OPTIMIZATION OF EV FLEET CHARGING STATION PLACEMENT WITH MATSIM

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Abstract: To increase the adoption of electric vehicles, an effective charging infrastructure is required, which also increases the future-peak power demands. In this paper, energy system-implications of an algorithm designed to minimize the walking distance from activity locations to charging stations are analysed, together with changes in charging accessibility parameters like walking distances and charging events, while the spatial and temporal energy demand with the accessibility driven-optimization across the Hamburg districts is investigated. So, in this study, mainly electric vehicle charging station placement is optimized by minimizing the average walking distance (in meters) between activity locations and charging stations in the Hamburg districts.

For this study, 2030 charging demand with 2024 public charging locations of Hamburg city are used, and its GTFS data have been utilized to simulate electric vehicle (EV) charging behavior across urban charging infrastructure using an agent-based transport simulation (MATSim)-based framework to model agent behavior and charging demand. Energy-related metrics, such as district peak loads, temporal demand profiles, and activity-based charging patterns in the Hamburg districts are calculated for accessibility-driven EV charging optimization. A spatial-temporal perspective on the energy impacts of accessibility-driven EV charging optimization is given by this study through the combination of district-wide energy demand, hourly peak loads, and activity-based charging behavior.

To create sustainable urban EV infrastructure, the significance of combining user-centric accessibility optimization with an integral energy system perspective is highlighted by these new findings. With analysing energy demand and peak loads with accessibility based-optimization, insights can be derived, that can support grid-charging infrastructure planning and identification of districts where and when local grid stress may occur.

Keywords: charging infrastructure, EV charging behavior, agent-based transport simulation (MATSim), user-centric accessibility optimization, grid-charging infrastructure planning.

1 Introduction

1.1 Context

The market for electric vehicles is growing rapidly due to the pollution and emissions challenges. [1] Sales of electric vehicles, including plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) are surpassed 10 million in 2022 [2]. As the use of electric vehicles increases, public charging infrastructure is becoming ever more important, particularly in densely populated cities where home charging is limited. Even while most charging still takes place at home, a strong public network is needed by towns to provide accessibility at the level of conventional refueling. By the end of 2024, over 5 million public charging stations were reported worldwide, with over 1.3 million being added in 2024 alone. This was marked as a 30% increase over 2023 [3]. Charging infrastructure planning mainly includes optimal charging station locations, their accessibility, and charging power, as that influences usage behavior and grid impacts.

Charging station locations and convenience are analyzed in many studies, while few studies focus on charging behavior and its translation into temporal and spatial energy demand patterns, with a gap that may compromise the dependability of the energy system as well as the reliability of user services.

This increasing importance is highlighted by recent work [4]. A spatiotemporal forecasting model for EV charging demand is created using differentiated user attributes in a 2025 study. It was found by the study that substantial impacts on load variations and grid stress were caused by uncontrolled charging patterns. In another study [5] in China, EV charging demand is coupled with urban land-use and mobility data and charging behavior at different times of the day is analyzed, also framework is applied to get the correlation and distribution of charging demand with public charging stations between urban areas and its land-use. The spatio-temporal charging pricing strategy is also proposed [5]. Similarly, varying prices study with different charging sizes [6] includes experimenting with varying budget levels and different charging size configurations stated that tight budgets can cause concentrated loads and increase EV travel costs.

1.2 Significance and challenges – charging duration and distance minimization

The major challenge in urban EV charging is posed by the mismatch between location of vehicles' charging demands and location of chargers. The number of studies has shown that charging decisions, station utilization, and user approval are significantly influenced by charging accessibility, particularly by the activity location of the closest charger [7, 8]. Due to the large walking distances from users to charging stations, more accessible charging stations are preferred by users, which can result in a higher number of charging events per station in certain areas, leading to localized overloads. It has been seen from [9] that improving charging station accessibility leads to higher charger utilization rates. As studies on improving charging station locations with user convenience have been conducted, the influence of this accessibility optimization on temporal and spatial energy consumption patterns continues to be investigated. These effects of accessibility-driven charging behavior can cause shifts in the district-energy-demand, peak loads and charging stations utilization, that show importance for EV-infrastructure planning by agent-based analysis.

1.3 MATSim introduction

MATSim is an agent-based simulation framework particularly used for large-scale transport modelling. In MATSim, modeling daily behavior, including travel routes, activity locations and departure timings, is possible, and then it can be iteratively optimized [10], which makes it especially suitable for modeling EV charging events that depend on user behavior. MATSim is used in multiple studies to simulate charging behavior, charging station utilization, and energy system impacts with mobility patterns. Battery dynamics, state-of-charge monitoring, and customized charging decision logic are provided by the MATSim EV extension simulation setup used by [11], which allows research for the integration of complex algorithms such as accessibility-based charging selection or grid-sensitive charging techniques. The activity-based structure and ability to simulate large-scale urban mobility with precise travel routes and synthetic population provided by MATSim makes it well-suited for the analysis of charging behavior in daily schedules and location preferences [12]. Because of these features, MATSim is an appropriate tool for studying how optimization of charging stations' accessibility, like by minimizing walking distance from an user to charging stations, affects energy demands across urban districts.

1.4 Minimizing distance between agent activities and charging stations

The objective of this study is to investigate the energy aspects of electric vehicles charging in Hamburg city. The focus is placed on optimizing charger accessibility and minimizing average walking distance from the activity locations of agents to charging stations, and its impacts on temporal and spatial energy demand across Hamburg district are evaluated. A comprehensive evaluation of how charger accessibility with an walking distance optimization algorithm affects the energy consumption demand and peak load across the city-districts is given in this paper by considering simulation results from every charging event. Though the method is based on agent-based EV charging modelling [8], the energy-system implications of charger accessibility are mainly focused on by this study rather than its mobility behavior. In contrast to earlier research, this research analyzes how an accessibility-driven optimization algorithm influences the city's spatial and temporal energy demand.

In the next section of literature, studies regarding developed algorithms, MATSim algorithms integration and charging infrastructure influence over travel behavior is discussed.

2 Literature

2.1 Developed algorithms and logics

Accurate determination of charging demand and optimal charging station locations is an important research question in public EV infrastructure planning. Better charging station locations could increase charging stations utilization rate. [9] Thus, studies have mainly focused on finding public charging demand and finding optimal charging locations considering this charging demand. Because of this individual travel behavior is captured and precisely spatio-temporal charging demand profiles are produced, agent-based and micro-level techniques have been employed to research EV charging demand and infrastructure design. For example, in the paper given by [8], an agent based-modelling approach is used for public charging demand estimation and charging locations optimization for urban regions. The authors create charging demand profiles using mobility simulation data and used location-optimization framework to control utilization of charging stations [8].

Similarly, [13] developed a methodology for the deployment of public charging stations for battery electric vehicles considering real charging behavior and interactions between individual EV agents and charging stations. Charging behavior is modelled based on the state-of-charge, mobility choices, and congestion. Results suggest that incorporating the behavior dynamics into deploying charging stations decision causes better charging demand satisfaction.

A novel agent-based simulation framework for an urban electromobility is presented by [14], is designed to analyze charging station utilization and user behavior. A co-evolutionary learning model that modifies individual charging behavior over time is incorporated into their methodology. The study has been carried out for Munich scenario, shows the necessity of considering individual travel habits and adaptive charging behavior in the development of public EV infrastructure.

Research done by [15] proposed Bayesian optimization framework for optimal charging infrastructure development in urban areas. MATSim framework is used and is extended with a probabilistic charging demand model, including plug-in probabilities, an initial state of charge distribution, and charging durations with parking regulations constraints. The framework is applied in Frederiksberg, Denmark indicating the critical role of planning the charging stations in densely populated areas and shift of charging behavior in solving the problem of charging station’s locations planning.

It is shown by these studies that realistic EV charging behavior can be captured and appropriate charging station placement may be determined by agent-based and detailed modeling approaches. However, majority of current research either concentrates on station optimization or charging demand prediction, with less focus placed on addressing the energy-system consequences of accessibility-driven optimization in a high spatio-temporal resolution.

2.2 Algorithms integration in MATSim

Optimization algorithms have been integrated with agent-based travel simulation frameworks, like MATSim or comparable systems, by a number of studies to enable precise infrastructure design choices for charging infrastructure planning. For example, some recent work has focused on coupling agent-based simulations and infrastructure planning algorithms. [15] employed a Bayesian optimization methodology with MATSim, i.e. the probabilistic charging demand models are integrated into the Bayesian optimization for charging infrastructure planning in densely populated areas including plug-in probabilities, state of charge distribution and parking constraints [15]. In large-scale urban simulations, MATSim is extended by Bischoff and Maciejewski to incorporate electric car characteristics and charging processes, highlighting how system-level results are affected by infrastructure supply and charging constraints under realistic travel demand [11].

Furthermore, study done by [19] includes MATSim travel simulation outputs, which are combined with multi-objective-optimization algorithm to evaluate and optimize EV infrastructure charging scenarios for the Berlin metropolitan area. Capital cost of charging stations and mean detour are taken as an optimization criterion, charging decision model is developed and simulation is done with different generations. So how the results of simulation can direct the infrastructure optimization and enhance planning choices is shown by this study [19].

In the paper given by [21]., Electrical Road System (ERS) are integrated in MATSim by enabling in motion charging and reducing frequency of charging stops for long trips thereby reducing emissions and battery sizes. With the use and integration of ERS in the MATSim framework by simulating long distance trips and EV charging patterns, its usage energy and ERS effectiveness on EV infrastructure has been studied in this paper.

To enhance decision-making and infrastructure review for EV charging planning, advanced algorithms have been directly combined with agent-based transport simulation frameworks by a number of research studies. In recent work by [20], the fundamental foundation of MATSim has been extended to model individual EV charging behavior within daily travel plans, allowing for the dynamic choice of charging stations used and the modification of activity schedules by agents accordingly.

Overall, these studies indicate how MATSim has developed into a versatile platform for combining behavioral decision logic and optimization algorithms for EV charging study. Subsequently, this study focuses on the effects of accessibility-oriented initiatives, including reducing walking distance, on the spatial and temporal urban energy demand.

2.3 Influence – charging infrastructure on travel behavior

A study done by [16] in Tokyo- Japan, generates high resolution daily trips from real life survey are using a synthetic population and deploys them in MATSim. This study also proposes charging rules for different types of EVs and energy consumption models, and energy demand with public charging demand is analyzed over different time steps and activities. The study suggests that with increasing charging stations capacity and improving utilization and deploying new infrastructure are essential to meet the energy demands [16].

Similarly, in the research done by [17], the EV charging behavior is integrated into MATSim travel plans, where charging choices are determined by travel routes and SOC thresholds. In order to anticipate usage patterns and infrastructure needs, many simulation runs are used by the system to algorithmically identify and assess potential locations for fast-charging stations. This study enables a possibility to assess how the locations of charging stations affect traffic, accessibility, and charging demand, revealing how agent-based simulation may successfully direct infrastructure planning [17].

[18] did a study applies MATSim to simulate shared electric autonomous vehicles in the suburbs of Vienna, considering accessibility and price-influencing travel type choices and emissions. It is indicated by the findings that only a small percentage of vehicle trips are replaced by shared autonomous electric vehicles (SAEVs) despite differing fleet sizes and pricing tactics, while significant shifts from walking, cycling, and public transportation are impacting total travel patterns. Also, in this

study the new Modal split service effects on energy consumption and travel are evaluated through MATSim simulations [18].

To analyze the relationships between travel behavior, charging infrastructure utilization, and energy demand, MATSim is used by [22] to model realistic daily activity plans and charging decisions. The significance of behavior-infrastructure interactions in EV infrastructure development is highlighted by the findings, which demonstrate that a substantial impact on the temporal and spatial distribution of energy consumption is made by behavior-driven charging decisions.

The significance of accessibility-driven analysis in urban EV infrastructure planning is further demonstrated by these findings, which indicate that charging demand pattens is influenced by infrastructure placement and accessibility [9].

Methodology followed by logic of walking distance minimization is described in the next section.

3 Methodology

3.1 Charging behavior

After arriving at an activity location, the agent decides whether to enter charging-station search mode.

If the agent is already in search mode, a station-search routine is executed.

If not in search mode, the agent either (i) triggers search deterministically for low SoC, or (ii) triggers search probabilistically via a logistic function.

Once the search is triggered, feasible charging alternatives are generated and evaluated, and one option is chosen.

3.1.1 Functional building blocks and equations

3.1.1.1 Probability of initiating search

The probability of starting a charging search is modelled as a logistic function of the state-of-charge (SoC):

$$P\_charge = 1 / (1 + exp(\gamma \cdot (SoC - \theta))) \tag{1}$$

where γ is a sensitivity parameter and θ is an individual critical SoC threshold.

3.1.1.2 Willingness-to-Pay (WTP)

Individual WTP is modelled as a monotone function of SoC, increasing as SoC decreases:

$$WTP = WTP\_max / (1 + exp(6 \cdot (SoC - WTP\_crit))) \tag{2}$$

3.1.1.3 Maximum acceptable walking distance

The maximum acceptable walking distance depends on SoC:

$$D\_max = (a / SoC) \cdot 1000 + D\_min \tag{3}$$

where a controls the slope and D_min is the minimum accepted walking distance.

3.1.2.4 Minimum required charging power during the activity

To cover a target energy amount during the planned activity, the agent computes:

$$P\_min = 0.2 \cdot batcap \;/\; t\_aktiv \tag{4}$$

where batcap is the battery capacity and t_aktiv is the activity duration.

3.1.2.5 Aggregated cost function for station choice

Among feasible alternatives, the agent selects the option with the minimum aggregated cost, combining monetary charging cost and walking-time disutility:

$$COST = t\_aktiv \cdot COST\_kWh + 2 \cdot (D \;/\; 4) \cdot PriceConstant \tag{5}$$

Interpretation: the walking component converts walking distance D into walking time using a reference speed of 4 km/h (D/4), counts a return walk (factor 2), and monetises time via PriceConstant.

3.1.2 Parameter values used in the simulations

Parameters of the charging-behaviour algorithm (as reported):

Table 1: Parameter values used in the simulation

Parameter	Value	Unit
θ	0.45	–
γ	10.00	–
WTP_max	2.00	€
WTP_crit	0.50	–
a	0.50	–
D_min	0.00	m
PriceConstant	15.00	€/h
AnxietyPercentage	20.00	%

Table 2: List of variables

Symbol	Description	Unit
SoC	State of charge of the vehicle	–
WTP	Willingness-to-pay for charging	€
D	Walking distance between activity location and charging station	m
D_max	Maximum acceptable walking distance	m
t_aktiv	Activity duration	h
batcap	Battery capacity	kWh

Note: the report equation for D_max includes D_min; the reported parameter table provides the minimum accepted walking distance as 0 m.

Across the compared scenarios, charging decision rules are identical: agents can choose when to charge and which charging option to use (home, workplace, public, depot) under the same behavioural model.

3.2 Walking distance minimization logic

The location of public EV charging stations in the Hamburg metropolitan region is optimized by this paper using an iterative methodology. The Hamburg-Takt concept [25], which ensures that public transport can be accessed by individuals within five minutes of walking distance, is used as a basis for this approach. In the same way, the accessibility and convenience of charging infrastructure are intended to be improved by the algorithm by minimizing the walking distance between EV charging stations and user activity locations. In order to study spatial charging needs and energy implications from this minimization of walking distance, a hexagonal grid is placed on the city and all movement of individual agents from MATSim is assigned to these hexagons. As uniform neighbor connectivity is provided by the hexagonal grid structure, and geometric artifacts at boundaries are reduced, yielding smoother partitions compared with square grids [26].

The goal is to add public charging primarily in zones where users systematically experience longer-than-target walking distances between activity locations and the charging stations they use. Zones with higher excess walking distance receive higher priority for new capacity.

The walking distance minimization process is shown below. Current charging station locations, individual agent activity plans, and mobility data are imported by the model during the initial stage. After the mobility simulation, during which agents make decisions to charge on a particular station during particular activities in accordance with the behavior model described above, the average walking distance between each charging event and the closest station is computed.

3.2.1 Step A: computing zone priorities probability(z)

For each zone z (e.g., a hexagon), the baseline simulation provides:

distance(z): a representative walking distance between activity locations and the used public charging stations in the zone;

sessions(z): a demand proxy such as the number of charging sessions/events in the zone.

We define a target accessibility threshold D_0 (in the simulated scenario D_0 = 50 m).

The zone's excess walking distance is:

$$excess(z) = max(0, distance(z) - D_o) \qquad (6)$$

Priorities are obtained by normalising excess distance across all zones within the same run/project:

$$probability(z) = excess(z) / (\textstyle\sum\_u excess(u)) \qquad (7)$$

Interpretation: zones that exceed the target walking distance more strongly receive a larger probability mass. Zones with distance(z) ≤ D_0 obtain excess(z) = 0 and therefore probability(z) = 0.

3.2.2 Step B: allocating N new public charging plugs

Given a fixed total number of new public charging plugs N, the algorithm distributes them across zones in descending order of probability(z), while scaling the desired allocation by local demand and respecting constraints.

Variables and parameters:

N: total number of new public charging plugs to create.

R: remaining plugs to place (initially R = N).

zones: list of zones after filtering (e.g., probability(z) > 0.001), sorted by decreasing probability(z).

sessions(z): demand proxy for zone z (e.g., count or number of sessions, depending on strategy).

k: scaling parameter (“sessions per new plug”).

M: maximum number of new plugs allowed in a single zone (set as 90 plugs).

want(z): desired number of new plugs for zone z.

take(z): actually placed number of new plugs in zone z, considering constraints.

Desired number of new plugs per zone:

$$want(z) = \lfloor sessions(z) / k \rfloor + 1 \tag{8}$$

Constraints are applied as: want(z) ← min(want(z), M) and take(z) ← min(want(z), R).

3.2.3 Embedding into the iterative optimisation loop

In the full accessibility optimisation workflow, Steps A–B defined in 3.2.1 and 3.2.2 can be executed iteratively. The iterative workflow is given as follows:

1. Run (or analyse) the baseline simulation to obtain distance(z) and sessions(z) per zone.
2. Compute probability(z) from excess(z) relative to the target D_0.
3. Allocate N new plugs across zones using the allocation procedure above and update the public charging network.
4. Re-evaluate walking-distance indicators on the updated network (e.g., via a re-run / assignment step).
5. Stop when the stopping criterion is met (e.g., target mean/quantile walking distance) or max iterations is reached; otherwise repeat.

Overall, each iteration shifts public charging capacity toward zones with systematically higher walking distances, while ensuring that additions are demand-relevant and bounded by practical constraints

The iterative approach, which is studied in the current paper, is not only associated with increased accessibility but also with the allowance of a thorough analysis of the energy implications. The model is depicted in terms of how optimal station location impacts temporal and spatial energy demand across metropolitan areas by connecting each charging event to activity type and time of day. Changed charge distribution patterns are frequently resulting from reduced walking distances, which may lead to the redistribution of peak loads and energy demand across the city districts. Urban EV infrastructure can be developed by planners that enhances user convenience and supports effective, sustainable energy management by combining accessibility optimization with energy system analysis.

4 Results and discussion

The results reported in this section are based on a MATSim simulation scenario that consists of existing charging stations data.

4.1 Scenario definition

MATSim scenario size and sampling.
The simulations are based on the Open Hamburg MATSim scenario using a 50% demand sample, resulting in 1,953,604 agents in the model, including 153,560 freight agents.
Both scenarios have the same number of used electric cars on the simulated weekday (304,600),

confirming that demand and fleet size are held constant across scenarios.

4.1.1 Baseline scenario (2030 demand on 2024 public charging locations)

We define the baseline as a future-demand scenario with 2030 electrification assumptions while keeping the public charging network fixed to the observed 2024 public charging station locations. To ensure a capacity-consistent comparison, the additional number of public charging plugs in the baseline is set to 2,214 plugs by scaling the number of plugs at the existing 2024 public stations (i.e., capacity is increased at fixed locations, without changing spatial accessibility).

4.1.2 Accessibility-optimized scenario (same demand and capacity, optimized placement)

The accessibility-optimized scenario uses the same 2030 demand as the baseline and the same total public charging capacity (2,214 plugs). Unlike the baseline, these 2,214 public charging plugs are spatially reallocated using an iterative placement algorithm that prioritizes areas with higher observed walking distances between charging and activity locations. This creates an apples-to-apples comparison in which the optimization affects only the spatial accessibility of public charging, while all demand assumptions and behavioural charging parameters remain unchanged.

In all comparisons, demand is identical (2030) and the total number of new public charging plugs is identical (2,214); the scenarios differ only in the spatial placement of public charging capacity.

Results mentioned in the below section are on a typical working day.

In large-scale agent-based transport simulations, the computational constraints of simulating millions of travelers are frequently navigated by employing population downscaling. Important traffic characteristics are demonstrated to be preserved by Ben-Dor et al. while urban transport dynamics are captured using a small portion of the population. It is stated in their analysis that essential traffic data is maintained by downscaling at 25% or more, however, notable variations can result from downscaling at less than 10%. This leads to the encouragement of a downscaled population that is large enough to balance computing efficiency and accuracy in frameworks such as MATSim [23]. Similar approach is used in this study. Simulations are performed with 50% down sampling and scaled later to obtain the correct matrices.

The main areas of the analysis are the district-level charging patterns and energy consumption of the Hamburg metropolitan region. The average walking distance between activity places and charging stations, the number of charging events per district, and subsequent energy and peak power profiles are assessed for the baseline scenario. Once the walking-distance minimization approach is used for charging infrastructure, these metrics are computed, allowing for a direct comparison of the baseline and optimized situations.

Based on this, the effects of enhanced charging accessibility on patterns of spatial and temporal energy demand are analyzed by the findings. Possible effects on local grid stress and load balancing are evaluated, along with district-level peak power needs, particular activity charging behavior, and charging load distributions throughout the day. Insights on how accessibility-oriented infrastructure planning influences energy demand density and temporal load profiles throughout the metropolitan network, in addition to improvements in user convenience, are provided by the findings through the analysis of the two scenarios.

4.2 Charging event distribution and average walking distances

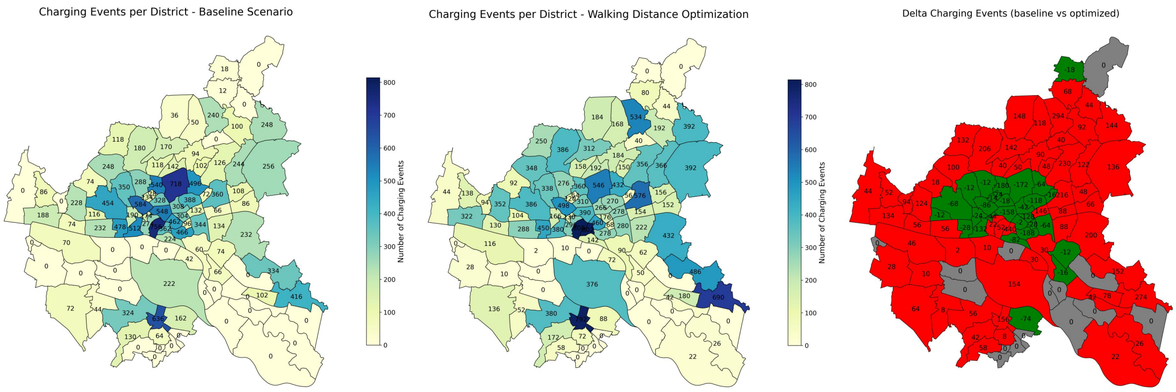

Fig 1. Charging events per district on a workday - baseline, walking distance optimization scenario, and delta plot

Figure 1 shows the number of charging events aggregated in the districts of Hamburg for the baseline scenario and the walking distance optimization scenario. With the walking-distance optimization, a spatial redistribution of charging activities is shown by the delta plot. Delta plot is the difference of number of charging events per district. Green color describes reduction in charging events across the districts from the baseline scenario to optimized scenario, whereas red color describes an increase in the charging events. While a decrease in charging events is observed in some of the centrally situated districts, an increase in charging events is noted in most of the districts and peripheral areas. This implies that charging demand is shifted from densely populated center locations to underutilized districts, which helps to balance the local grid load and reduce peak load across the city.

With the walking-distance optimization, the total number of charging events are increased. Similarly, the average number of charging events per charger are reduced from 25 to 13 (i.e. median dropped from 26 to 14), and the standard deviation is dropped from 11 to 7. This implies that comparatively more balanced utilization of the charging infrastructure with walking distance optimization, where the demand for charging is distributed over a number of charging stations, thereby lowering peak utilization pressure and local congestion at individual chargers.

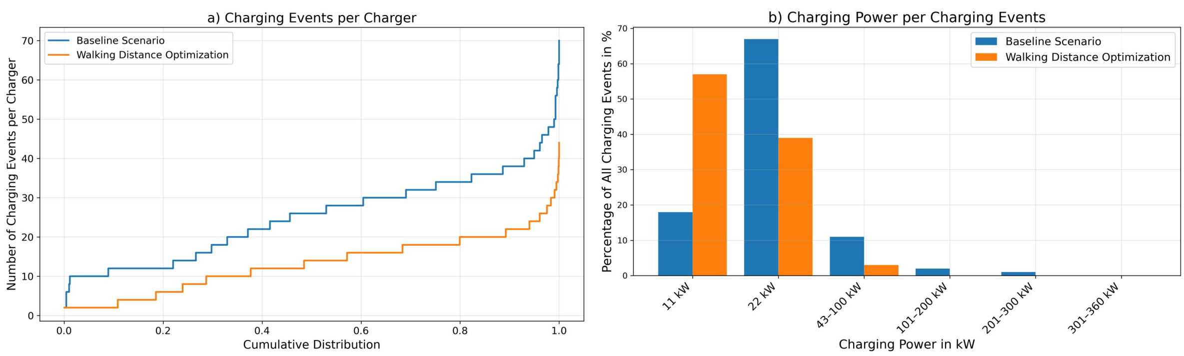

Fig 2. Distribution of charging events on a workday - baseline and walking distance optimization scenario

The results show that minimizing walking distance has an impact on charging power distribution as well as charger utilization. Fig.2.a) indicates that for the majority of chargers in the optimized scenario, the number of charging events per charger remains very low compared to the baseline scenario. In the baseline scenario, few chargers show a high concentration of charging activity, with some chargers servicing up to almost 70 charging sessions during the examined day, as shown in Fig 2.a) The optimal scenario, on the other hand, restricts the maximum number of charging events per charger to about 45, suggesting a more even distribution of charging activity throughout the available infrastructure and a reduction mainly in the extreme utilization of individual chargers.

Similarly, fig. 2.b) shows that the optimal scenario results in a higher number of charging events at low-power chargers. Particularly, the percentage of charging events at 11 kW chargers is increased from more than 10% in the baseline scenario to around 56% in the optimized scenario, whereas the percentage of charging events at 22 kW chargers decreased from roughly 68% to 38%. Additionally, the percentage of charging events seems to decrease for other charging powers like 43 kW - 100 kW, and with the optimized scenario. These results suggest that rather than putting more emphasis on fast-charging facilities, increased accessibility is mainly redistributing charging activity and balancing load throughout the current infrastructure.

In the improved-accessibility scenario, the total number of charging sessions at public charging stations is higher overall. At the same time, a substitution effect is observed: charging sessions at workplace and home locations are slightly lower. This highlights a key implication for spatial and temporal grid-load assessment: charging accessibility directly affects when and where energy demand materialises. Notably, the total amount of energy transferred in the simulation remains practically unchanged between scenarios.

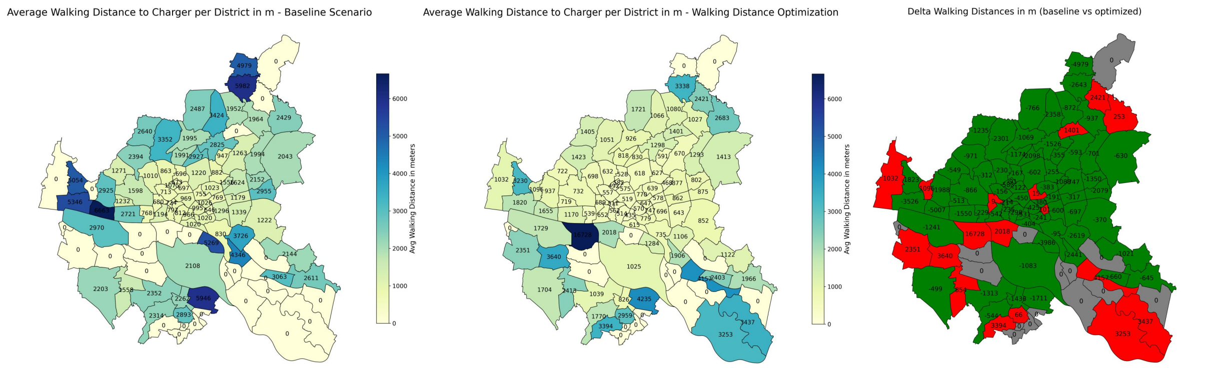

Fig 3. Walking distances per district on a workday - baseline, walking distance optimization scenario, and delta plot

Similarly, Figure 3. shows the walking distances for the baseline scenario and after implementation of the walking optimization algorithm. For each charging event, the walking distance is calculated between the activity point and the assigned charging point. The network was constructed using OSMnx [27], and shortest-path distances along walkable streets were computed with NetworkX to get realistic walking distances for accessibility analysis. These computed distances for the following analysis may differ from MATSim due to network details, but OSMnx provide detailed, realistic walkable paths. [27] Since districts are made up of one or more hexagons, aggregated district-level averages may still exhibit local variances. The optimization is carried out at a finer hexagonal level, where local charging stations are changed iteratively to balance walking distances.

It can be seen from the delta plot that the average walking distance across most districts is reduced by walking-distance optimization, notably in locations where excessive walking distances have been observed in the baseline scenario. While a decline in walking distances continues to be seen in central districts even when local charging activities are decreased, a slight increase is observed in certain peripheral areas, along with some local exceptions to the general trend. So optimization tends to reduce the extreme walking distances and more uniform distribution.

Overall, mean of walking distances through the Hamburg city per district is reduced from 1618 meters to 1067 meters. Similarly, median changes from 770 to 633 meters, the standard deviation is reduced from 3722 meters to 2385 meters, indicating that optimization primarily affects the districts with extreme walking distances, while improving the user experience. This accessibility optimization benefit the districts with poor charging accessibility by reducing spatial disparities in walking distances.

4.3 Spatial distribution of energy demand and peak loads

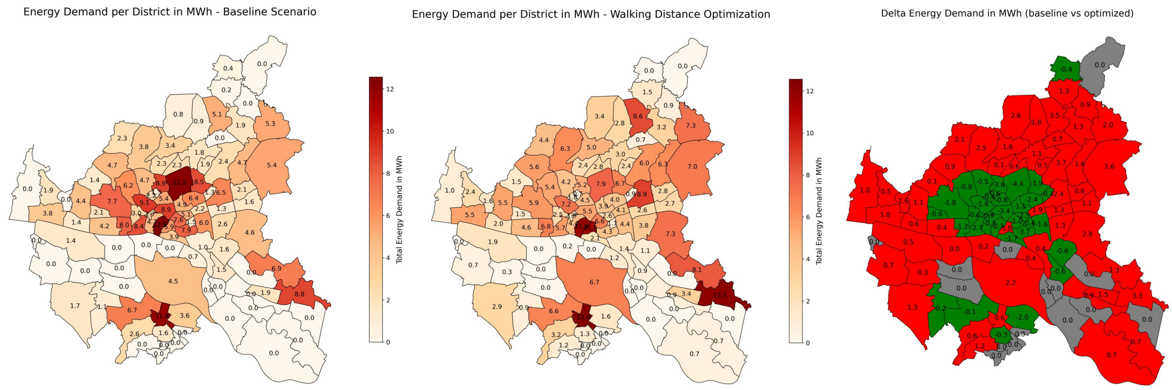

Fig 4. Energy demand per district on a workday - baseline, walking distance optimization scenario, and delta plot

Figure 4 shows the total charging demand aggregated per district in Hamburg for the baseline and walking optimization scenarios. Following optimization, an increase in overall energy demand is shown by several peripheral and most of the districts, while a decrease of energy consumption is shown by centrally situated districts as shown by delta plot. This energy demand plot shows a direct relation with charging events changes as shown in Figure 2. As the charging events are reduced from baseline scenario to optimized scenario, the energy demand is also reduced for those districts. So, it is shown by the findings that a redistribution of energy demand among districts is caused by the implementation of the walking distance minimization algorithm corresponding to charging events.

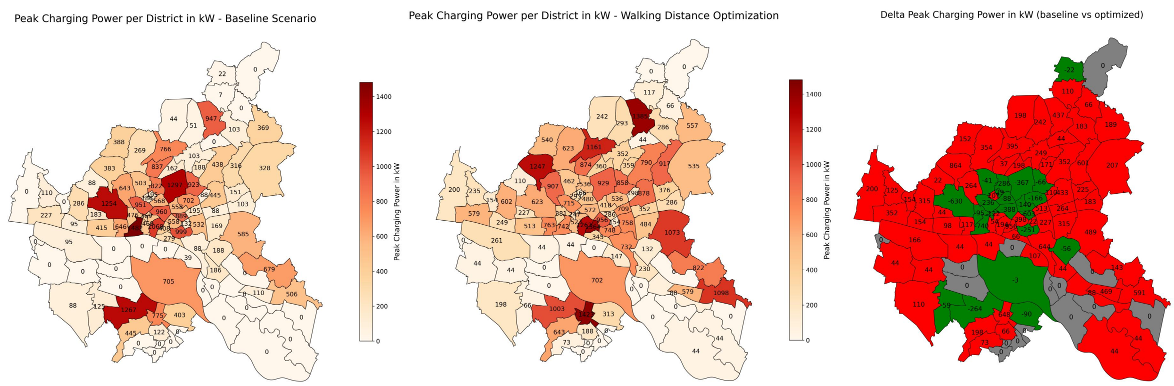

Fig 5. Peak power per district on a workday - baseline, walking distance optimization scenario, and delta plot

The peak power per district for both the baseline and walking-distance optimization scenarios is shown in Figure 5. Following optimization, a decrease in peak power is observed in central districts, while an increase in the peak power across peripheral districts is observed in the optimized walking scenario, similar to energy demand and charging events figures, which indicates a redistribution of charging loads. It is shown that rather than consistently reducing peak loads in every district, accessibility-driven optimization mostly modifies where charging takes place, and peak loads and energy demand has been changed accordingly. It is shown by the findings that peak power and energy demand most of the times moves in the same direction.

This implies the reduction of grid stress in central areas, which consists of higher network utilization and dense infrastructure. Conversly, peripheral areas experience an increase in the peak loads, which could potentially stress the local network in peripheral areas.

4.4 Charging activity distribution – hourly demand

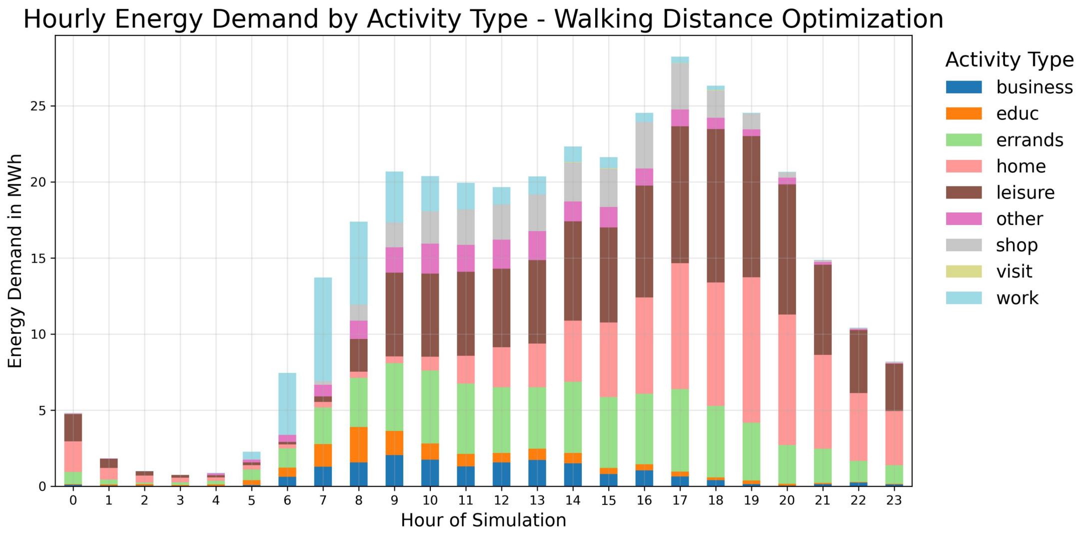

Fig 6. Hourly energy demand on a workday - Walking distance optimization scenario

The hourly energy demand in MWh after optimization of walking distance is shown by Figure 6. Hourly energy demand is calculated by integrating the simulated charging load over each hour. Daytime charging (06:00–14:00) is distributed among work, business, errands, leisure, and shopping activities, with a diverse charging pattern is observed. Home charging is dominated by evening hours (16:00–22:00). This post-work charging behavior is typical, as vehicles are connected for extended periods of time, resulting in an increase in the total amount of energy consumed. On the other hand, the energy demand is very low at midnight hours (about 00:00–04:00). During off-peak hours, lower energy demand is observed. In general, a distinct temporal separation between home and leisure charging in the evening, low charging demand in the midnight hours and work charging in the early-morning hours is shown through analysis, while in daytime more heterogeneous charging profile is observed.

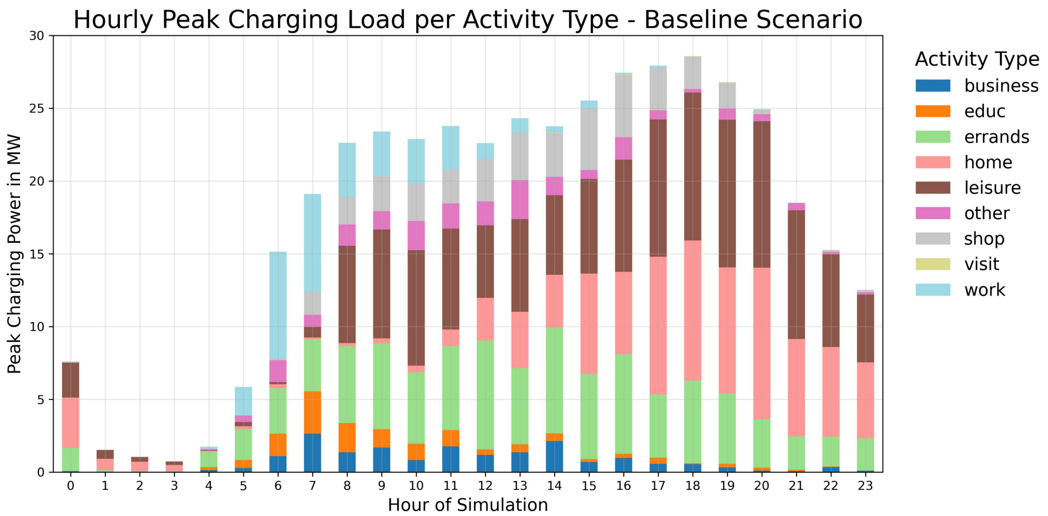

Fig 7. Hourly power peaks on a workday - Walking distance optimization scenario

The hourly peak charging power during a typical workday using the walking-distance optimization scenario is shown in Figure 7. The greatest peak loads are observed in the evening (16:00–19:00), mainly due to home and leisure charging, while during night-time (00:00–05:00) power peaks are low. Most of the daytime charging (6:00–15:00) is accounted for by work, errands, leisure, business, followed by shopping in the afternoon hours. It is shown by these temporal patterns that while nighttime peaks are low for public charging and can help to utilize the available capacity, stress may be put on the local grid by home charging in the evening. An understanding of these load patterns is considered necessary for planning EV charging infrastructure.

5 Conclusion and future scope

In this study, agent-based transportation (MATSim) is used for simulations with 2030 charging demand and 2024 public charging locations GTFS data, which consists of a baseline scenario and an optimization scenario for optimization of walking distances between agents and charging stations. The study shows that minimizing the walking distances between agents (i.e., EV users) and charging stations causes the effective redistribution of charging activity in Hamburg districts. With walking distance optimization, a decrease in the average walking distance is shown by most districts, especially in areas with extreme walking distances. In few peripheral districts, walking distances are observed to be increased, whereas lowering the walking distances tends to be exhibited by central districts for more balanced utilization. A decrease in the median walking distance per district from 770 m to 633 m is observed after the optimization of walking distances, standard deviation of walking distances reduced from 3722 meters to 2385 meters. This results in a more uniform distribution of walking distances by lowering extreme values of walking distances by spatial optimization of charging stations across the Hamburg districts.

Similarly to walking distance optimization, the charging demand between districts is changed. The peripheral areas showed an increase in charging events, whereas charging events in the central areas are reduced. Similar behavior to charging events is exhibited by energy demand and peak loads. Central districts showed a reduction in peak loads and energy demand, whereas peripheral districts showed an increase in the charging demand. This implies the reduction of grid stress in central areas, which consists of higher network utilization and dense infrastructure. Conversely, peripheral areas experience increases in the peak loads, which could potentially stress the local network in peripheral areas. Similarly, an optimal scenario results in a higher number of charging events at low-power chargers. The city‘s overall energy consumption seemed to be almost the same, but the accessibility-driven optimization affects how charging demand is distributed between districts. This optimization influences the temporal and spatial patterns of EV charging demand, offering helpful insights for infrastructure planning.

Similarly, temporal analysis shows that the energy use is dominated by home and leisure charging in the evening, and work charging in the early-morning hours. Charging demand is low during the midnight hours, while during the daytime more heterogeneous charging profile is observed. For better charging infrastructure and grid planning, overnight charging might be beneficial, as power peaks and energy demand is low for public charging during off-peak hours.

In the future, by adding planned city layouts, full-year data with seasonal mobility patterns, future urban growth scenarios, and renewable energy generation, this suggested accessibility-driven optimization can be extended, allowing an evaluation of potential spatial and temporal charging demands. The strategy is adaptable to different locations and could facilitate a more balanced redistribution while preserving user convenience. Similarly, dynamic pricing could be considered in the future along with this optimization, which may result in the reduction of peak load and thus improve grid stability. [24] To further improve charging infrastructure placement, future studies should investigate different accessibility criteria, such as multimodal walking distances.

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