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Charging Infrastructure Requirements for 100% Battery Electric Vehicle Adoption in Sweden

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Executive Summary

This study assesses the charging infrastructure requirement to support a fully electrified vehicle fleet in Sweden, considering the sensitivity of battery electric vehicle (BEV) users to their charging behavior preferences. Using a synthetic population with daily travel activity plans, we simulate BEV charging and discharging patterns across multiple charging strategies. The corresponding energy demand drawn from the electricity grid is then estimated, followed by a geographic mapping of charging infrastructure needs across Sweden. The existing charging infrastructure in Sweden is found to be insufficient to meet future energy demand. Our findings also reveal significant variations in load profiles and infrastructure requirements at public places depending on assumed charging behaviors.

Keywords: Electric Vehicles, Modelling & Simulation, Consumer Behavior, Consumer Demand, Trends & Forecasting of e-mobility

1 Background

As a key technology in combating climate change and transitioning the transport system, battery electric vehicles (BEVs) are replacing traditional internal combustion engine vehicles (ICEVs). The European Union has enacted legislation that prohibits the sale of new ICEVs starting in 2035 [1]. By 2050, the sales volume of BEVs is expected to surpass that of ICEVs globally [2, 3]. Sweden, in particular, has established itself as a frontrunner in sustainable mobility, trying to transition entirely to BEVs in the coming decades. However, the uptake of BEVs is dependent on sufficient charging infrastructure. A future scenario with 100% BEV adoption will increase electricity demand for charging, posing possible challenges for the operation and planning of the power system [4]. Understanding these behaviors is essential for efficient infrastructure deployment and for minimizing grid-stress and user inconvenience [5].

The infrastructure deployment could develop very differently depending on the charging behaviors of the users [6]. While much research has been conducted on EV charging simulations and projections, there still is a sizeable research gap in linking the charging energy demand with user charging behavior preferences. In planning the placement and capacity of BEV charging infrastructure, existing research often relies on overly simplistic assumptions regarding user charging habits and access to private home chargers [4, 7, 8]. However, with the transition to BEV adoption, residents across all types of housing — detached houses and apartments

— will require reliable access to charging [7, 9]. This highlights a critical gap in current planning models. As such, determining the necessary scale and distribution of public charging stations remains a central policy challenge. Accurate forecasting must consider diverse living arrangements, urban density, and socio-economic disparities to ensure equitable and effective infrastructure deployment.

This study offers valuable insights into the charging infrastructure requirement assuming 100% BEV adoption in Sweden by incorporating BEV charging and discharging behaviors. A key innovation of this work lies in the use of a large-scale synthetic population that retains realistic socioeconomic characteristics and diverse daily activity patterns for performing a detailed estimation of charging demand across various dwelling types. Additionally, we introduce a classification of charging strategies. Our findings reveal that the spatial and temporal patterns of charger usage as well as the required number of charging points at home, workplaces, and other locations are significantly influenced by the diversity of charging strategies considered.

The remainder of the paper is structured as follows. In the next section, relevant literature pertinent to BEV charging infrastructure, charging behavior preferences and their interaction are reviewed and presented. The Methodology section outlines the analytical framework, including details on the datasets used, simulation components, and the analysis for estimating charging demand. In the Results and Discussions section, we present simulation outcomes including spatiotemporal energy demand & the corresponding charging infrastructure requirement and interpret these findings. The Conclusions section highlights the key contributions and limitations of the study.

2 Literature Review

Advancements in charging technologies are pivotal for accommodating the growing BEV market. Effective deployment of BEV charging infrastructure necessitates integrated planning across transportation and power distribution networks [10]. The International Energy Agency (IEA) projects that the number of public charging points worldwide will need to increase sixfold by 2035 to support mass-market EV adoption [11]. This expansion must encompass both slow and fast charging options to accommodate diverse user needs and ensure accessibility across urban and rural areas [12]. However, despite its critical importance, the deployment of charging infrastructure is costly and often entangled in a classic chicken-and-egg dilemma: infrastructure providers are hesitant to invest due to uncertain profitability, while potential BEV users are discouraged by limited charging availability [6, 8]. Identifying optimal locations and appropriately sizing charging stations is essential to encouraging BEV adoption and ensuring a seamless driving experience without disrupting users' daily routines. A comprehensive classification of charging options can support this goal by considering various factors — such as the underlying technology (e.g., wireless or inductive charging) [13, 14], power levels (e.g., slow, medium, fast, and ultra-fast charging) [13, 15, 16, 17], and usage scenarios (e.g., destination-based charging) [14, 17, 18].

Charging behavior is fundamentally a spatiotemporal phenomenon, referring to the timing, location, and duration of BEV users' interactions with charging points [8]. Previous studies have identified various factors influencing EV charging behavior by analyzing diverse user groups. These factors may generally be categorized into scenario-related attributes, socio-demographic attributes and behavioral habit attributes. Scenario-related attributes are defined by conditions associated with the vehicle or charging facility and are often referred to as alternative factors [19, 20]. Among scenario-related factors, State of Charge (SOC), charging cost, and range anxiety are particularly influential. SOC, which indicates the remaining energy in the vehicle's battery (ranges from 0% to 100%), is widely considered the most critical factor [8, 19]. Statistics show that most charging events occur when SOC is between 20% and 80%, and public charging sessions tend to start at higher SOC levels compared to those at home [21, 22]. Charging price is another key consideration for EV users. While drivers typically prefer lower prices [14], they don't always opt for the cheapest option. Time-sensitive individuals, for example, may prioritize convenience over cost [20]. Furthermore, the uncertainty of dynamic pricing means that higher price levels tend to disproportionately influence user decisions [20, 23].

In contrast, socio-demographic attributes capture individual differences, including age, gender, and other personal characteristics, which significantly shape users' charging preferences and decisions [4, 9, 23]. Studies have explored strong existing relationships between socio-demographics, activity engagement, and travel behavior [24, 25]. The travel patterns of low-income people and high-income people are significantly different, as well as age, gender, and education level [23, 24]. Apart from these observable attributes, there exist behavioral habit attributes which mainly focus on individual habits, user perceptions, mental models, and refilling strategies [5, 26, 27, 28]. These attributes account for individual heterogeneity by treating them as latent variables that are specific to each person.

Most of the existing studies do not account for the impact of all those three classes of attributes on charging behavior preferences and overlook realistic charging behaviors [8, 29]. Some models have attempted an oversimplification approach by assuming that BEV users only initiate charging once the SOC drops below a specific threshold value [28, 30]. These assumptions often stem from our familiarity with refueling ICEVs, despite the fundamental differences between ICEVs and BEVs [5]. BEVs require considerably more time to recharge, which influences how drivers schedule charging to align with their travel plans [31]. This oversimplification of charging behavior in the literature is partly due to limited availability of detailed user data. Most studies rely on patterns from early BEV adopters, who typically have convenient home charging access [4, 19]. However, as BEV adoption expands, future users are likely to adopt more diverse charging strategies shaped by their daily activity patterns, mental models, electricity pricing schemes, and willingness to pay [5, 8]. How these evolving strategies will influence overall charging demand and infrastructure needs remains uncertain. Furthermore, studies that assume universal access to home charging [22] often conclude that the demand for daytime charging at workplaces or public locations is minimal [28], which may not hold true for broader segments of future users [8].

The extent and location planning of electric vehicle charging infrastructure often revolves around the field of optimization and operation research. Some studies have used classic mathematical programming approaches (such as p-median, p-center, maximum coverage methods, etc.) that can generate effective charging infrastructure layouts by optimizing specific objectives from various perspectives [32, 33, 34]. However, due to the interdisciplinary nature of the problem, characterized by high complexity and uncertainty, these models often remain largely theoretical only [32]. To ensure their practical relevance, such approaches need to be validated in environments that closely resemble real-world conditions, such as large-scale vehicle movement simulations. In response to this need, several agent-based models (ABM) have been developed to assess and refine charging infrastructure deployment strategies. These models simulate diverse agents such as potential EV buyers, current EV users, passengers, and fleet operators, each endowed with a degree of decision-making intelligence, enabling more realistic evaluations of charging infrastructure planning [33, 35, 36]. These ABMs have the capability to simulate realistic charging strategies and integrate different charging decisions from individual user' perspective, while being able to handle a large number of agents.

In this study, we try to circumvent the concerns regarding optimal locations of charging infrastructure by assuming that BEV users use charge points when they want to. This assumption helps in simplifying the charging demand and potential charging points locations and presents scenarios based on the charging needs of the users. We apply an agent-based modeling approach with a synthetic population of Sweden and simulate BEV charging and discharging dynamics considering different charging strategies over a typical weekday.

3 Methodology

The simplified broad methodological framework is shown in Fig. 1. The steps are discussed below.

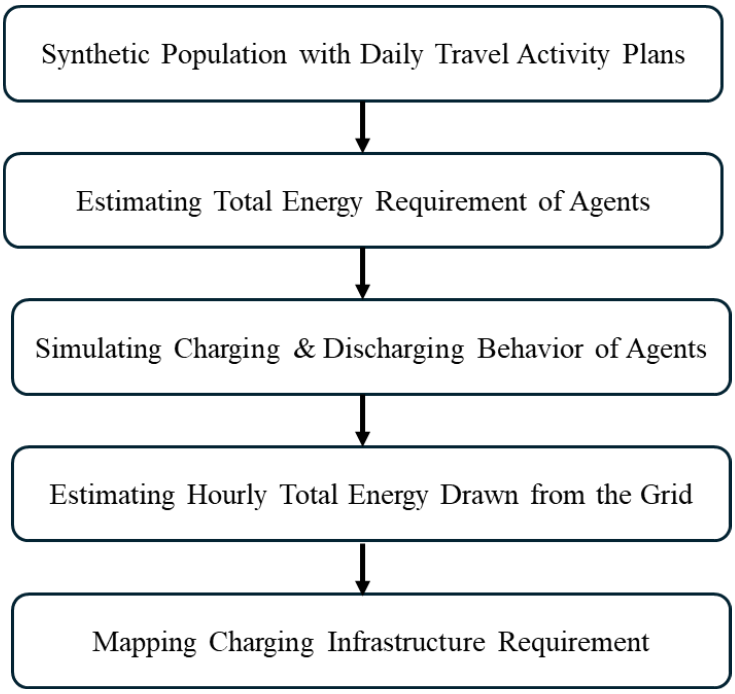

Figure 1: Methodological framework for the study

3.1 Synthetic population with activity plans

Our study utilizes Synthetic Sweden Mobility Model (SySMo), an agent-based decision support framework to explicitly simulate BEV driving behaviors and charging needs with high spatial (coordinates) and temporal detail (second). SySMo provides a synthetic replica of over 10.2 million Swedish individuals (i.e., agents), their socio-demographic characteristics, and activity-travel plans for an average weekday while preserving privacy [37]. For this study, we focus only on the car agents (agents that drive cars on the simulated day) in Sweden, the total number of which is around 3.26 million.

For preparing the input dataset, the daily activity plans of all the car agents along with the road network are fed to a MATSim environment for simulating the agents' movement trajectories and thereby getting realistic estimation of travel times of individual agents. Each agent is characterized by a set of socioeconomic attributes, including age, gender, income level, employment status, and dwelling type. Additionally, every agent follows a daily activity schedule consisting of four possible activities: home (H), work (W), school (S), and other (O). The majority of car agents reside in detached houses (60.2%), while the remaining (39.8%) live in apartments. The frequency distribution of daily distance travelled by all car agents is shown in Fig. 2(a). It follows a Pareto distribution which is expected as the majority of the car agents travel for comparatively shorter distances over a day [38].

3.2 Estimation of total energy requirement

We consider that each agent has the hindsight to know the exact distance to be travelled on the simulated day. Using the data from a previous study on future charging infrastructure planning in Sweden [39], we simulate the discharging dynamics of BEVs for different battery sizes. The BEV fleet is assumed to include three battery sizes: 40 kWh (12%), 60 kWh (49%), and 100 kWh (39%) [8, 39]. These battery sizes are assigned to the agents based on their income levels and extent of daily travel distance; the proportions of assigning are determined heuristically. For discharging, each battery size has a lookup table of energy efficiency (kWh/km) as a function of travel speed (m/s) and road slope (%). The detailed vehicular characteristics corresponding to different battery sizes and their energy efficiency tables are provided by Márquez-Fernández et al. [39]. Based on the travel distance requirement of each agent and energy efficiency maps, we estimate the corresponding energy consumption during each car trip for an individual agent. Then we estimate the daily total energy requirement (or consumption) of an agent by summing energy consumptions values over all activities. The frequency distribution of daily energy requirement of all car agents is shown in Fig. 2(b).

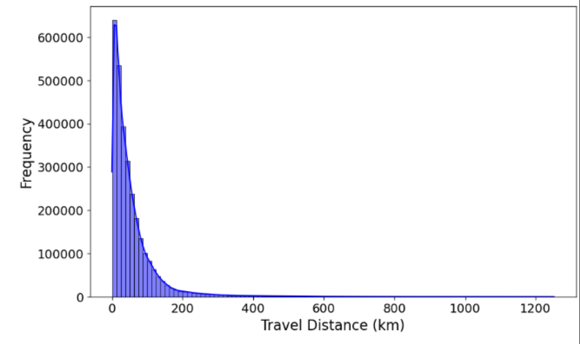

Figure 2(a): Travel distance distribution of agents

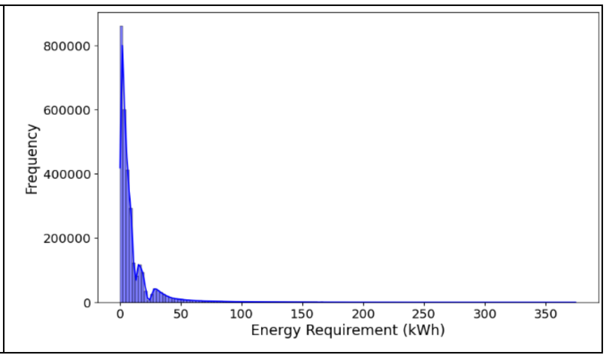

Figure 2(b): Energy consumption distribution of agents

3.3 Simulation of charging and discharging behavior

As earlier mentioned, we simulate BEV usage for approximately 3.26 million individual car agents, considering overnight charger access, the current EV fleet composition (in terms of battery sizes) in Sweden, the road network, and BEV charging and discharging dynamics. During charging, the power delivered by the charge point is constrained by the battery's SOC; as the SOC increases, the effective charging rate decreases and subsequently the required charging duration increases. The SOC-dependent charging profiles for different battery sizes are also provided by Márquez-Fernández et al. [39]. The parking duration (activity duration) provides the opportunity to charge the BEVs; so, the charging duration is constrained by the parking time, battery capacity and other assumptions we have considered for different strategies.

Two charging strategies are simulated - 'Plan Ahead' (PA) and 'Event Triggered' (ET) [5, 8]. The PA strategy involves anticipating future charging needs. For instance, before parking, drivers assess whether their BEV has sufficient charge for the next trip. If not, they choose to plug in and charge in advance. For ET strategy, drivers charge their vehicles whenever they park at certain locations (such as workplaces or shopping stops) regardless of whether the stop allows for a full charge. This often results in opportunistic partial charging. As ET involves more frequent charging events and leads to charging beyond what is immediately necessary, the energy requirement is likely to be higher as compared to PA. The details of considerations regarding the two strategies are presented in Table 1.

Four types of charging points are provided based on dwelling types of agents, parking duration, and the SOC: (1) fast charging (50 kW), (2) intermediate charging (22 kW), (3) home charging (11 kW), and (4) apartment charging (11 kW). Agents residing in detached houses are assumed to have access to home chargers, while apartment dwellers rely on non-home-based charging points (apartment chargers) for end of day charging (see Table 1). For daytime charging at public parking spaces, if the parking time is below 60 minutes and SOC is below 80%, agents are assigned fast chargers; otherwise, intermediate chargers are used. We limit the maximum possible SOC to 90% with reference to the battery degradation standpoint.

Table 1: Summary of charging strategies

Charging Strategy	Description	End of Day Charging (Detached house)	End of Day Charging (Apartment)
1. Plan Ahead (PA)	Plan ahead for when charging is needed – focused on the energy requirement to complete the trips for the day.	Charge if SOC is insufficient for the next day energy requirement. When plugged in, charge up to 90% capacity.	Charge if SOC is insufficient for the next day energy requirement. When plugged-in, charge up to 90% capacity.
2. Event Triggered (ET)	Plug in to charge whenever parking at a specific location.	Always plugged in to charge to 90% capacity.	Charge if SOC is insufficient for the energy requirement corresponding to the next day 1st travel activity. When plugged-in, charge up to 90% capacity.

The initial SOCs of the agents at the start of the day range from 20% to 90%, randomly drawn from a skewed normal distribution with skewness of -4 [8]. For both the charging strategies, we run ten consecutive simulation days with the same sets of daily planned activities to eliminate possible bias in simulation results. After running the simulation continuously over several activity days, the initial SOC patterns reach a steady state, and the results from the tenth day are then used for further analysis.

3.4 Estimation of energy drawn from the grid

From the BEV simulation output, we get the simulated charging amount and SOC during each activity duration for an agent. The charging amount and SOC are recorded at the end of each individual activity. We then aggregate the individual charging patterns over a day as well as the spatiotemporal energy demand at DeSO zone level[1]. The occurrence of peak charging demand for both strategies and how it aligns with the existing scenario are also investigated.

3.5 Mapping of charging infrastructure requirement

Charging points are allocated based on agents' charging needs. Accordingly, the required number of charging points in each DeSO zone is determined by identifying the maximum number of BEVs plugged in simultaneously within that zone at any given minute throughout the simulation day [8]. As we assume that every detached house has access to a personal home charger, the total number of home chargers becomes equal to the total number of detached houses. So, we quantify the charging points requirement for fast, intermediate and apartment chargers at DeSO zone level.

4 Results and Discussions

The BEV simulation results show variations in individual charging profile by the charging strategy. As a sample result, hourly SOC levels of two different agents – one living in detached house and the other in apartment – are presented for both charging strategies in Fig. 3(a) and Fig. 3(b) respectively.

[1] DeSO zone - Swedish Demographic Statistical Areas which follow municipal boundaries. Each municipality consists of a number of DeSO Zones, for a total of 5984 zones.

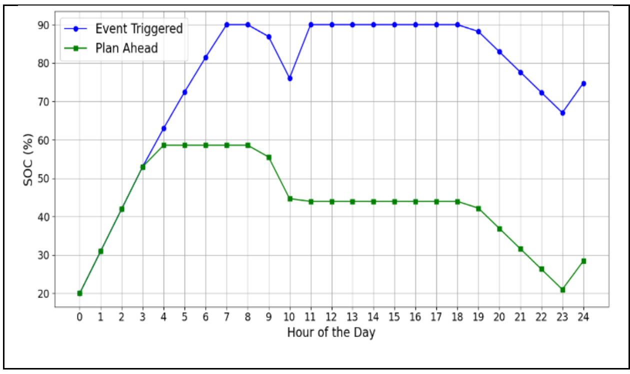

Figure 3(a): SOC levels of a detached house agent

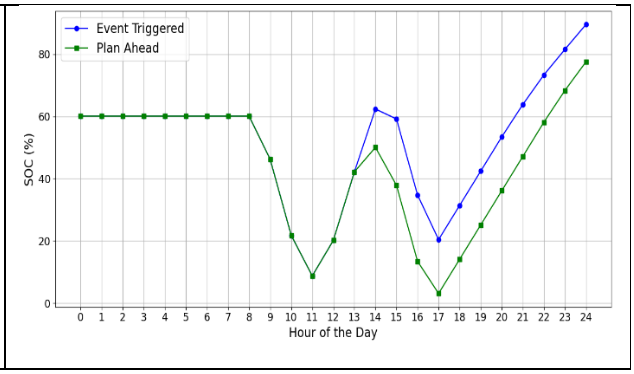

Figure 3(b): SOC levels of an apartment agent

The detached house agent starts with 20% SOC, and during ET simulation (blue line), the charging continues during the first home activity using the home charger until 90% SOC is reached. Whereas, for PA simulation (green line), the charging stops when it reaches the required energy level for covering the daily trips and stays horizontal till the end of the home activity. The segments depicting the decrease in SOC represent discharging BEVs due to travelling. For the apartment agent, no charging is done during the first home activity as the apartment dwellers do not have access to home charging points (barring the last home activity). When the agent returns back to home at the end of the day, they start charging using the available apartment charger as the SOC is not adequate enough to cover the next day trips. The amount of charging differs for different charging strategies. For both the agents, charging at public places is done using intermediate chargers.

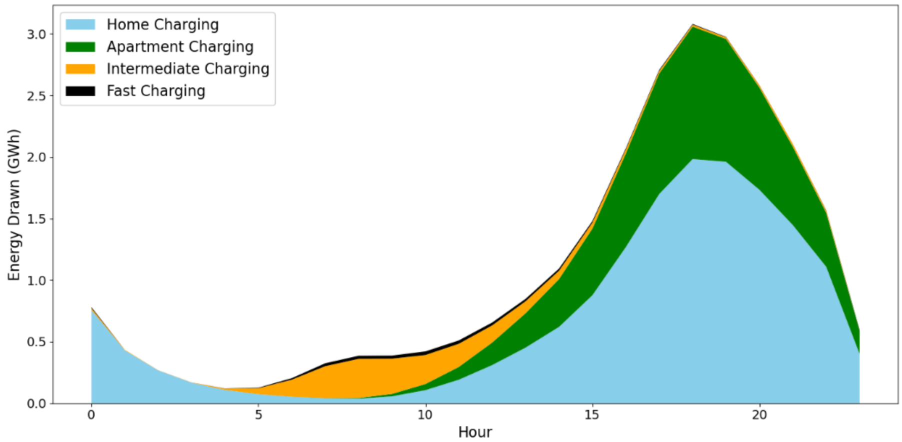

Figure 4: Hourly energy drawn from the grid corresponding to PA Charging Strategy

The results also indicate variations in hourly energy drawn from the grid by the charging strategy, as illustrated in Figs. 4 and 5. The daily total energy demand for the ET strategy is found to be about 15% higher than that of the PA strategy, which is expected as ET being an opportunistic strategy, is more energy-intensive than PA strategy. For the PA strategy, 11 kW slow charging (home and apartment chargers) contributes most to the energy profile, with peaks occurring during evening home activities. This pattern aligns with the occurrence of current peak hourly electricity load in Sweden (about 25 GWh during evening) [40]. On the other hand, the ET strategy shows higher reliance on public charging places (workplace/school/other), with intermediate chargers dominating the energy profile. The peak occurs during morning hours (typically around 7-8 am when most of the agents reach their respective first trip destinations). For both strategies, the peak load is found to be around 3 GWh. Though no reliable statistics are available regarding how much of the current peak demand in Sweden comes from charging EVs alone, it is projected to be in the range of 0.5-1

GWh [41]. So, in case of 100% BEV adoption, the peak load component of BEV charging may increase by up to 300-600%. That may have a significant impact on the overall energy demand and grid congestion.

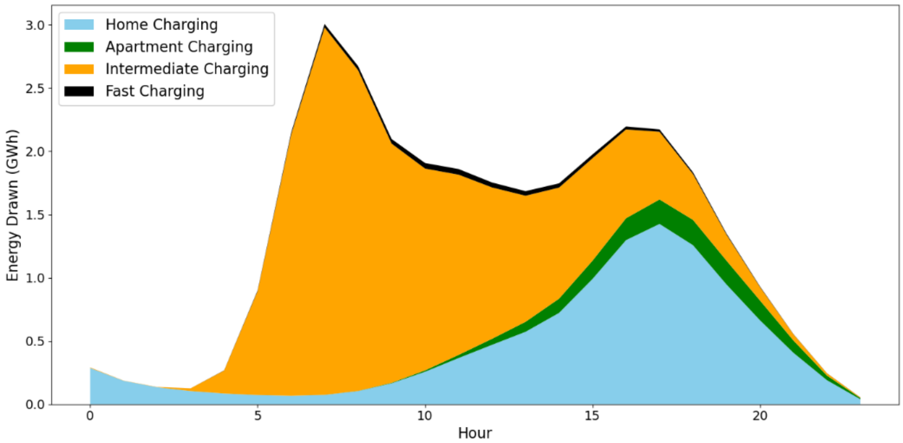

Figure 5: Hourly energy drawn from the grid corresponding to ET Charging Strategy

The overall charging points requirement to cater for all car agents is summarized in Table 2. The demand of apartment chargers for PA strategy is almost 3 times that of ET strategy, while the intermediate charging point demand for ET is more than 6 times that of PA. Considering our assumption regarding the allotment of fast chargers to agents, the corresponding infrastructure requirement is comparatively lower. As of 2023, Sweden has approximately 32,000 public EV charging points (including 3000 fast charging points) distributed across the country [42]. Now, we have only considered private cars to be electrified in this study (ignoring other vehicles that may need more intermediate and fast charging points), so, the existing infrastructure is somewhat sufficient to cater the need for intermediate and fast charging points for PA strategy. However, there still needs to be a larger infrastructure deployment for apartment chargers (for both PA and ET). In addition, ET strategy necessitates more than 5 times the existing intermediate charging infrastructure.

Table 2: Summary of charging points requirement

Charging Strategy	Apartment Charging Points (11 kW) #	Intermediate Charging Points (22 kW) #	Fast Charging Points (50 kW) #
Plan Ahead	434061	22720	1093
Event Triggered	150553	137394	1032

As both home and apartment chargers are assumed to be located at respective dwelling locations of agents, and the demand for fast charging points is lower, we focus more on the infrastructure requirement for intermediate charging points. The spatial distribution of intermediate charging points requirement at different activity locations (workplace and other place) is shown in Fig. 6. As expected, the charging infrastructure demand is much more intense for ET strategy than PA strategy. Across both strategies, charging demand in terms of energy is a bit higher at other places as compared to workplaces. This is primarily due to the higher frequency of ‘Other’ activities relative to work-related ones in the dataset.

For major cities (e.g., Stockholm, Gothenburg, Malmo, etc.), a higher concentration of charging demand is observed near the city-centers. Many DeSO zones are observed with only 1-2 public charging points requirement, regardless of strategy. However, in most cases, varying charging strategies lead to significant differences in the density of charging points requirement.

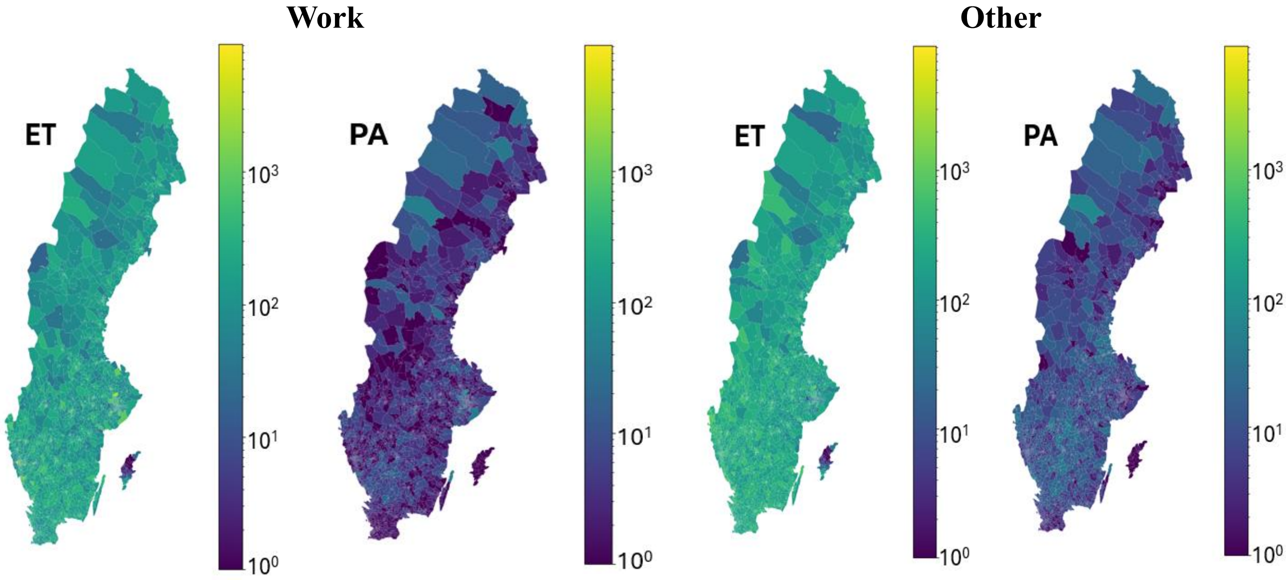

Figure 6: Spatial distribution of intermediate charging points at work and other places by charging strategy

5 Conclusions

This study attempts to investigate the charging infrastructure requirement from the perspective of BEV users under a future scenario of full BEV fleet in Sweden. Using a synthetic population of Sweden, we conduct an agent-based simulation to examine charging demand over an average weekday, considering various charging strategies and dwelling types. The analysis captures individual-level charging behaviors with high spatial and temporal resolution, offering insights at a local scale. By incorporating realistic charging behaviors and home charger availability (both with and without access), our study provides valuable insights into charging infrastructure planning , highlighting the infrastructure BEV users prefer, rather than only what they require.

We simulate two different charging strategies — Plan-ahead and Event-triggered, and quantify the charging demand across two dwelling types — detached houses and apartments. The spatiotemporal distributions of desired apartment, intermediate and fast charging points are approximated across different activity locations such as residential areas, workplaces, and other public venues, and a comparison of corresponding infrastructure requirement across charging strategies is performed. As per the results, the existing charging infrastructure in Sweden is found to be insufficient to meet future energy demand. The PA strategy demands the installation of more 11kW home and apartment chargers, whereas the ET strategy requires a significant expansion of public charging infrastructure, especially in central areas of major cities like Stockholm and Gothenburg.

The study has several limitations associated with the input dataset and underlying assumptions. The most significant one is the lack of charging cost consideration from users' as well as infrastructure's perspectives. One possible future work may involve consideration of time-of-use electricity price and other relevant cost components to simulate more realistic charging strategies and explore the price-sensitivity of users. Another limitation is that we simulate agents' activity plans for an average weekday without considering weekends or continued activity plans over multiple weekdays. This assumption results in under-representation of long-distance travel which in turn leads to under-estimation of fast charging demand. We may employ a more refined and updated synthetic population dataset containing multiple days of continuous activity plans in the future. The approach could be further improved by incorporating the effect of temperature on battery charging-discharging dynamics and investigating the seasonal variations . Our ongoing research focuses on the potential impacts of consumer charging preferences and economic incentives on infrastructure requirements, with particular attention to equity-related issues across different dwelling units. The future direction includes investigation of regional disparities in infrastructure availability and their effects on equitable access to charging facilities, as well as the varied economic burdens associated with charging infrastructure.

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Dr. Kaniska Ghosh is a post-doctoral researcher in the Department of Space, Earth and Environment at Chalmers University of Technology. He holds a Ph.D. in Civil Engineering from Indian Institute of Technology Kharagpur, with specialization in Transportation Engineering. He has experience of working in several research and consultancy projects related to traffic engineering, road safety, travel behavioral analysis, and spatial data infrastructure during his tenure as a doctoral candidate. His recent research focuses on sustainable mobility solutions, with core emphasis on electric vehicles & charging infrastructure, agent-based simulation, smart-charging & V2G, intelligent transportation systems, etc.