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Article

Analysis of Charging Infrastructure for Private, Battery-electric Passenger Cars: Optimizing Spatial Distribution using a Genetic Algorithm

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Abstract: To enable the deployment of battery-electric vehicles (BEV) as passenger cars in the private transport sector, a suitable charging infrastructure is crucial. In this paper a methodology for efficient spatial distribution of charging infrastructure is evaluated by investigating a scenario with a market penetration of BEVs of 100 percent (around 1.3 million vehicles). It aims towards the development of various charging infrastructure scenarios - including public and private charging - which are suitable to cover the charging demand. Therefore, these scenarios are investigated in detail with focus on number of public charging points, their spatial distribution, the available charging power and the necessary capital costs. For the creation of those charging infrastructure scenarios a placement model is developed. It uses the data of a MATSim (Multi-Agent Transport Simulation) traffic simulation of the metropolitan area of Berlin to evaluate and optimize different distributions of charging infrastructure. The model uses a genetic algorithm and the principle of multi-objective optimization. The capital cost of the charging points and the mean detour car drivers must cover additionally are used as optimization criteria. Using these criteria should lead to cost efficient infrastructure solutions which provide high usability at the same time. The main advantage of the method selected is that multiple optimal solutions with different characteristics can be found and suitable solutions can be selected by using other criteria subsequently. The optimized charging infrastructure solutions show capital costs between 624 and 2950 million euro. Users must cover an additionally mean detour of 254m to 590m per charging process to reach an available charging point. According to the results a suitable ratio between charging points and vehicles is between 11:1 and 5:1. A share of fast charging infrastructure (>50kW) of less than ten percent seems to be sufficient, if it is situated at main traffic routes and highly frequented places.

Keywords: charging infrastructure; e-mobility; electric vehicle; optimization; private electric car; transport simulation; distribution of charging Infrastructure; battery electric; genetic optimization; high-power charging

1. Introduction

During the last decades, air pollution in cities and greenhouse gas (GHG) emissions continued to rise worldwide. To slow down this development and reduce the negative impact on human health and the global warming, especially governments of industrialized countries are seeking for technological solutions to reduce their overall GHG emissions. One of the biggest emitters of pollutants and GHGs is the motorized individual transport [1]. The European Union tightened the emission limits for the transport sector continuously since the introduction of the *Euro 1* exhaust emission standard in 1992 [2]. Furthermore, the German government aims to reduce GHG emissions in the transport sector by 40% until 2030 [3]. To reach this goal, alternative power train concepts are needed. Therefore, the German government focuses on the promotion of electric mobility. The preferred strategy for the private transport sector is the deployment of battery electric vehicles (BEV). The

Klimaschutzprogramm 2030 by the German government includes, inter alia, the *Masterplan Ladeinfrastruktur* which constitutes objectives for the expansion of charging infrastructure in Germany. It is assumed that there are approximately ten million BEVs in Germany in 2030. To supply these vehicles with the necessary electric energy, one million charging points should be erected. According to these assumptions, a ratio of vehicles to charging points of 10:1 would be appropriate [4]. These plans show that the expansion of charging infrastructure is crucial for the transition to electric mobility. However, it remains difficult to determine an exact number of necessary charging points and power due to the dependency to diverse variables: technical factors such as charging time, which in turn is determined by the battery capacity of the car, the state of charge of the battery and the available charging power, as well as non-technical factors such as the charging behavior of users.

The authors of this paper developed a genetic algorithm (GA) to automatically place the required charging infrastructure to supply BEVs in densely populated areas and applied it to the urban area of Berlin. This approach provides information about the number of required charging points, their usability and the spatial distribution of the charging infrastructure. To verify the functionality of the developed algorithm, it is used to investigate the required charging infrastructure in the city of Berlin. The input data for the algorithm is provided by the MATSim Open Berlin Scenario, an agent-based transport simulation [5]. In the investigated scenario, it is assumed that all private passenger cars in Berlin and Brandenburg are BEVs. Private vehicles with admission in Brandenburg are considered to account for the impact of commuters on the availability of public charging infrastructure. The results of the simulation of the MATSim Open Berlin Scenario contain full day plans of agents which represent the population of Berlin and Brandenburg aged 18 and above according to the *Zensus 2011*. The scenario realistically represents the traffic in the city of Berlin and contains all relevant forms of traffic e.g. walking, riding bicycle, private cars and public transport. The schedule of the public transport is based on the real schedule [5]. It is important to mention that the vehicles used in the MATSim scenario are conventional vehicles with internal combustion engines. Therefore, the activities of the day plans do not include the charging of the BEVs. The authors of this paper use the GA to find a suitable charging infrastructure without changing the daily plans of the agents which are based on the usage of internal combustion engine vehicles (ICEVs). Applied to the real world, this means that a switch from ICEVs to BEVs would not imply any change in the mobility behavior of traffic participants.

2. State of the Art

With the prospect of ever-increasing numbers of BEVs in metropolitan areas worldwide, strategic planning of charging infrastructure is becoming the focus of urban planning, policy making, and academia. One major problem is the spatial positioning of infrastructure. Consequently, a large number of publications have been issued in the past decade, using different data sources, different methodological approaches, different levels of detail and different degrees of realism to approach this problem. Due to the large number of published studies and the importance of the research topic, several major meta studies have been published in recent years. Since the aim of this report is not to conduct another comprehensive literature review, but rather to further explore the research topic and present relevant new findings, we refer in this section to the most important meta studies and summarize their findings to outline the need for further research.

Pagany *et al.* [6] identify 119 studies published between 2010 and 2016 that address the spatial positioning of charging infrastructure. Only about half of these publications use empirical data and refer to a real use case, while the other half merely develop mathematical models and test them in synthetic environments. A major problem is seen in the availability of data. Many of the empirical studies are based on statistical and census data, while others use very limited data sets with real trajectories, such as cabs (compare [7]). The latter usually use data sets from ICEVs and assume an unchanged usage behavior of the vehicles when switching to BEVs. An important distinguishing factor of the studies examined is their orientation to either travel routes (trip from point a to point b) or to users and their points of interest (work, housing, shopping, leisure activities) as a basis for the placement of infrastructure. So far, there is a lack of approaches that link trips and thus specific consumption with dwell times at points of interest. It is also noted that almost all studies optimize infrastructure based on cost parameters. Other factors such as the walking distance between charging stations and the actual point of interest are mentioned here as possible further optimization variables for future research. Finally, it is pointed out that there is still a research gap in the modeling of charging times and different charging powers, as this is not a consideration in hardly any studies. It is suggested to shift from studies based on one optimization parameter and a limited data base to integrated studies.

Khadem *et al.* [8] analyzed 58 studies between 2013 and 2019. One finding obtained in this meta-analysis is that in recent years an increasing number of publications have focused on mathematical approaches such as the genetic algorithm (GA), the multi objective GA as well as heuristic approaches. Very few recent studies rely on different approaches such as behavioral models. The greatest potential for further improvement of studies on the spatial allocation of charging infrastructure is the consideration of different charging powers and the resulting duration of the charging process. In addition, travel frequency and trip length should be included in the considerations. Another important aspect mentioned was the user acceptance of certain locations for the infrastructure.

In the most recent study considered here, Unterluggauer *et al.* [9] conducted a comprehensive analysis of 49 studies between 2013 and 2022 considering the placement of charging infrastructure with a focus on studies that also consider the energy grid. As a summary of their study, they formulate several directions in which further research should be oriented. The first research gap identified is that planning objectives are mainly focused on the minimization of grid losses and infrastructure cost. So far, there are insufficient probabilistic approaches, which would also be able to temporally and spatially resolve network usage, and thus identify the need for network reinforcements. Second, it is proposed to increase the level of detail on the demand side in future studies. So far, many studies use simple models for traffic that cannot represent real situations. Therefore, complex effects of real traffic systems cannot be adequately represented. Another important finding is that too few studies examine different charging performance. Finally, the authors suggest that a more realistic focus of the studies should be achieved in general, instead of merely underpinning theoretical problems with simplified example networks.

In summary, a number of lessons and challenges for further research can be derived from the metastudies reviewed. First, a trend toward nature-inspired optimizers such as the genetic algorithm has been observed in recent years. Many studies show that these algorithms are well suited for the present research topic of charging infrastructure positioning. Furthermore, all of the studies examined agree that future research should focus on the demand side, i.e., on the underlying traffic model or the traffic data used. It is shown that in order to increase the plausibility and the realism of the results, real or at least very realistic input data must be used to correctly represent the complexity of traffic and the resulting implications for charging. Another research gap identified by all meta studies is the consideration of different charging powers. Although this is associated with a more complex optimization task, it enables more realistic results which can be better used as a basis for planning. The last research gap identified across all studies is the expansion of the optimization task to include other factors such as the additional distance to the actual destination if a specific charging infrastructure is chosen. This makes it possible to present and consider the benefits of the planned infrastructure for drivers. In this study, we plan to address these research gaps by using the detailed travel patterns of an agent-based microscopic transport simulation as an input for a genetic multi criteria optimization of charging infrastructure placement considering different charging powers and optimizing for both infrastructure cost and necessary detour for the users.

3. Methodology

To investigate the need of charging infrastructure in Berlin a genetic algorithm is used. To optimize the quantity and the distribution of charging infrastructure, in the first step, it is necessary to define an optimization problem with suitable optimization criteria and to choose an optimization method [10, p. 517 f.]. Furthermore, an electric vehicle population is required, considering the real distribution of vehicle classes in Berlin and Brandenburg. Moreover, a GA needs a starting population of solutions to start the optimization. The starting population can have a high influence on the process of optimization and should be set appropriate to the optimization problem. In addition, it is crucial for the simulation of the GA to develop a charging decision model which determines the criteria for starting a charging process.

3.1. Optimization Problem

There are many possible criteria to evaluate the quality of electric charging infrastructure [11]. These criteria can be divided into the categories operator, power grid and traffic flow. The operator level should represent the mainly economic interests of the operator of the charging infrastructure. The main criteria to evaluate charging infrastructure are the capital costs, operating costs and the occupancy rate of the charging infrastructure. The latter is crucial to estimate the possible return of investment for the operator. The power grid level represents the limits of the available power supply grid. The decisive criteria are the available installed power at the location of the charging infrastructure and the total load on the power supply grid. Furthermore, the traffic flow level should represent the usability of the charging infrastructure which determines the grade of acceptance by users of the charging infrastructure. The criteria for the traffic flow level are the detour agents have to cover to reach the next available charging point and the number of vehicles not able to cover their charging needs. This means the vehicle would reach a state of charge (SOC) of zero percent. To minimize the complexity for this first version of the developed algorithm, only two criteria are chosen for the optimization. The main criteria of the GA are the capital costs and the detour which is necessary to reach the next available charging point. This will be called agent detour in the following. The goal for both of these criteria is to minimize them. These criteria are very suitable for the evaluation of charging infrastructure and enable a search for the best compromise between economic efficiency and usability of the charging infrastructure. Since this paper does not aim to figure out how to operate charging infrastructure in a way that is profitable for the operator, the operating costs and the occupancy rate of the charging infrastructure can be neglected. Moreover, the limits of the currently available power supply grid in the city of Berlin are not considered in this paper.

3.1.1. Optimization Method and Genetic Algorithm

For the problem at hand, multi-objective optimization (MOO) is used. The MOO allows to find any number of optimal solutions in relation to the criteria used. This results in solutions with very high capital costs and low agent detour and vice versa with other pareto-optimal solutions in between. Specifically, one solution of the described optimization is a specific distribution of charging infrastructure across the area of the city of Berlin. The solutions contain the number of charging points, their charging power and their location. The MOO can optimize according to multiple criteria at the same time and a weighting of the criteria is not necessary. A pareto-optimal solution dominates other solutions and is non-dominated by other solutions. Domination means that a solution is at least equal in all objective function values and better in at least one objective function value than the solution it is compared with [10]. To evaluate the most suitable pareto-optimal solutions for the present use case, further information, which is not considered during the optimization of the GA, must be included. This shows that it is reasonable to find many solutions distributed over the whole search space. Figure 1 shows an example for a front of pareto-optimal solutions in relation to the criteria chosen for optimization.

The GA used to execute this optimization is called Elitist Non-Dominated Sorting Genetic Algorithm (NSGA-II). It is chosen due to the fact that it contains in addition to a mechanism that preserves the best individuals of a population, a mechanism for the preservation of diversity of the population. The principle of the NSGA-II is described by Dan Simon in [10].

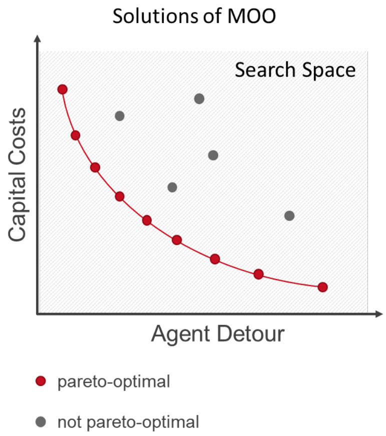


Figure 1. Qualitatively Representation of a Pareto Front

3.1.2. Criterion One: Capital Costs

The capital costs are determined by the number of charging points and their installed power. The prices of the charging points are fixed depending on the installed power. The assumed costs for each charging point are shown in Table 1. The charging infrastructure is divided into normal and fast charging (≥ 50kW).

Table 1. Capital costs per charging point and installed power

Charging Power [kW]	Capital Costs [€]
3.7	1 700 [12]
11	5 000 [13]
22	5 000 [13]
50	45 000 [14]
150	120 000 [14]

The chosen charging powers are based on the charging powers mentioned by *Nationale Plattform Zukunft der Mobilität* in [13]. The economies of scale for the charging infrastructure are neglected in this paper: the stated costs for the different solutions of the GA are rough estimations. Primarily, the capital costs serve the comparability of the solutions in terms of the optimization of these.

3.1.3. Criterion Two: Agent Detour

The agent detour means the detour an agent has to cover to reach the next available charging point. This situation occurs if there is no charging point available at the arrival link of the agent. If there is an available charging point on another link within a previously specified, maximum distance the agent makes a decision whether the detour is worth it to execute a charging process. The charging decision model is explained below. The mean value of all detours the agents executed during the simulation represents the criterion Agent Detour. The detour is calculated by a Dijkstra algorithm from the center of the arrival link to the center of the link with an available charging point [15]. The detour is executed only theoretically. The agent does not change his daily plan of the MATSim simulation. This means he starts his next tour on the original arrival link and not on the link the vehicle was charged on. Due to this fact, the agent does not consume energy to execute the detour. However, the length of the detours is limited to 1000m. Thereby, the impact of the detour on the energy consumption can be neglected.

3.2. Electric Vehicle Population

The agents in the MATSim Open Berlin scenario use an ICEV by default. Therefore, it is crucial to specify different types of BEVs for the simulation. These vehicles are divided into four different classes according to the *Kraftfahrtbundesamt (KBA)*. The shares of classes in the total number of vehicles is shown in a study by the *Bundesministerium für Verkehr und digitale Infrastruktur*. The distribution of vehicle classes is shown in Table 2.

Table 2. Distribution of Vehicle Classes in Berlin/Brandenburg [16, p. 254]

Vehicle Class Category	Share Berlin [%]	Share Brandenburg [%]
Small	24	23
Compact	34	36
Medium	27	28
Large	9	7
Nonassignable	6	6

The share of the nonassignable class is distributed equally on the four other classes. A representative and currently on the market available BEV is assigned to each class. The attributes of these vehicles are used for the simulation in the GA. The chosen vehicles are shown in Table 3.

Table 3. Vehicle Attributes

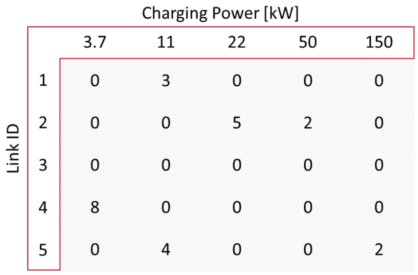
Vehicle Class	Model	Battery Capacity [kWh]	Energy Consumption (ic/ot/mw)* [kWh/100km]
Small	Renault Zoe [17]	41	15,4 (11,7/17,0/17,8)
Compact	Nissan Leaf e+ [18]	62	20,6 (15,6/21,8/24,5)
Medium	Tesla Model 3 LR [19]	75	17,5 (16,2/17,9/18,1)
Large	Audi e-tron [20]	83,6	22,9 (20,8/23,9/23,0)

*ic = inner-city, ot = out of town, mw = motor way

The data of the energy consumption of the vehicles refers to real data from tests of the ADAC [21]. The results of these tests show the average energy consumption divided into the categories inner-city (ic), out of town (ot) and motor way (mw). The links of the MATSim model are assigned to one of those categories according to their speed limit. So it is possible to adapt the energy consumption of the vehicles during the simulation of the GA according to the link they drive on. Moreover, the energy losses during the charging progress should be considered as well. Since it is not possible to determine a universally valid value of charging losses due to differences of the vehicles and e.g. environmental factors, this study uses empirical data from the ADAC. For which the effective amount of energy needed to charge 15 different BEVs was measured. The results range from 9.9% to 24.9%. For the calculations in this paper the average of 16% is used for each charging process [22]. Furthermore, the charging process up to 80% can be seen as nearly linear but thereafter the charging speed decreases drastically [23]. Therefore, the vehicles are charged only up to 80% of their available battery capacity. However, in this scenario it is also assumed that the vehicles can be charged with every charging power mentioned in Table 1 even if the real possible charging power is lower than 150kW. The reason is that the authors of this paper assume that in a future scenario where BEVS have a very high share in motorized individual transport (MIT) it is very likely that every BEV can handle charging powers up to 150kW. This assumption is supported by the progress report 2018 of the *Nationale Plattform Zukunft der Mobilität* which explains that there will be many new models of BEVs supporting charging powers of 150kW or higher.

3.3. Starting Population for Genetic Algorithm

The creation of a starting population is crucial for running a genetic algorithm [10]. It is the first population of solutions the GA starts the optimization with. The results shown in this paper are from a simulation with a population size of 20 solutions. Since the population size does not change over the generations it is necessary to create a starting population with 20 solutions or 20 different charging infrastructure scenarios, respectively. The initial charging infrastructure scenarios are created in a random procedure. Figure 2 shows an exemplary illustration of a solution of the GA. One solution represents one distribution of charging infrastructure and each link of the network represents a gene which can be modified by the GA in terms of the number or power of charging points.



	Charging Power [kW]				
Link ID	3.7	11	22	50	150
1	0	3	0	0	0
2	0	0	5	2	0
3	0	0	0	0	0
4	8	0	0	0	0
5	0	4	0	0	2

Figure 2. Example for a solution

For the creation of the starting population a random number of charging points with a specific charging power is assigned to each link. A link can receive one kind of normal charging points (3.7kW, 11kW, 22kW) and one kind of fast charging points (50kW, 150kW) at the same time. However, the number of charging points is limited by two factors. Firstly, the length of the link. By that, it should be considered that the vehicles need a specific amount of space for parking. Since 90% of the public parking lots in Berlin are aligned longitudinally at the streets and should have a length of at least five meters it is assumed that a link can contain one charging point per 50m length. Mention that one charging point in the simulation corresponds to ten charging points in the reality due to the fact the MATSim scenario works with ten per cent of the traffic volume. The second limiting factor is the maximum number of activities on a link which are executed at the same time. This assures that a link with a maximum of n activities executed simultaneously at any time of the day gets assigned a maximum of n charging points. The solutions which should be optimized only contain public charging points, but the availability of home chargers is also considered. Since in Berlin 40% of the population have access to a private parking space, home chargers are assigned randomly to 60% of the agents with home link in Berlin. In Brandenburg only 13% of the population do not have access to a private parking space [16]. Therefore, every agent with home link in Brandenburg gets a home charger. Agents with home charger can charge on their home link regardless of available public charging points and start with 100% SoC while the agents without home charger start with an SoC between 50% and 90%. This increases the plausibility of the scenario. Furthermore, the quality of the results of the optimization can be improved by a suitable starting population. Therefore, the vehicle-to-charging point ratios of the solutions of the starting population are oriented towards the reference value of 10:1. Like described in Section 1, the Bundesregierung assume this value as suitable for charging infrastructure.

The first generation of the GA used for the simulation in this paper shows ratios between 23:1 and 6:1. Note that a generation of the GA contains two populations, the parents and the offsprings. That means the first generation contains 20 parents (starting population) and 20 offsprings, which were created in an initial run of the simulation. A generation contains parents and offsprings to be able to preserve the best individuals of the parents population if they are better than the offsprings.

3.4. Charging Decision Model

To determine when the agents decide to charge their vehicle, a charging decision model is necessary. This is derived from a charging decision model in [11] Before the decision model is used, it is checked whether the agent is at his home link and has a home charger. If this applies, the agent charges the vehicle with a power of 11kW. This charging power seems to be suitable for home charging considering the longer standing times. Moreover, in Germany the installation of a wallbox up to 11kW charging power does not require a registration with the local network operator [24]. If the agent does not charge at home, the charging decision model is applied. At first, it is checked if the charging process can be precluded. Therefore, the detour to the next available charging point is determined. If there is an available charging point on the arrival link, the detour is set to zero. Otherwise, it has to be calculated like it is described in 3.1.3. The charging process is precluded, if there is no available charging point within the maximum distance, the parking time is less then the minimum parking time or the SOC of the vehicle is higher than the maximum SOC the vehicle can be charged up to. These limits have to be set by the user before the start of the algorithm. Does one of these criteria apply to the situation no charging process is executed. Otherwise, the necessity of the charging process is checked. A charging process is necessary if the SOC falls below the minimum SOC or the range of the vehicle is less than the length of the next tour of the agent. In this case, the agent charges his vehicle. If a charging process is not necessary it has to be decided if the charging process is possible. A charging process is possible, if the detour falls below the tolerated distance set by the user or if the agent does not have a home charger. If this applies the agent also charges his vehicle. Otherwise he parks without charging.

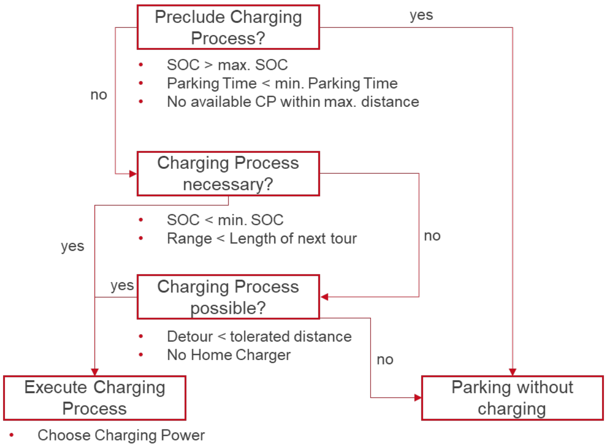


Figure 3. Agents Charging Decision [11]

3.5. Simulation

Before the simulation can be started a few input parameters shown in Table 4 must be set.

Table 4. Input parameters

Parameter	Description	Value
Max Vehicle SoC [%]	Maximum SoC the vehicles can be charged up to or agents start a charging process	80
Min Vehicle SoC [%]	SoC from which an Agent classifies a charging process as necessary	30
Min Standing Time [s]	Minimum duration from arrival to departure necessary to start a charging process	300
Tolerated Distance [m]	Maximum detour an agent will cover if the charging process is classified as not necessary	500
Max Distance [m]	Max Detour an agent will cover to execute a charging process	1000
Number of Generation	Number of Generations simulated	100

Furthermore, a random seed is used to ensure reproducibility of the results. A random seed is a number used to initialize a pseudorandom number generator. The random seed used, determines the sequence of numbers generated which means, that the algorithm produces the same results in every run if the same random seed is used. The MATSim output data and the starting population serve as input data for the simulation. The simulation uses the network file and the events file of version 5.3 of the MATSim Open Berlin ten-percent scenario. The network file is used for the calculation of the detour, which agents have to cover to reach a available charging point, like it is described in Section 3.1.3. For the simulation itself the events file is used. Mention that most of the data of the event file which is necessary for the simulation is pre-processed and stored in an agent related object to simplify the procedure of the simulation. There is for example information about the covered distance, routes and standing times of each agent.
In the first step of the algorithm, there is an initial run to create the first generation of solutions from the starting population. The first generation consists of 20 solutions from the starting population and 20 offsprings from these. The population size of the starting population is freely selectable. Now, the simulation of the MATSim events can be executed for each solution of the generation to gain information about the quality of the charging infrastructure. Crucial for the simulation are the departure and arrival events from the MATSim event file. These events are processed in chronological order. If a departure event is processed, it is checked if the related agent has charged his vehicle. In case he did, the charging point he occupied is released. If the charging link distinguish from the departure link the charging point is released on the charging link but the agent starts his next tour still on the original departure link. Thereafter, the next tour of the agent is simulated. That means the new SoC of his vehicle after fulfilling this tour is calculated. If the SoC reaches zero percent, this is saved in the agent related object for subsequent analyses but the agent remains part of the simulation. The processing of the departure event ends here and the next event is simulated. If an arrival event is processed, the agent has to decide if he will execute a charging process. The charging decision is already explained in Section 3.4. If an agent decides to charge the vehicle, he chooses the highest available charging power. Moreover, one of the available charging points on the related links is occupied until the agent leaves the link. Afterwards, the new SoC after the charging process is calculated and the processing of the arrival event ends.
After this procedure is executed for each solution of the generation, the solutions can be compared in terms of the defined criteria. The comparison and the following creation of the new generation is performed by the NSGA-II. This is repeated until the set number

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of generations was created and simulated. The final generation should contain mostly pareto-optimal solutions. The recombination method used is a three-point crossover and the mutation rate is set to two percent.

4. Results

Firstly, there is given an overview of the development of the solutions over the generations of the GA. Subsequently, the results of the final generation are described and compared to the first generation. At last, three different solutions of the final generation are described in detail.

4.1. Development over Generations

Since the results are calculated with only ten percent of the population of Berlin, they are multiplied by ten to get the results related to the full population. Figure 4 shows the development of the generations of solutions over the 100 generations.

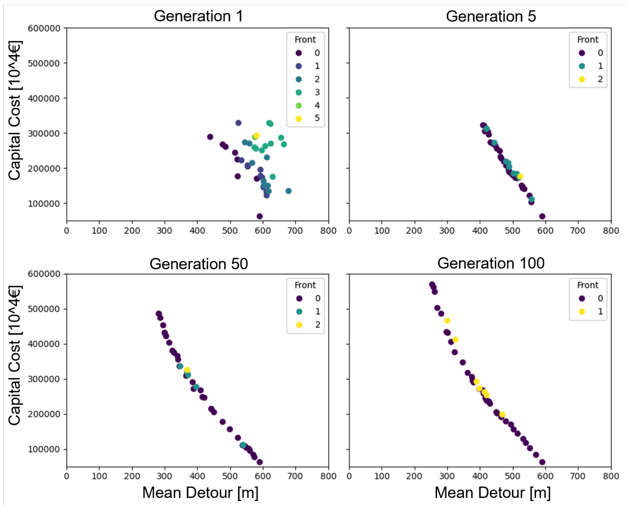

Figure 4. Development of Results over Generations

The colour of the data points provides information about the front of solutions a solution was assigned to. Front zero means that the solution is non-dominated or a pareto-optimal solution, respectively. Generation one shows the influence of the randomly created starting population. Only a few solution are assigned to front zero. Furthermore, there are more fronts of solutions compared to the later generations. That means that there are more unsuitable solutions, which are dominated by one or more other solutions. After five generations the functionality of the algorithm is already visible. Many of the dominated solutions were sorted out. This results in less fronts of solutions and more solutions in front zero. After 50 generations, the algorithm tries to reduce the mean detour of the agents while the minimum capital costs remain the same. It is noticeable that the solution with the least capital cost remains over all generations. This means that no cheaper solutions with a comparable mean detour are found. Moreover, the crowding distance mechanism of the NSGA-II prevents this solution from getting lost accidentally by preferring edge solutions. Additionally, this mechanism ensures that the solutions are well distributed over the search space. The last generations contains only two different fronts. Most of the solutions are situated in front zero. These solutions are now the potential solutions of the optimization problem. Figure 5 shows more details of the development of the key values of the solutions.

The values refer to the mean value of all 40 solutions of a generation. Firstly, the algorithm starts to sort out expensive and non-optimal solutions. This results in lower capital costs and less detour, although the solutions contain more charging points. It is interesting that the average mean detour decreases while the average total detour increases. This can be explained by the fact that solutions with few charging points or with inappropriate spatial distribution of charging points are sorted out. In those solutions less charging processes are executed because there is often no charging point available for the agents. No

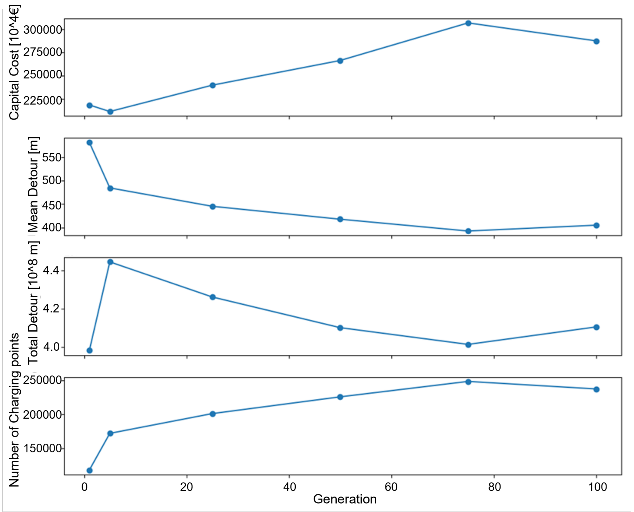

Figure 5. Development of key values of solutions over generations

charging process also means no detour. Therefore, the mean detour decreases due to better distributed charging infrastructure while the total detour increases due to a higher total number of charging processes. In generation one, 700,000 charging processes were executed compared to 900,000 charging processes in generation five. The development from gen five to gen 75 shows continuously decreasing mean detour and total detour while the number of charging points and the capital costs continuously increase. This development is inverted from generation 75 to 100 since the number of charging points is slightly decreasing.

4.2. Results of the final generation

Generation 100 is the final generation of the simulation reviewed in this paper. The solutions situated in the optimal front of this generation can be considered as equivalent, possible solutions of the optimization problem. In the following, the results of this generation are analyzed. Table 5 shows the mean values of different parameters of generation one and generation 100.

Table 5. Average values of different parameters of generation one and generation 100

Parameter	**Mean Value Gen 1**	**Mean Value Gen 100**
Charging points	118 250	237 150
Capital Costs [10^6 €]	2 184	2 876
Mean detour [m]	581	405
Total detour [10^6 m]	398	411
Charging Processes	696 530	1 046 240
temporal occupation rate [%]	41.03	38.18
Mean start SoC [%]	85.93	85.93
Mean end SoC [%]	70.12	71.33
Share AC charging points [%]	79.2	89.9
Share DC charging points [%]	20.8	10.1
Agents with 0% SoC	40 180 (3.0%)	35 880 (2.68%)

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The number of charging points of the solutions in generation 100 ranges from 112,040 to 379,690. This is on average twice as much as in generation one. The ratio between vehicles and charging points takes values between 3:1 and 11:1. The mean capital costs increased by approx. 32% to 2.8 billion € while the mean detour decreased by approx. 30%. However, the total detour increased by 3%. This contradictory development is due to the increase of charging processes by 50%. In consequence of the higher number of charging points the temporal occupation rate decreases slightly. Nevertheless, the quality of the charging infrastructure improved according to the increased mean end SoC and the decreased number of agents which reached an SoC of zero percent. Moreover, the share of fast charging infrastructure with charging power over 50kW decreased from 20.8% to 10.1%. In generation 100, there are no outliers. This shows an extraordinarily high share of fast charging infrastructure. The share ranges from 2.9% to 14.3%. Figure 6 shows the solutions of generation 100. The correlation between capital cost and mean detour is clearly visible. Considering the right chart, one point can be identified where the reduction of charging points leads to more detours with a length over the maximum distance and thereby lead to more agents declining a charging process.

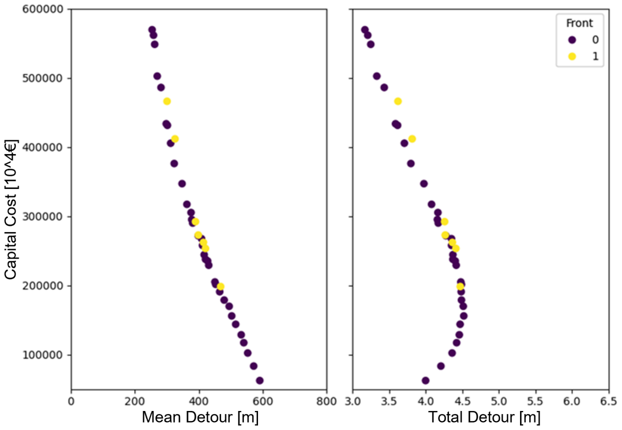

Figure 6. Results of Generation 100

4.3. Analysis of different solutions of the final Generation

In this section, three of the 40 solutions of generation 100 are analysed.This pertains a solution from the middle of the optimal front and the edge solutions highest cost/lowest detour and lowest cost/highest detour. The analysis of individual solutions provides information about the exact numbers of charging points, their charging power, spatial distribution and the agent detour among other things. Table 6 shows the values of the three analyzed solutions.

4.3.1. Bottom Edge Solution

Firstly, the bottom edge solution is analyzed. The solution contains 112,040 charging points. This corresponds to a ratio of 11:1 between vehicles and charging points. Table 7 shows the distribution of the charging points between the different charging powers.

The capital costs for the charging infrastructure amount to approx. 624 million Euro which is significantly below the capital costs of the other analyzed solutions. Although the ratio between vehicles and charging points is slightly above the reference value of 10:1, set by the European parliament, the low capital costs make this solution interesting. These are mainly caused by the low share of fast charging infrastructure of 2.94% and the high number of charging points with a charging power of 3.7kW. On the downside, the low number of charging points causes higher detours for the agents. These are on average 590m in the bottom edge solution which means the detour even is above the tolerated distance of 500m from which the agents only execute a charging process if it is crucial. This is also reflected in the number of charging processes which is significantly lower compared to the other analyzed solutions. However, it can not be determined if a charging process is not executed

Table 6. Values of three different solutions of generation 100

Parameter	Bottom Edge	Mid of Front	Top Edge
Charging points	112 040	246 630	379 690
Capital Costs [10^6 €]	624	2 950	5 692
Mean detour [m]	591	378	254
Total detour [10^6 m]	400	416	317
Charging Processes	676 760	1 100 340	1 246 130
temporal occupation rate [%]	40.69	38.3	29.07
Mean start SoC [%]	85.93	85.93	85.93
Mean end SoC [%]	69.7	71.58	72.11
Share AC charging points [%]	97.1	89.2	85.8
Share DC charging points [%]	2.9	10.8	14.2
Agents with 0% SoC	40 830 (3.05%)	35 130 (2.63%)	33 720 (2.52%)

Table 7. Charging Points per Power of the bottom edge solution

Charging Power	Number of charging points	Relative Share
3.7 kW	59 390	53.00%
11 kW	25 000	22.32%
22 kW	24 360	21.74%
50 kW	1 580	1.41%
150 kW	1 710	1.53%

because the detour was above the tolerated distance or because it is above the maximum distance. Despite the low number of charging processes, the temporal occupation rate of the charging infrastructure amounts to 40.69%. Furthermore, the mean end SoC of this solution, which is the lowest value within generation 100, shows that the power supply of the vehicles is slightly below the other analysed solutions. Nevertheless, it can be stated that only 0.5% more agents reaching an SoC of zero percent as there are in the top edge solution. Overall 96.95% of the agents does not reach an SoC of zero percent. 29,030 of the 40,830 agents which reach an SoC of zero percent are living in Brandenburg and only 11,800 are living in Berlin. A possible cause of this is that agents can also start activities in Brandenburg although there are no public charging points installed because this paper only observes charging infrastructure in Berlin. Agents with home link in Brandenburg are only observed to take the influence of commuters into account like mentioned in Section 1. They can only charge their vehicle on their home links (see Section 3.3). Therefore, agents who mainly execute activities in Brandenburg have an increased probability to run out of energy. Another cause could be that agents with residency in Brandenburg cover longer distances on average and there is no sufficient charging infrastructure to supply the vehicle. The length of trips where the agents reached an SoC of zero percent is approx. 62km on average. The median is 55km. The total distance traveled of these agents is 193km on average. The median is 184km. Thus, these agents belong to the five percent of agents which cover the highest distances within one day. At last the spatial distribution of the charging infrastructure is investigated. The results are shown in Figure 7. Obviously the charging infrastructure is more concentrated in the western part of Berlin than in the east. It concentrates especially in the districts Charlottenburg and Wilmersdorf. In the rest of Berlin, the density is rather low and there are hardly any accumulations of charging points on single links. If there are such accumulations the charging points mostly have a charging power of 3.7kW. These are particularly recognizable in Neukölln, Kreuzberg and edge districts like Hohenschönhausen, Reinickendorf and Köpenick. The sporadic accumulations of charging points can be associated with hotspots of activities. The distribution of fast charging infrastructure is similar but the bottom edge solution only contains a very low share of fast charging points. Furthermore, it is remarkable that accumulations of fast charging points are situated along the Berlin urban highway.

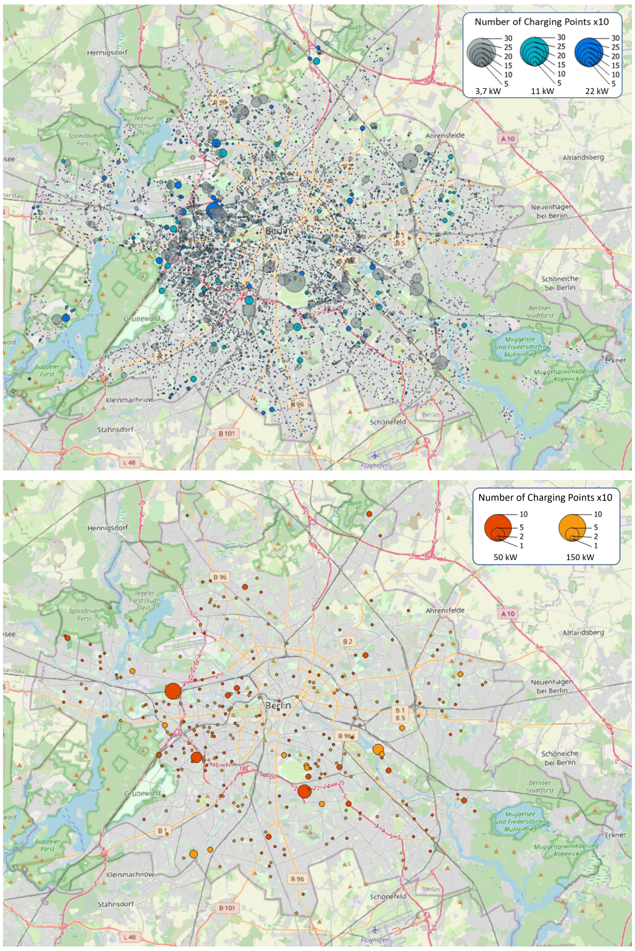

Figure 7. Spatial Distribution of public charging infrastructure in Bottom Edge Solution

4.3.2. Mid Front Solution

This solution is situated in the middle of the solution front and represents a trade-off between the bottom edge and the top edge solution. It contains 246,630 charging points which is similar to a vehicle-to-charging point ration of 5:1. Thus, it is significantly lower compared to the reference value from the European Parliament. Table 8 shows the different shares of charging powers.

The capital costs of the charging infrastructure amount to approx. 2.95 billion Euro. Furthermore, the share of fast charging infrastructure is 10.8%. Again, most of the charging points have a charging power of 3.7kW. The higher total number of charging points in this solution leads to a significant reduction of the mean detours to 378m. This has an especially high impact on the total number of charging processes executed, due to the decreased mean

Table 8. Charging Points per Power of the mid front solution

Charging Power	Number of charging points	Relative Share
3.7 kW	89 690	36.37%
11 kW	66 870	27.11%
22 kW	63 540	25.76%
50 kW	13 840	5.61%
150 kW	12 690	5.15%

detour, which is clearly lower than the tolerated distance. The total number of charging processes amounts to 1,100,340 with a temporal occupation of the charging infrastructure of 38.3%. Moreover, there is also an impact on the mean end SoC of the agents which is 71.58% in this solution. This points to a better power supply by the charging infrastructure. Furthermore, the share of agents which reach an SoC of zero percent is 2.63%. This corresponds to a total number of 35,130 agents. 24,730 of these agents have their residency in Brandenburg and 10,400 in Berlin. Compared to the bottom edge solution the number of agents decreased by 14%. The average length of journeys of these agents barely changed. The mean value is 62km while the median is 54.5km. The distance covered over the course of a whole day is 197km on average while the median is 187km. Moreover, the spatial distribution of charging infrastructure in this solution is also reviewed. It is shown in Figure 8. Compared to the bottom edge solution, there is a significantly higher density of charging points in all areas. However, the trend of the spatial distribution continues. There are many charging points in western Berlin in the districts Charlottenburg and Wilmersdorf. Apart from that, the density of charging points is also high in Steglitz, Schöneberg, Tempelhof and Neukölln. Additionally, there are much more charging points in the center of Berlin compared to the bottom edge solution. Edge districts like Spandau, Reinickendorf and Köpenick are supplied significantly better. In these districts, the density of charging points is slightly lower but several accumulations of charging points on links can be observed. The spatial distribution of the fast charging infrastructure shows a similar trend like in the bottom edge solution and does not noteworthy deviate from the observations mentioned for the normal charging infrastructure. Interesting is that bigger accumulations of fast charging points on single links appear especially on places like hospitals or train stations near the city highway or big parking spaces. As example can be mentioned the Vivantes Klinikum Spandau or the city train station Grunewald near the city highway, which is highly frequented by commuters between Berlin and Potsdam.

4.3.3. Top Edge Solution

The last investigated solution is the top edge solution of the final generation. It contains 379,690 charging points in total which corresponds to an vehicle-to-charging point ratio of 3:1. Table 9 shows the distribution of the different charging powers.

The capital costs of this solution amount to 5.7 billion Euro and the share of fast charging infrastructure is the highest among the compared solutions with 14.2%. Among the normal charging powers, the shares are nearly equal. Moreover, this solution shows an increase in the number of executed charging processes to a total of 1,246,130. However, this increase is small compared to the difference between bottom edge and mid front solution. Contrary, the temporal occupation of the charging infrastructure drops to 29.07%. The mean end SoC is with 72.11% slightly above the mid front solution. Furthermore, in the top edge solution 33,720 agents reached an SoC of zero percent from which 23,750 have residency in Brandenburg and 10,150 in Berlin. Also in this solution, the average length of journeys, on which the agents run out of energy, is nearly the same as in the solutions

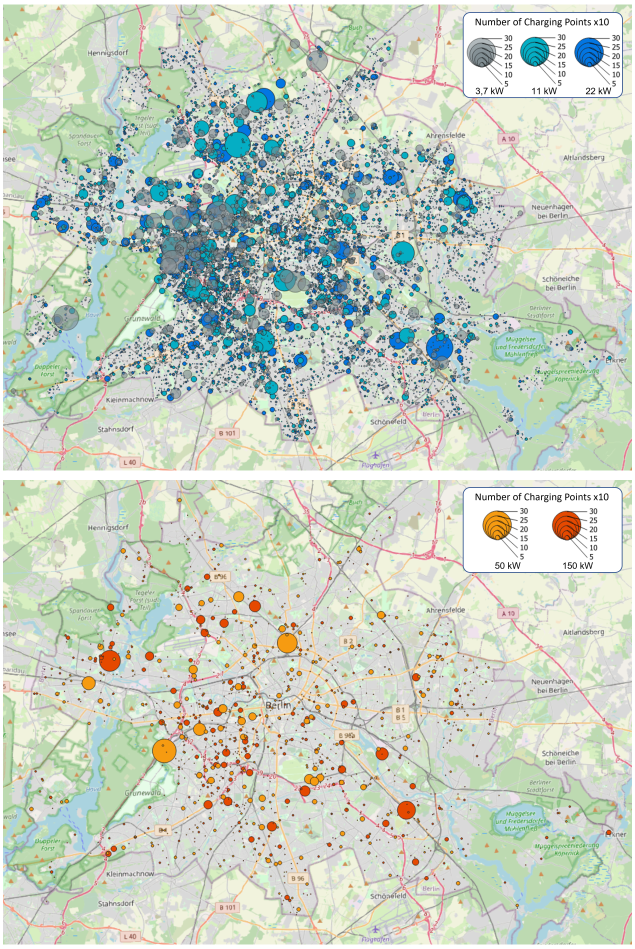

Figure 8. Spatial Distribution of public charging infrastructure in Mid Front Solution

before. The mean value is 62.0km and the median is 54.5km. The total covered distance of these agents amounts to 197km on average. The median is 188km. Moreover, the spatial distribution of the charging infrastructure is investigated which is shown in Figure 9. It can be stated that in this solution nearly the whole urban area of Berlin is well covered with charging infrastructure. Even in the edge districts are no supply gaps. A slight dominance of the western part of Berlin is still recognizable. The tendency, that bigger accumulations of fast charging points appear near hospitals, big parking spaces or train stations near the urban highway is confirmed.

5. Discussion

The results explained in Section 4 were generated using an genetic algorithm developed by the authors which is based on data from the MATSim Open Berlin Scenario. The main goal of this algorithm is to investigate how electrical charging infrastructure could be distributed in Berlin if BEVs reach a market share of 100%. Firstly, the results are summarized shortly. The results of the 100th generation show charging infrastructure scenarios which have between 112,040 and 379,690 charging points. Charging points with a power of 3.7kW have the biggest share with 36.5% on average while the average share of the charging powers 11kW and 22kW is 26.6% and 26.1%. The share of fast charging infrastructure amounts to 10.1% on average and is distributed equally to 50kW and 150kW. The capital costs are between 624 million euro and 5.7 billion euro. Furthermore the average detours of agents reaches from 254m to 590m over all solutions. Moreover all solutions are able to cover the energy requirements of most of the agents during the investigated MATSim Scenario. The biggest share of agents that run out of energy was 3.05% while the lowest share was 2.52%. The investigation of the spatial distribution of the charging

Table 9. Charging Points per Power of the top edge solution

Charging Power	Number of charging points	Relative Share
3.7 kW	113 480	29.89%
11 kW	106 430	28.03%
22 kW	105 860	27.88%
50 kW	27 100	7.14%
150 kW	26 820	7.06%

infrastructure shows that solutions are prevailed where the charging infrastructure has a similar spatial distribution like the activities of the agents in the MATSim scenario. The distribution of activities is shown in Figure 10. The summarized results are discussed in the following as well as the used methodology.

5.1. Results

Back in 2014 the directive of the European Parliament for the deployment of alternative fuels infrastructure specifies that there should be on average at least one charging point for ten vehicles [25]. With an ratio of 11:1 between vehicles and charging points the bottom edge solution comes closest to this directive within the three investigated solutions. Since this solution is able to supply most agents in the MATSim Scenario the statement of the European directive can be scrutinized in relation to the requirement of charging infrastructure in urban areas. Moreover, the saturation effect mentioned by Stroband [11] should be taken into account. It shows that the additionally required charging infrastructure decreases with an increasing market penetration of BEVs. Additionally, it can be assumed that this effect is amplified in densely populated areas, where the distances between charging points are lower compared to rural areas. That's why a vehicle-to-charging point ratio of 11:1 could be appropriate in a city like Berlin if the market share of BEVs is 100% and the spatial distribution of the charging infrastructure is adequate. From this point of view, the mid front solution and the top edge solution seem to be oversized. Contrary, the amount of charging points cannot be assessed without taking the average detour of agents to the next available charging point into account. These have a strong influence on the usability and the efficiency of the charging infrastructure. Due to a deficiency of empirical data regarding the operation of comprehensive charging infrastructure it is not possible to make a statement about which average distance of detours leads to the highest possible acceptance of the users. Here, it may be useful to draw a comparison to the infrastructure planning of the public transport (PT). In the Berlin local transport plan 2019-2023, it is specified that for 90% of the population the distance from residence to the next PT station should not exceed 500m [26]. Another comparative value could be the distance of car sharing stations. According to the Bundesverband CarSharing, a distance of 300m to the next car sharing station is considered as very accessible, while a distance of 500m is considered as still acceptable [27]. These examples all have in common that the distances have to be covered by the user to get access to the service offered. Therefore, it can be assumed that if there is acceptance of users for other transport services under the given circumstances there is also acceptance of users of BEVs for the public charging infrastructure under similar circumstances. The mean detours effect the costs of the charging infrastructure significantly. The bottom edge solution with mean detours of 590m can be evaluated as still acceptable considering the tolerated distance of 500m. According to the assumptions of the local transport plan and the Bundesverband CarSharing, the mean detour of 590m is slightly to high for high user acceptance. Considering this, solutions like the mid front solution and the top edge solution with mean detours of 378m and 254m are rather required. However,

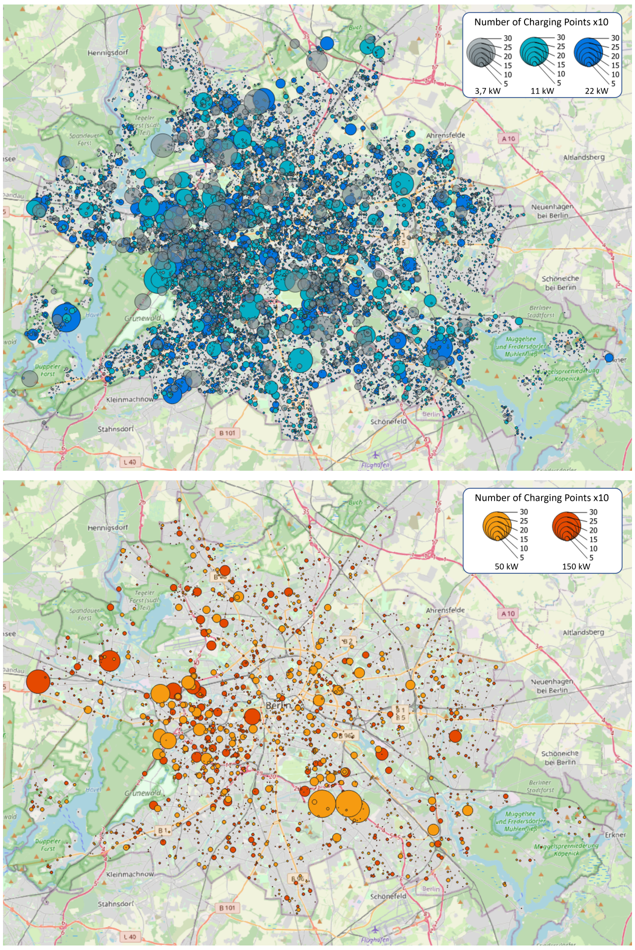

Figure 9. Spatial Distribution of public charging infrastructure in Top Edge Solution

these solutions are leading to much higher capital costs. Therefore, an effective planning of charging infrastructure should consider which detours still lead to high user acceptance.

Moreover, the calculated capital costs for the different charging infrastructure scenarios have to be discussed critically. It is necessary to note that the capital costs should be considered as a rough estimation of the real capital costs. They are primarily used to compare solutions with each other. There are different factors which could lead to changes of the capital costs. Not considered are i.e. future price changes and economies of scale which in consequence the acquisition of a large number of charging points could lead to. Furthermore the calculation of capital costs does not consider that the first charging point on a link is more expensive than following charging points at the same link. One reason is that certain prerequisites like transformer stations are only needed once for a certain number of charging points. Also this paper does not consider the investments for the expansion of the power grid, which would be necessary for the provision of the required power.

Besides the detours and capital costs it is important if the charging infrastructure can cover the energy demand of the agents appropriately. The three investigated solutions show a difference of only 0.5% in the number of agents that run out of energy. Every solution was able to supply nearly all agents of the MATSim scenario. It can be stated that the higher the covered distance of an agent is during the day, the higher is the probability that the agent runs out of energy during the simulation. In the bottom edge solution the average distance these agents covered is 193km, while it is 197km in the top edge solution. This means the top edge solution can supply agents which cover long distances slightly better. This can be caused by different reasons, i.e. by a higher share of fast charging infrastructure or the higher spatial coverage with charging points in general. However, the small

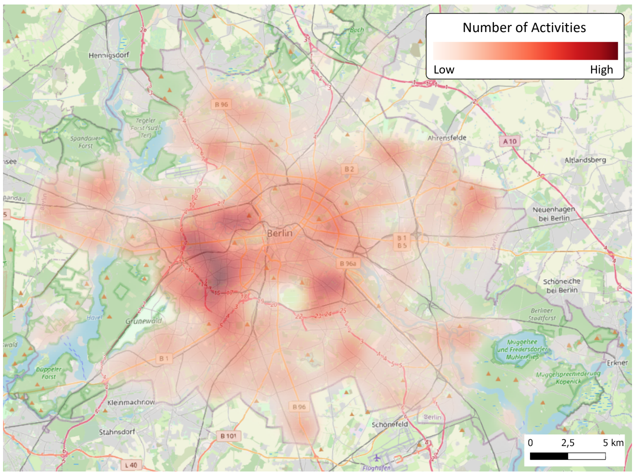

Figure 10. Spatial Distribution of activities in the MATSim Scenario

advantage in supplied agents is not justifiable considering the huge difference in capital costs between the solutions. Furthermore, the aspects which the algorithm does not yet cover are discussed. For example, it is not possible to gain information about which agents would run out of energy, if the scenario of the simulation would last a couple of days and not only 36h. In a scenario like that, agents could reach an SoC of zero percent who cover short distances every day but have no charging points available in their environment. Since a multiple-day-scenario would claim much more computational capacity it would be more efficient to extrapolate the SoC of the agents based on the availability of charging points on their trips. This additional step of the algorithm can be implemented without much effort but would lead to a much better quality of information about the energy supply of the agents. Moreover, it can not be determined which agents run out of energy because they only execute activities outside of Berlin where no charging points are available except the home charger on their home link. Also an inconvenient assignment of the vehicle class can cause an SoC of zero percent if an agent who covers a high distance is assigned a vehicle with a small battery. Although the shares of the different vehicle classes in the simulation are related to the real share of vehicle classes the final assignment of the vehicle class to an agent happens randomly. This inconvenient combination of agent and vehicle class increases the probability of reaching zero percent SoC. In reality, a person would probably choose his vehicle appropriate to its demands.

Furthermore, the shares of the different charging points are discussed. The solutions show that charging points with a charging power of 3.7kW dominate. A high share of these charging points in cities can be promising because they can be easily integrated in the posts of street lights and are sufficient to charge a vehicle if the standing times are sufficient. They also cause less load on the power grid compared to charging points with higher power. The share of fast charging points is 10.1% on average of all solutions of the final front. That is why this seems to be an appropriate share according to the conditions of the MATSim scenario. However, the low share of fast charging infrastructure in the bottom edge solution shows that there are also suitable infrastructure scenarios with less fast charging points, if these are situated in the right places. These solutions would show lower capital costs accordingly.

The last part in the discussion of the results is the spatial distribution of the charging infrastructure. It is clear that the solutions show a comprehensive charging infrastructure (Section 4). The spatial distribution correlates with the distribution of activities started in the MATSim scenario. There are no large areas without any kind of charging infrastructure observable. The tendencies which are already observed in the bottom edge solution continue also in solutions with a higher total number of charging points. Besides the comprehensive distribution of the charging infrastructure there are single links which show an accumulation of charging points. These links also show high numbers of simultaneous activities which means that the limitation of charging points using maximum numbers of simultaneous activities and link length delivers realistic results. The links featuring accumulations of charging points are mainly situated near train stations, public parking spaces, hospitals and other highly frequented places for leisure activities i.e. the Tempelhofer Feld, the Tierpark Berlin, the environment of the Gärten der Welt in Marzahn-Hellersdorf and the environment around the train Station Charlottenburg. These examples are taken from the mid-front solution but the described observations in general can be confirmed by all investigated solutions. It seems that the algorithm calculates reasonable solutions considering the used input data. This indicates that extending the input data by also considering other influential factors on the requirement of charging points or ability of a link for hosting charging points could lead to much more significant results. The separate investigation of the fast charging infrastructure shows that it corresponds to the observations already described. Except for the bottom-edge solution which shows some supply gaps because of the very low share of fast charging points. The fast charging infrastructure also concentrates on highly frequented streets or train stations. Especially interesting are the accumulations along the city highway where several links with a high number of charging points can be observed. This is even observable in the bottom-edge solution despite the low share of fast charging infrastructure. This seems reasonable because the urban highway is very high frequented especially in the rush hour traffic. Therefore, it is likely that many activities are started relatively close to it. Moreover, the urban highway is often used to cover long distances within the city or for entering or leaving the city. Therefore, it seems reasonable that the agents can increase their range in a short amount of time due to the near fast charging infrastructure. It is important to mention that this can not be done intentionally from the algorithm using the MATSim Open Berlin scenario 5.3. Since this MATSim scenario does not feature electric vehicles it also does not consider activities especially started for charging a vehicle. The need for charging points depends on the number of activities with other purposes only. Another example for this is the accumulation of fast charging points in the mid-front solution located at the train station Grunewald in western Berlin. The train station is situated next to the highway which connects Potsdam and Berlin and is highly frequented by commuters. Theoretically, it is very reasonable that there are fast charging points for the commuters leaving or entering Berlin to increase their range in less time. Since those activities are not featured by the scenario, the reason for the algorithm to put the charging points there is the high number of leisure activities, which are started at this location. Furthermore, not all accumulations are easy to justify. In a few cases, there are i.e. accumulations of 100 or more charging points on small streets. In these cases, further investigations are needed. Even though the algorithm considers the space on a link indirectly by considering the length of the link, it must be taken into account that the algorithm can not consider the available power supply or the structural conditions on the link i.e. bike lanes or rail transport facilities. This means the algorithm does not consider if the power grid on the affected link is able to supply the amount of charging points or whether the link is not suitable for the charging infrastructure due to its special structural conditions. The potential of load shifting between power grid and battery electric vehicles is also not investigated. These issues are investigated by Straub et al. [28].

5.2. Methodology

In the following, the developed methodology will be discussed. For the calculation of the results an genetic algorithm with multi-objective optimization is used. Considering the results discussed before, it could be established that this kind of algorithm is suitable for evaluating and optimizing different charging infrastructure scenarios with very different expressions of the optimization criteria. The procedure is able to generate significant results based on the corresponding input data of a MATSim scenario. The presented approach can also be applied to other MATSim scenarios with little effort. With higher effort it is also possible to use real world data or data from other agent-based traffic simulations. An advantage of the used methodology is that the charging infrastructure scenarios can be observed holistically. This means that the addition of a charging point on a link can lead to an observable change in the use of a charging point on another link by influencing the charging decision of an agent, which executes activities on both of these links. Moreover, by allowing agents to make detours to the next available charging point the coverage of charging demands on a link does not only depend on the available charging infrastructure on the link itself, but also on the available charging infrastructure on links in the near environment. This enables a more efficient distribution of charging infrastructure. The randomness of the optimization brings advantages and disadvantages. Since the changes from generation to generation are not checked on their plausibility it can happen that single solutions be worsened. The use of methods for a more targeted evolution of the solutions could lead to better results and a more efficient algorithm. Contrary, the randomness is a very important part for the evolution of solutions. It benefits the diversity of solutions and prevents that some kinds of solution are preferred over others which could result in other equally suitable solutions not being found. Approaches for enhancing the procedure to get more significant results are touched upon in Section 6.

6. Conclusion/Outlook

To address the major challenges of climate change and air pollution in cities, Germany and the European Union are aiming towards a decarbonization of the transport system. To achieve this, the roll out of electric mobility for the motorized individual transport is crucial. In consequence there will be a large increase in the number of BEVs on the streets of Germany and Europe. To supply these vehicles with electric energy, a large-scale set up of public charging infrastructure will be required. The set up of charging infrastructure is a complex optimization problem and should be considered as such from the beginning, in order to be able to provide an effective charging infrastructure even with increasing numbers of BEVs. Until now there is not much empirical data on the large-scale operation of BEVs and the charging infrastructure. Therefore, methods are required which are able to estimate the required charging infrastructure. In this paper the results of a genetic algorithm which uses a multi-objective optimization based on the data of the microscopic traffic simulation MATSim for the metropolitan area of Berlin are reviewed. The algorithm developed by the authors is able to evaluate and optimize different charging infrastructure scenarios based on the input data of a MATSim scenario. It can be stated that the charging infrastructure solutions calculated by the algorithm are promising results, provide relevant findings in this field of research and set a ground for further investigations. Although the results are not yet ready to be implemented in reality, we can show that the developed procedure is able to model suitable charging infrastructure based on the corresponding input data. The results are summarized shortly in the following. The results indicate that for a good trade-off between detours and capital costs a vehicle-to-charging point ratio between the bottom-edge solution (11:1) and the mid-front solution (5:1) is adequate. A ratio like in the top-edge solution (3:1) seems to be quite oversized due to the non significant improvements in the supply of agents and significantly higher capital costs. Thus, the required capital costs range from 624 million euro to 2.95 billion Euro. Furthermore, the importance of detour was discussed due to their high influence on the usability of the charging infrastructure. Thus, it is possible to make an assumption about the detour users are willing to cover to reach an available charging point in the simulation. However, this does not guarantee the transferability to reality. Due to the lack of empirical data, similar values from the sectors of public transport and car sharing were used for the evaluation of detours. Referring to these values an appropriate mean detour should be between 300m and 500m to achieve user acceptance. Further research on the prerequisites of acceptance of charging infrastructure still would be helpful to make more accurate assumptions.

Moreover, some tasks that future research following this paper should address are mentioned. Firstly, a MATSim scenario should be implemented that features electric vehicles including their special needs of charging. Thus, execution of charging processes should be part of the daily plans of the agents. This enables the agents to adapt their daily plan to charge their vehicle efficiently without significant time spent. The procedure investigated in this paper could provide initial data on charging infrastructure for such a MATSim scenario. In turn, the new MATSim scenario could provide adapted daily plans of agents for a more significant optimization of the charging infrastructure with the placement algorithm. Another problem of the MATSim Open Berlin scenario in terms of optimizing charging infrastructure is the duration of the scenario. The simulation includes an exemplary working day and lasts 36 hours. For modelling charging infrastructure, it would be reasonable to extend the scenario to an exemplary week. This would lead to more significant results investigating the charging infrastructure due to the identification of insufficiently supplied agents that do not run out of energy within one day because they only cover short distances. Furthermore, the algorithm itself shows major potential for improvements, which are required to achieve the transferability to reality of the charging infrastructure scenarios. One measure could be to include more criteria into the optimization which are able to represent the quality of the charging infrastructure. The results discussed in this paper show that it is reasonable to consider the number of agents which ran out of energy and the temporal occupation of the charging infrastructure in the process of the evolution of solutions. This would also offer the possibility to calculate the economic efficiency of the charging stations. One option to consider insufficiently supplied agents is to use penalties on the capital costs of a solution. By using a exponential increasing function small numbers of agents could be accepted while high numbers of agents are severely punished. Contrary, the consideration of the temporal occupation of charging points can be used for a more efficient adaption in the number of charging points. Thus, it would be possible to add more charging points where existing charging points already show a high occupation, while charging points with low occupation could be removed. At last it should be mentioned that the algorithm should also allow sensitivity analyses to investigate i.e. different tolerated distances by the users and different market shares of BEVs.

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