate, and the energy delivered per station in one day.

The middle plot in Fig. 7 presents a color-coded map illustrating station utilization across the network. Higher utilization is concentrated along major travel corridors and within urban centers, while remote and less-frequented areas exhibit substantially lower usage rates. This spatial distribution reflects an inherent trade-off between maximizing geographic coverage and achieving high utilization, as some stations are deliberately maintained in low-demand areas to ensure accessibility. The current UFCS network appears sufficient to support long-distance electric vehicle travel; however, the results also point to opportunities for improving operational efficiency through more targeted station placement and capacity adjustments.

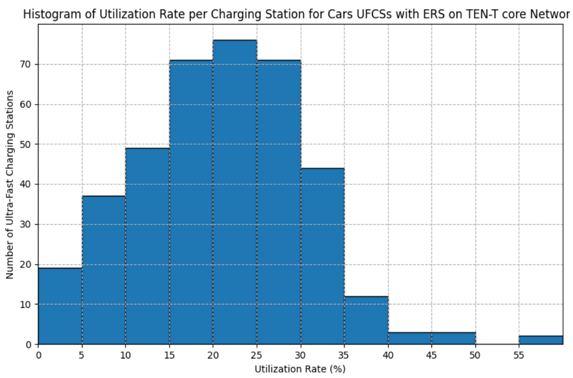
The right plot in Fig.7 shows the spatial distribution of 400 UFCSs across Sweden, with each station's color reflecting its daily delivered energy in MWh. Notably, the highest-demand stations, reaching up to 400 MWh/day, cluster along major corridors, especially the E4 running from Malmö/Copenhagen through Stockholm to Luleå. Stations off primary travel routes exhibit comparatively lower demand (5–25 MWh/day. While most UFCSs deliver under 50 MWh/day, a small number exceed 100 MWh/day. Summing over all 400 stations yields a total of about 22.8 GWh/day, underscoring the substantial charging demand for long-distance EV travel.

3.2 Scenario 2: Combined ultra-fast charging stations and electric road systems.

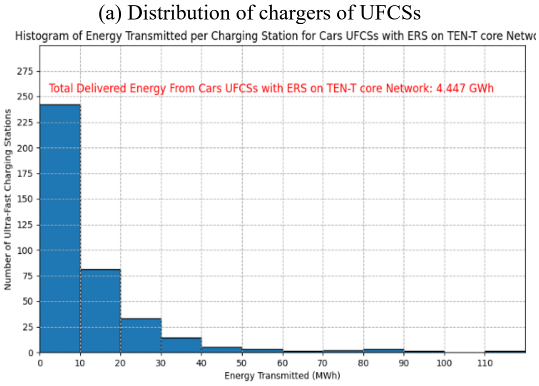
In scenario 2, a combination of ERS on the TEN-T core network and UFCS is analysed. The 400 UFCS locations from scenario 1 are kept (although not all of them are always used). The trip and EV modelling remain unchanged. The distribution of the number of chargers at each UFCS location with ERS on TEN-T core corridors is shown in Fig. 8(a). Compared to Scenario 1, the required charger numbers per station are notably lower. The presence of ERS along major corridors reduces the need for large-scale stationary charging hubs, resulting in a total charger count reduction from 29,287 to only 7,505 chargers. Fig. 8(b) displays the utilization rates of the UFCSs. A broader spread of moderate utilization values is observed, with peak utilization decreasing compared to the UFCS-only case. Fig. 8(c) depicts the daily delivered energy per UFCS, showing that energy demand at stationary chargers diminishes. Fig. 8(d) demonstrates that the total UFCS energy demand is dramatically reduced. The peak demand reaches only about 400 MWh during the midday period, representing a reduction of nearly 80% compared to the UFCS-only case. The temporal pattern remains similar, with a peak around noon, but the amplitude is significantly dampened. Early morning and late evening energy demands are also notably lower.



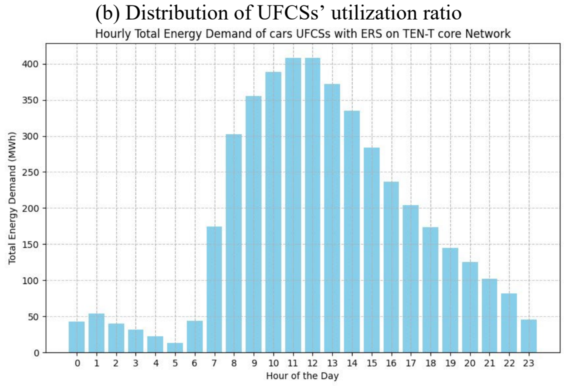
(a) Distribution of chargers of UFCSs



(b) Distribution of UFCSs' utilization ratio



(c) Distribution of UFCSs' delivered energy



(d) Hourly Total Energy Demand of UFCSs

Figure 8: Simulation results with ERS on TEN-T core corridors and 400 UFCSs.

Figure 9 provides a spatial overview of the key characteristics of UFCSs in Scenario 2, where the TEN-T core network is partially equipped with ERS. The three subplots illustrate the distribution of the number of chargers, station utilization rates, and total daily energy delivered per station. The number of chargers installed varies significantly across the country. Higher charger counts (ranging from 100 to over 250 chargers per location) are concentrated along the E20 between Stockholm and Gothenburg, as well as other major highway corridors not fully covered by ERS. In contrast, most rural and northern regions require fewer chargers (10–50 units), reflecting lower long-distance trip volumes. Given the limited ERS deployment in these areas, travelers are expected to rely more heavily on UFCSs and possibly larger battery capacities to ensure sufficient driving range, rather than depending on ERS for range extension. The utilization rates of UFCSs show a heterogeneous pattern across Sweden. Most stations exhibit utilization rates between 20% and 40%, with a few high-demand sites (over 50%) mainly located near Stockholm and other major metropolitan areas. Stations situated along the ERS-equipped corridors tend to experience lower utilization, highlighting the effectiveness of ERS in offsetting the need for fast-charging stops and reducing congestion at charging facilities. The energy delivered by each station also displays a clear spatial pattern. The highest energy throughput (up to 100 MWh/day) is observed at UFCSs near urban centers and key transport hubs, whereas stations along well-electrified ERS corridors generally report lower daily energy outputs. This demonstrates that ERS coverage successfully shifts a considerable portion of the energy delivery from stationary infrastructure to dynamic, in-motion charging systems.
Fig. 10 provides a spatial analysis of ERS energy usage and the underutilization patterns of UFCSs in Scenario 2. This map shows the total energy consumed (in MWh) along each ERS-equipped segment of the TEN-T core network. High energy consumption is concentrated along the southern and central corridors, particularly around Stockholm, Malmö, and Gothenburg regions. Certain stretches near Sundsvall and Luleå also exhibit notable energy demands, reflecting areas with higher traffic volumes or longer driving distances. In contrast, northern sections of the network, characterized by lower population density and reduced traffic flow, show minimal ERS energy usage, often below 5 MWh per link.
The ERS energy usage is normalized by link length (MWh/km), emphasizing intensity rather than absolute volume. Normalization reveals specific highway segments with high per-kilometer energy demands, particularly near Stockholm and certain bottleneck corridors in central Sweden. These regions may require prioritization for ERS maintenance, upgrade, or reinforcement due to heavier dynamic charging loads. On the other hand, extended stretches in the north experience very low energy demand per kilometer, suggesting limited cost-effectiveness for dynamic charging infrastructure in those areas. The underutilized UFCS are primarily located in sparsely populated areas or along ERS-covered corridors where dynamic charging sufficiently meets vehicle energy needs. The findings emphasize the importance of adaptive and demand-responsive planning, suggesting that certain UFCS installations could be downsized, relocated, or delayed until higher demand materializes.

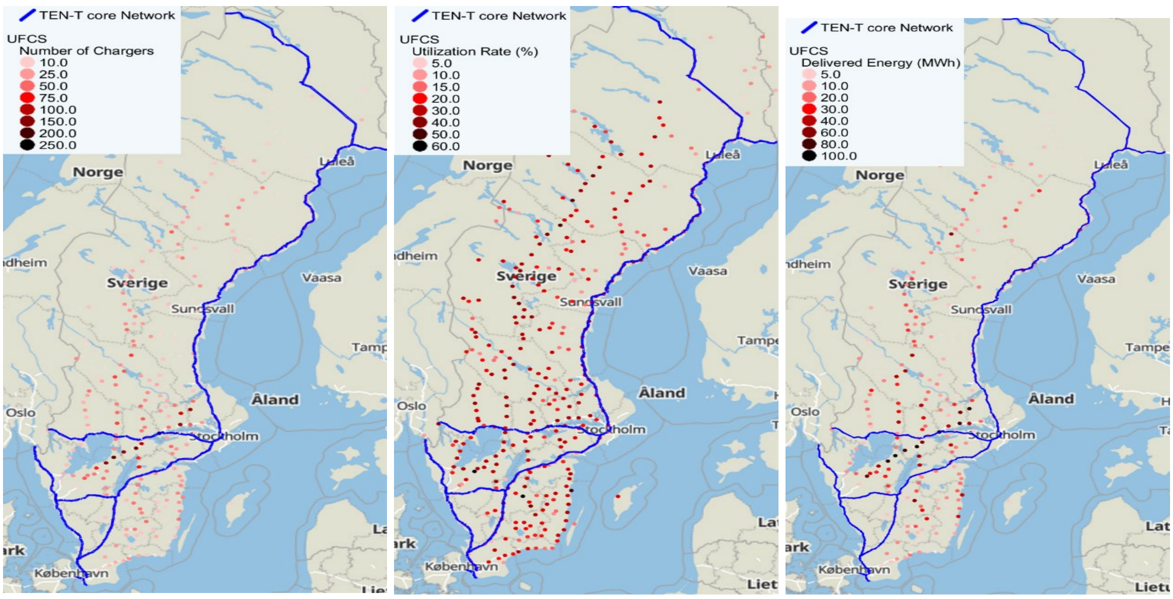


Figure 1: Simulation results for long-distance passenger cars in Scenario 2 indicate the size of the stations (number of chargers), their utilization rate, and the energy delivered per station in one day. The ERS is marked in blue.

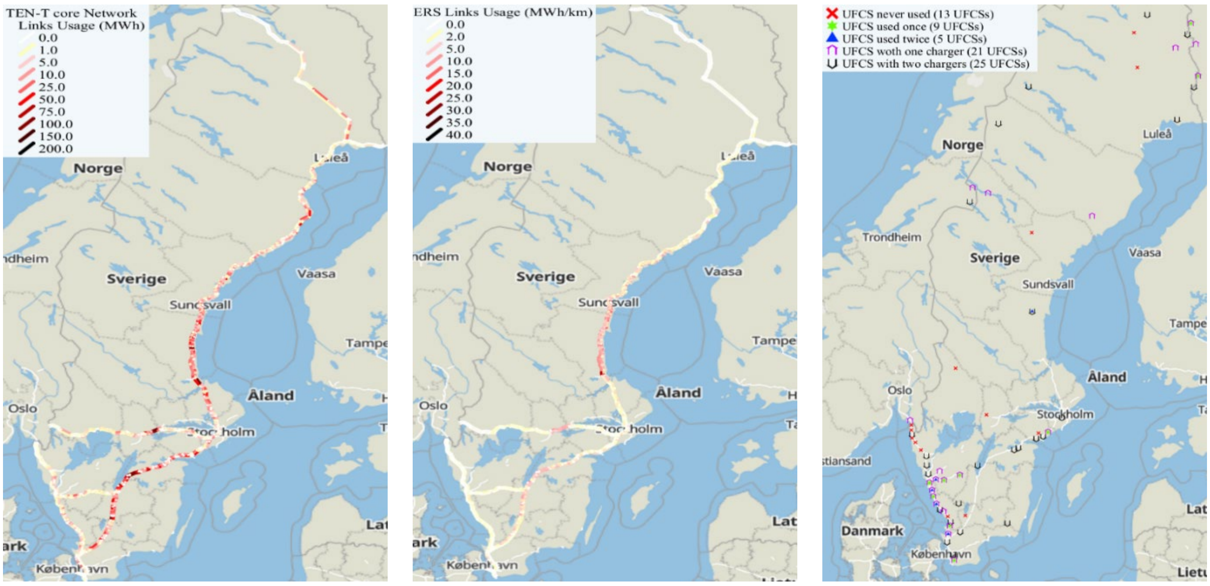


Figure 10: Simulation results for long-distance passenger cars in Scenario 2 indicate the total energy usage for each like equipped with ERS in MWh, and MWh/km. The left plot shows the total energy consumption per ERS-equipped link (in MWh), identifying major energy-demanding segments. The middle plot presents normalized energy usage (MWh/km), revealing road sections with the highest energy intensity relative to their length. The right plot maps the locations of UFCSs that are either unused or lightly used, indicating the number and spatial distribution of underutilized charging stations.

4 Conclusion

This study presented a detailed, agent-based simulation framework to assess charging infrastructure needs for long-distance electric vehicle travel in Sweden. By integrating ultra-fast charging stations with electric road systems on the Swedish TEN-T core network, we developed a dynamic and behaviorally informed infrastructure planning methodology.
The results demonstrate that it is feasible to support large-scale EV adoption with a relatively compact number of strategically located UFCSs. Specifically, 200 UFCSs equipped with 27,744 chargers were sufficient to electrify approximately 95% of long-distance trips, while 400 UFCSs increased successful trip coverage to 97%. The incorporation of ERS substantially alleviates the need for high-power stationary charging, reduces the number of necessary stops, and enables smoother energy delivery along major corridors. Additionally, ERS deployment led to underutilization at about 60 UFCS sites, indicating the potential for further optimization by adjusting the balance between dynamic and stationary infrastructure.
Future research should extend this framework by incorporating queuing effects, real-world grid and land-use constraints, and dynamic pricing models to capture user behavior more realistically. Sensitivity analyses on ERS deployment intensity, vehicle fleet characteristics, and travel demand variations are also recommended. Additionally, cost-benefit assessments comparing ERS and UFCS investments, as well as international applications of the model, would enhance its practical relevance for policymakers and industry stakeholders.

Acknowledgments

This work was supported by the Swedish Transport Administration (Trafikverket) through the project Charging Infrastructure Needs for Light and Heavy Vehicles in Sweden.

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