# Feasibility Study, Optimization of Charging Infrastructure Locations and Economic Analysis for Electrification of Urban Taxi Fleet

Master Thesis

by


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*Karlsruhe, 15/01/2018* *Rolf Nungesser*

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# Acronyms

| | |
|---|---|
| BGM | Balancing group manager |
| BEV | Battery electric vehicle |
| CAPEX | Capital expenditure |
| CCS | Combined charging system |
| CP | Charging point |
| CS | Charging station |
| DO | Drop-off |
| DSO | Distribution system operator |
| FCEV | Fuel cell electric vehicle |
| GHG | Greenhouse gas |
| HEV | Hybrid electric vehicle |
| ICE(V) | Internal combustion engine (vehicle) |
| LCA | Life-cycle assessment |
| NOx | Nitrogen-oxide |
| (N)PV | (Net) present value |
| OPEX | Operational expenditure |
| PEV | Plug-in electric vehicle |
| P(H)EV | Plug-in (hybrid) electric vehicle |
| PM | Particulate matter |
| REEV | Range-extended electric vehicle |
| SOC | State of charge |
| TCO | Total costs of ownership |
| TS | Taxi stand |
| TSO | Transmission system operator |
| VKT | Vehicle-kilometers traveled |
| V2G | Vehicle-to-grid |
| WPT | Wireless power transfer |

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# 1 Taxi fleet electrification as local measure to reduce pollution

Across the world, people living in cities are suffering from urban air pollution and ubiquitous noise. Together with the rural population, they are also negatively affected by global warming causing e.g. extreme weather events. As the transportation sector strongly contributes to these three developments, with a 14% share of GHG emissions (see US Environmental Protection Agency 2006) and a much higher share of particulate matter emitted in urban areas (see World Health Organization 2018), it must be held responsible for playing an active role in tackling them. The first two of these have aggravated in recent decades due to increasing urbanization (see United Nations 2014), the third one e.g. due to the economies of China, India and other developing nations growing at such a high pace that collective action against climate change fails to keep up. (The New York Times, 2017) If state governments cannot keep global warming in check on their own so as to prevent extreme weather events from happening, and local governments do not dare to implement driving bans so as to improve urban air quality, why not give an important task to local businessmen, the taxi owners of Karlsruhe, Germany?

The electrification of its taxi fleet may be the optimal starting point for Karlsruhe to reduce the emission footprint of local vehicle traffic. Thereby, improvements in the three mentioned areas shall be pursued. Taxis in Germany, on average, are typically replaced every five years due to their high utilization (cf. NYC Taxi & Limousine Commission 2013) as opposed to private passenger car which are only replaced about every nine years. (European Automobile Manufacturers Association, 2015) Therefore, new technologies such as the electric powertrain can be introduced more quickly and the impact can be leveraged as the daily operational time and mileage of taxis in urban areas is about eight times as high as for private vehicles (cf. Ajanovic and Haas 2016). Hence, the electrification of one taxi would have about the same impact as of eight private cars. (NYC Taxi & Limousine Commission, 2013) Fleet electrification is deemed important foremost in China where authorities have decided to launch large-scale programs of the sort, a fleet of 70,000 taxis is set to be electrified in Beijing alone. (Electrek, 2017a) Although the top-down approach taken in China might work there, the decision of when to replace their Diesel cars with new battery electric vehicles shall be made by local taxi businesses alone. However, it shall be BEVs, not just PHEVs, in order to maximize the ecological impact of replacing Diesel with electricity. Since electric vehicles cannot be refueled at conventional gas stations, a set of new charging stations is needed. That is why researchers and utility companies need to help in setting up an efficiently placed charging infrastructure so that taxi drivers are able to recharge during operations without loss of potential revenue. One major advantage of this joint effort is that supply may be matched with demand in order to ensure economical utilization rates of the charging stations at all times.

The objective of this study is to illustrate how few fast-charging stations the taxi fleet of Karlsruhe would need, so that daily operations would not be compromised, if all conventional vehicles were to be replaced by electric vehicles. The analysis includes the search for an optimal set of locations on the basis of a large dataset of taxi trips, the determination of the minimal needed number of charging stations so as to ensure sufficient utilization, and an economic assessment (OPEX and CAPEX) of the fast-charging stations.

In order to do that, we proceed as follows: in chapter two, the topic is motivated by a discussion of the negative side-effects of urbanization, followed by an overview of the measures that local governments pursue in order to diminish these, with a focus on fleet electrification. The question of whether and to what extent the replacement of conventional with electric taxis will result in emissions reduction will be discussed in chapter three, on the basis of a comparison of the different electric vehicle classes. Subsequently, the appropriate charging standard and technology will be selected and future benefits of integrating the fleet into the power grid will be explained. After reviewing the theoretical literature on optimization models and systematically selecting one modeling approach for the placement of charging stations in Karlsruhe in chapter four, the process of extracting the necessary information from the raw dataset is described in chapter five. This will be amended by a visualization and discussion of the extracted information, before conducting the optimization of locations and capacities of the charging infrastructure so that the recommended set of stations will be sufficiently utilized to ensure an economical operation. The thesis will be concluded by a detailed investment analysis of the charging stations on a worst-case basis and an outlook on future research.

# 2 Negative by-products of urbanization and measures to counteract

Today, more than 50% of the world population live in urban areas. Since 1950 the share of people living in cities has been increasing from 30%, and it is projected to rise to 66% until 2050 (see Figure 1). Nearly 90% of the total increase will be concentrated in Asia and Africa, led by the countries with the world's largest urban populations, India and China. The number of so-called mega-cities (with over 10 million inhabitants) is projected to be 41 as early as 2030. The urban areas which are likely to grow the fastest are located in Africa or Asia, each medium-sized and home to less than one million people. However, even the low-fertility country Germany in Central Europe, in which overall population is declining, is further urbanizing at an average annual rate of 0.3%. There, the urban population will reach a share of 83% in 2050. (United Nations, 2014) (United Nations, 2016a) The cities are the economic hubs of the growing world economy; 80% of global GDP is accounted for by cities and the respective contribution to national incomes is greater than the share of national populations. (United Nations, 2016b) They attract corporations which in turn create job opportunities. (Center for Strategic & International Studies, 2017) A majority of these jobs are located in the service industry, where currently 69% of the output of the world economy is created. (World Bank, 2017) As a consequence, while the share of people working in the agricultural sector has already been historically low for decades in the G20 countries, it is projected to further decrease in the rest of the world, as well. Hence, a majority of people literally quit tilling their fields and move to the city for a job in the service industry, instead. Since cities are growing in population and area, the influx theoretically and practically results in longer daily commutes for people not migrating to the "city proper", but to the respective "urban agglomeration" or "metropolitan area".[1] (United Nations, 2016b)

As the cities are at the center of the world economy, the generally positive effects of decade-long growth in GDP per capita (see e.g. Piketty and Goldhammer (2014)) are clearly visible there: with increasing GDP per capita, people, especially workers, potentially have growing amounts of income at their disposal. Hence, commuters, especially in Africa and Asia, are increasingly able to afford buying their own car in order to use it for their daily commute to work. So, along with the economic growth comes a rise in passenger vehicle sales and ownership. Emerging countries in Asia and Africa such as China, India and Nigeria are driving this development. (PwC,

[1] "City proper" means the city enclosed by its administrative boundaries, the "urban agglomeration" names the contiguous urban area and the boundaries of the "metropolitan area" are defined by the degree of economic and social interconnectedness of nearby areas. (United Nations, 2016a)

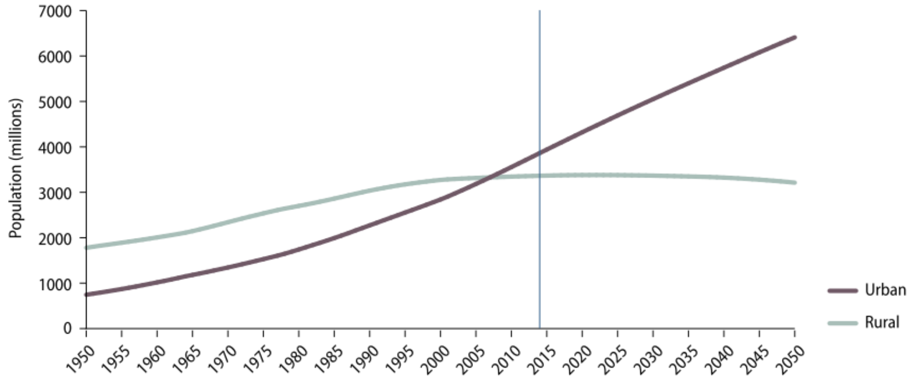


Figure 1: Development of urban and rural population of the world from 1950 until 2050 (projected after 2014). Based on United Nations (2014).

2016) In China alone, more than 23 million cars have been sold in 2016, a growth of 17% compared to 2015. It is projected to remain the world's largest car market. (Carsalesbase, 2016) The consequences of simultaneous growth in population and vehicle stock for inhabitants of urban areas will be further discussed in the following sections.

## 2.1 Negative effects of urbanization in emerging and developed countries

People increasingly own and use a car for their daily routine - in the US, for example, 86% of workers commute to work by means of private vehicles. (see US Census Bureau, 2015) Moreover, commercial transport grows at roughly the same rate as the economy, putting even more cars and trucks on urban and inter-city roads. Therefore, the roads become increasingly congested by vehicles every year. These preceding observations are supported by the findings of INRIX Research which they summarize in their Global Traffic Scorecard. (INRIX Research, 2016) They find traffic to be an indicator for the health of the economy but at the same time identify population and economic growth as the root causes for congestion. That is, since vehicles carry people and goods around, more traffic equals more people engaged in economic activity, more jobs and therefore greater prosperity. The costs of traffic - cost of additional fuel, opportunity cost of time that drivers spend on congested roads as well as climate and health problems resulting from greenhouse gases (GHG) and particulate matter (PM, see definition 1, p. 5) emissions - are simply passed on by small businesses and corporations in the form of higher resale prices for their goods and services. However, private road users cannot dodge these side-effects. Traffic congestion causes higher stress levels (see e.g. Hennessy and Wiesenthal, 1999) and therefore imposes health risks on car drivers. Even worse, people walking or riding bicycles on the street are completely exposed to polluted air. In the following section, the causes of health hazards associated with air pollution will be examined and the extent of these hazards be outlined.

### 2.1.1 The growing problem of air pollution

Especially in the light of the recent Diesel scandal which began in 2015 with Volkswagen[2] - one of the three largest car makers, the others are Toyota and Renault-Nissan - and subsequently involved all major manufacturers and sellers of Diesel cars, car emission levels appear to be an important piece of the puzzle of urban air pollution. Volkswagen and its competitors basically installed a "defeat device" in every Diesel car. This is a software that senses when the car is on a test stand by recognizing steering, throttle and other inputs in order to switch to another operating mode specifically designed for the test stand. Only in this mode, these cars comply with all US federal emission levels. However, when they are being driven normally fuel pressure, injection timing and exhaust-gas recirculation change back. Thus, actual emissions of nitrogen oxides ($NO_x$) are up to 40 times higher than specified under US federal law. (Car and Driver, 2017) This revelation is especially relevant since the Diesel car has been regarded until 2015 as relatively friendly to the environment with its relatively low $CO_2$ emissions. Thus, the manufacturers have been able to comply with the mandatory emission reduction targets set by the European Commission e.g. by producing and selling more Diesel cars.

Urban outdoor air pollution is among the ten leading risk factor causes of death in middle- and high-income countries. Among the most relevant substances are PM, $NO_x$, carbon monoxide (CO) and non-methane volatile organic compounds (NMVOC). (Jochem et al., 2016b) While $NO_2$ can cause lung cancer, emissions of PM are even more dangerous to humans.

**Definition 1: Particulate matter:** *Term for a mixture of solid particles and liquid droplets found in the air. [...] Particle pollution includes:*

- $PM_{10}$: *inhalable particles, with diameters that are generally 10 micrometers and smaller*
- $PM_{2.5}$: *fine inhalable particles, with diameters that are generally 2.5 micrometers and smaller.*

*(US Environmental Protection Agency, 2017)*

[2]The Volkswagen Group owns Audi, Porsche and some other brands.

PM is associated with a broad spectrum of acute and chronic illnesses such as lung cancer and cardiopulmonary disease. Around 8% of lung cancer deaths, 5% of cardiopulmonary deaths and 3% of respiratory infection deaths[3] worldwide can be attributed to PM. (World Health Organization, 2009) It is therefore at the center of the discussion about urban air pollution. Although over 70% of $CO_2$ (carbon dioxide) emissions can be attributed to cities (see United Nations, 2016b) and it is the most discussed compound in the Climate Change context, $CO_2$ negatively affects human bodies to a far lesser extent than PM and hence will be disregarded in this context. Other common air pollutants, besides $NO_2$ and PM, are sulfur dioxide ($SO_2$) and ozone ($O_3$). (International Gas Union, 2015) The respective WHO guidelines for concentrations of these pollutants in the air (see International Gas Union (2015)) are exceeded by 98% of cities in low- and middle-income countries, and by 56% of cities with populations above 100,000 in high-income countries. (World Health Organization, 2016a) The worst mega-cities with respect to $PM_{10}$ emission levels exceed the WHO guidelines by up to eleven times and the picture is similar for $PM_{2.5}$ and the other pollutants. (World Health Organization, 2016b) (The Guardian, 2017) In Germany, Stuttgart is dubbed as the "German capital of air pollution". There, the concentration of $PM_{2.5}$ in the air exceeds the legal limit more often than anywhere else in Germany. (Deutsche Welle, 2016) For further analysis of urban air pollution in Europe the reader may refer to the respective report by the European Environmental Agency (2016), issued in 2016.

The main sources of PM emissions are traffic (25%), combustion & agriculture (22%), domestic fuel burning (20%), natural dust and salt (18%), and industrial activities (15%). (European Commission, 2015) Most of the policy measures suggested to reduce air pollution in cities therefore concern cars and traffic. Some of the more popular and realistic short-run measures could be: first, to reduce traffic by promoting cycling & walking, second, to establish zones with limited access for vehicles, third, to stop building new roads, fourth, to increase green spaces in the cities, fifth, to make the construction industry further improve the energy efficiency of new buildings and the construction process itself and sixth, to retrofit polluting vehicles - starting with all the Diesel cars that were mentioned earlier. (Urban Times, 2014) In the long run, the most effective measures for reducing PM emissions in urban areas are, however, a complete electrification of the transport sector and a simultaneous de-carbonization of the energy sector. Along with improvements in the energy efficiency of industrial processes, more than 40% of PM emissions could thereby be accounted for and potentially eliminated.

[3]Cardiopulmonary illnesses concern both, heart and lungs. The respiratory system is responsible for the breathing process. (Medicine Net, 2016)

### 2.1.2 Noise pollution caused by road traffic

Noise from road traffic has been classified by the WHO as the second worst environmental health risk in Europe. (European Environment Agency, 2017) It is measured using a logarithmic scale, meaning that an increase of 10 dB(A)[4] means a doubling of perceived loudness. Heavy traffic causes noise on a level of 85 dB(A). Other everyday noises may serve as reference points: a quiet library generates 30 dB(A), a normal conversation 60 dB(A), a vacuum cleaner 70 dB(A), a chain saw 110 dB(A) and a jet takeoff generates a sound level of 120 dB(A). (Earth Journalism Network, 2014) Hence, heavy traffic causes nearly three times as much noise as a vacuum cleaner. That is troubling because human exposure to such noise levels can lead to annoyance, stress, tinnitus, sleep disturbance and related increases in the risk of hypertension and cardiovascular diseases. These would at least lead to a decrease in perceived quality of life. Moreover, exposed children may, in addition, suffer from cognitive impairment including attention, concentration, sound discrimination, memory and reading ability. (European Environment Agency, 2017) (World Health Organization, 2011) The WHO recommends minimum target values of 65 and 55 dB(A), medium target values of 55 and 45 dB(A), and long-term targets of 50 and 40 dB(A) during the day respectively night. (Umweltbundesamt, 2017) About 40% of the population in EU countries is exposed to road traffic noise levels higher than 55 dB(A), 20% even to 65 dB(A) during the day and 30% to more than 55 dB(A) at night. (World Health Organization, 2017)

In order to quantify the described problem, the German company Mimi developed the World Hearing Index by gathering data through a hearing test application and paired it with research from the WHO on noise pollution in 50 selected cities. They find the average hearing loss of tested citizens in one of the large cities to range from 10.63 to 19.34 years, meaning that on average city inhabitants hear as bad as people living in rural areas who are between one and two decades older. As is the case with air pollution, the worst cities in terms of hearing loss are mostly located in Africa and Asia - Delhi, Mumbai, Cairo, Beijing, Guangzhou are some examples (see Figure 2). While the German cities in the sample are all part of the better 50%, even living in the relatively quiet Munich is associated with an average hearing loss of about 12 years. (Mimi, 2017) The results underline the urgency of the problem of noise pollution. As most of the damage to the ears of urban citizens is caused by road traffic noise, the counter-measures focus on avoiding, mitigating or compensating this type of noise. Among the avoidance measures are: first, to reduce the number

[4]dB(A) is the A-weighted value of decibels, it weights sounds in the audible range of humans. (Earth Journalism Network, 2014) The unit measures relative loudness perceived by the human ear. The "d" stands for "deci". The "B" stands for "bel", a tenth of which is a decibel.

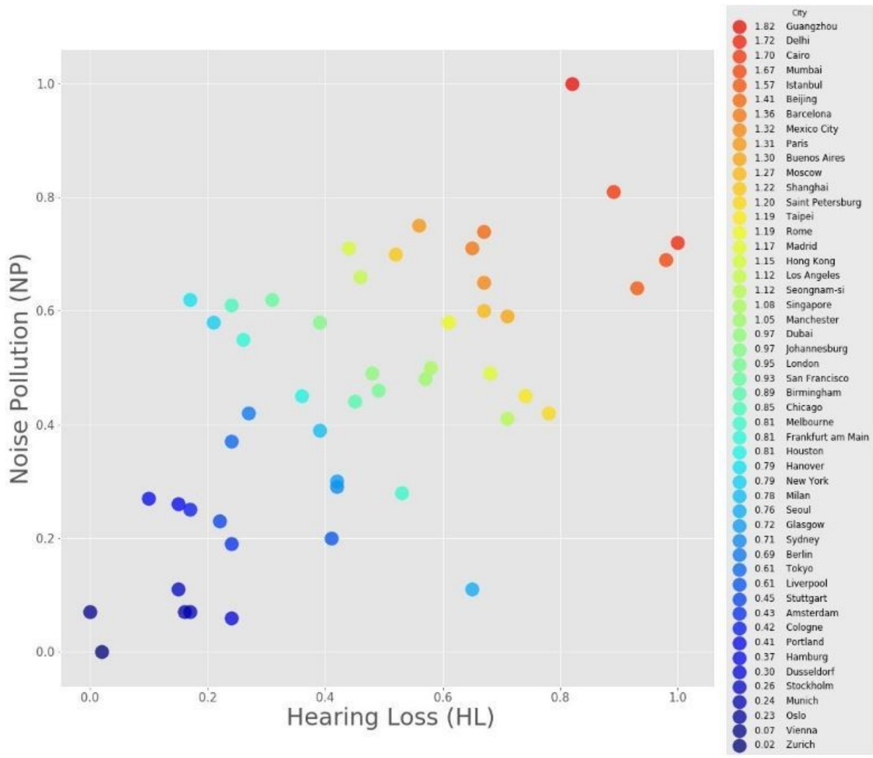


Figure 2: Combined plot of hearing loss and noise pollution in major cities (ranging from best to worst). (World Economic Forum, 2017) (Mimi, 2017)

of internal combustion engine vehicles (ICEVs) and, second, to increase vehicle utilization rates. While the latter can be achieved through car-pooling, a reduction in the number of combustion engines on urban roads can be achieved either through a reduction in overall numbers or a replacement of ICEVs by electric vehicles (EVs). (Umweltbundesamt, 2017) Since human ears perceive noise in a strongly non-linear way, the recognized loudness of a vehicle very much depends on the prevailing background noise. Hence, the more congested roads already are, the less disturbing for humans is an additional car on the road, and vice versa at night when roads are much less crowded and residents therefore notice every single car passing by. The total loudness or audibility of a vehicle, as shown in Figure 3, depends foremost on its rolling noise (caused by tires and aerodynamics) and its engine noise. At speeds lower than 30 km/h, the engine noise dominates the rolling noise. (Jochem et al., 2016b) Since the average speed in major cities at times of congestion is only around 14 km/h and in large cities many important roads are always congested in peak periods, inhabitants (residents, cyclists, pedestrians, etc.) are exposed to car noise mainly caused by engines every day. These noise levels could be diminished by replacing ICEVs with EVs. Even in un-congested periods when the average speed is over 30 km/h, EVs with their almost silent electric motors can reduce overall traffic noise.

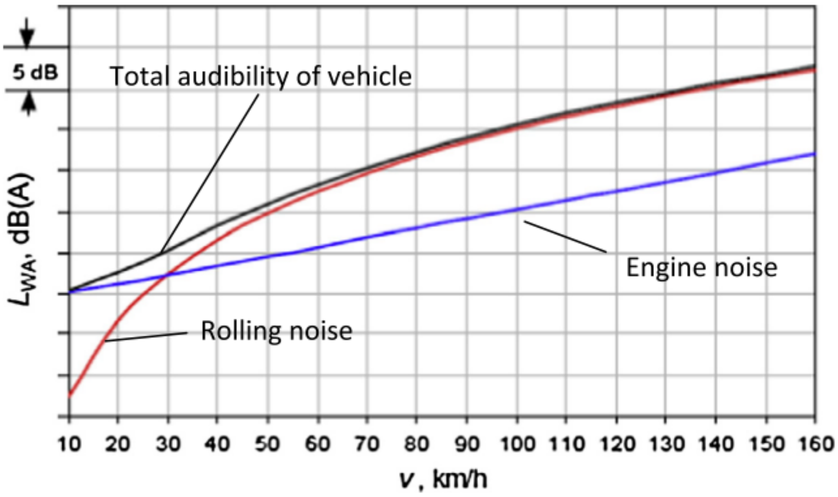


Figure 3: Audibility of passenger cars depending on their velocity. Audibility depicted in steps of 5 dB(A). Velocity ranging from 10 to 160 km/h. (Jochem et al., 2016b)

Summarized, urban road traffic noise below 40 km/h, which is well above the average vehicle speed in most major cities around the world (see INRIX Research 2016), will be perceptibly reduced by performing a wide-spread replacement of ICEVs by EVs. (Clean Technica, 2016) Therefore, a complete electrification of the transport sector would make a great contribution to the reduction of noise pollution in urban areas all over the world. Hence, the second objective of our project, the reduction of urban noise pollution, may be achieved for Karlsruhe by electrifying its taxi fleet.

## 2.2 Barriers to EV adoption and governmental measures to dissolve them

EVs are preferably used in urban areas because of the following reasons: first, they have zero local/tailpipe emissions, second, they barely make a sound when in operation and, third, they have very little power consumption when stationary e.g. in congestion situations. (Newman et al., 2014) Hence, the electrification of the transport sector would greatly contribute to a mitigation of both, air and noise pollution, in urban areas. However, there are barriers to EV adoption for the EV buyer, the investor in the charging system and other involved parties. Some of them can be lowered by local governments implementing smart policies. The first major barrier is the lack of public charging infrastructure. (Mersky et al., 2016) (Madina et al., 2016) This is troubling because, due to their relatively low range, BEVs need to be recharged far more often than ICEVs. However, even state-of-the-art fast-charging stations (CSs) cannot compete with ICEVs averaging at 4 min recharging time including payment. (Sierzchula et al., 2014) Consequently, the switch from ICEVs to BEVs can be inconvenient for EV drivers on trips longer than the range of their EV. They would need to make detours for recharging and take breaks of at least 15 minutes. Otherwise, the EV can be recharged at home and overnight. Moreover, many people may depend solely on public CSs since the installation of home chargers may not be practicable in apartment blocks with limited off-street parking. (Ajanovic and Haas, 2016) However, investments in the charging infrastructure only pay off in case of widespread adoption of plug-in electric vehicles (PEVs) - hence, this constitutes a classic chicken-and-egg-problem: in order to interest more people in the purchase of a PEV, more chargers need to be deployed and vice versa. (Van Deventer et al., 2015) Due to their higher population density, and therefore potentially higher utilization of CSs, urban areas provide a more investment-friendly environment for EV infrastructure build-up. Consequently, EV fleet operations are more worthwhile to pursue (see Newman et al. (2014)) as it is likely that investments in charging stations dedicated to a taxi fleet would be amortized much quicker than investments in regular public charging infrastructure. The reason is that high utilization rates would be achieved if the amount and spatial distribution of CSs were carefully planned, not leading to over-abundance (cf. Comodi et al., 2016).

The second major barrier is the high purchase price of EVs (see e.g. Sierzchula et al., 2014) which is driven by their expensive battery packs. The price may, however, be offset by significantly lower operating costs, so that the total costs of ownership (TCO) for a PEV (PHEV or BEV) could beat those of ICEVs. Moreover, the production costs of battery packs have been drastically reduced through a considerable growth of production capacities in recent years, and are projected to continue on this path in the coming years (see e.g. International Energy Agency 2017). Still, data on operating costs, lifetimes of batteries, etc. have been scarce and are just about to pile up as most major automobile companies start bringing EV models to the markets. Potential early adopters, which are crucial to the diffusion of innovations (see Rogers, 1962), may not yet be aware of favorable TCOs of some EV models. Research on this topic is not definitive, see for example Hagman et al. (2016) and Bubeck et al. (2016). It is clear, however, that operators of vehicles with high annual mileage, as is the case for taxi and delivery services, profit from electrification to a greater extent than private vehicle owners. (Ajanovic and Haas, 2016) The global stock of EVs has grown rapidly since 2010. Although the share of EVs in the total number of passenger light-duty vehicles is still only 0.2% (see International Energy Agency, 2017), there are certain hot spots for EV sales. These are 14 large cities, together accounting for nearly 33% of global EV sales. (International Council on Clean Transportation, 2017) Therefore it is especially interesting to see how they have been promoting the adoption of EVs and which measures seem to be most successful.

### 2.2.1 Incentives for EV adoption in the "Global EV Capitals"

As research on whether and to what extent EVs achieve lower TCOs than ICEVs when used as private passenger vehicles is not yet conclusive, it is advisable for countries or cities that pursue the de-carbonization of their transport sector to support EV sales by nudging (see Thaler and Sunstein 2009) consumers into buying them. In the global EV landscape, some large cities act as leaders in the development and testing of new policy measures. By determining best practices for supporting the adoption of EVs, they serve as role models for other cities and for national governments. The International Council on Clean Transportation (2017) finds that support measures implemented in these "Global EV Capitals" can be grouped into five categories (see Table 1). First, cities may use financial incentives e.g. subsidies in order to catalyze EV sales or, second, they may use non-financial incentives respectively grant EV owners special privileges e.g. free parking. Third, they may facilitate deployment of public CSs in their municipality e.g. through financing or install them themselves. Fourth, cities can steer local research facilities and take part in promotional campaigns in order to further develop technology and markets. Fifth and lastly, they may advance the electrification of their transit system and fleets, including buses, shared cars and taxis. The most successful of these "capitals" are the two biggest cities in Norway, Oslo and Bergen. While Norway's EV market share of 28.8% is already the highest in the world, these two cities even achieved EV shares of new passenger car sales of 36% respectively 47.7%. (International Energy Agency, 2017) Therefore, an examination of policy approaches implemented in Norway respectively Oslo should deliver valuable best-practice insights and some policies may just be copied by other cities. (Bjerkan et al., 2016)

The country of Norway offers the following subsidies, in total making EVs more attractive than ICEVs in terms of TCO: exemption from vehicle purchase tax, value-added tax, toll road charges, registration tax and annual circulation tax. Norway also supports initiatives to install more fast-CSs along highways. On top of those incentives, the city of Oslo provides free travel on road ferries, free charging at municipal CSs, free parking in municipal parking spaces and access to bus & taxi lanes. (Ajanovic and Haas, 2016) The mentioned national and municipal policies are mainly financial incentives that reduce the high upfront costs associated with the purchase of EVs and the setup of charging infrastructure. The findings of Bjerkan et al. (2016) validate this scheme. Based on a survey among 3384 Norwegians, they find the most critical incentives for buying an EV to be the exemptions from purchase

| Nr | Classification | Examples |
|---|---|---|
| 1 | Financial incentives | Subsidies, in addition to federal- and state-level, for purchase of EVs and installation of CSs at home |
| 2 | Non-financial incentives | Special benefits for drivers: free parking, access to high-occupancy lanes & low emission zones, exemption from fees in tunnels and congestion areas |
| 3 | Charging infrastructure | Deployment of public CSs |
| 4 | Research & campaigns | Steering of research, market development and promotional campaigns |
| 5 | Transit & fleets | Electrification of bus & taxi fleets and electric car-sharing programs |

Table 1: Classification of policies by municipalities supporting EV adoption. Adapted from (International Council on Clean Transportation, 2017).

tax and value-added tax - more than 80% of respondents agreed. Exemptions from road toll charges and registration tax follow next. (Bjerkan et al., 2016) In addition to the incentives for private EV users, which led to 35,000 EVs in the region, Oslo is replacing its entire fleet of 1,100 vehicles with EVs. (City of Oslo, 2017) Although Oslo is providing a wide range of incentives to potential EV buyers, Amsterdam is the most progressive city in Europe regarding the electrification of taxi fleets. Since 2014 a fleet of 167 BEVs (Tesla Model S) has been operated by the company Taxi Electric at Schiphol Airport near Amsterdam. As of 2015, Taxi Electric and two other taxi companies also have 172 BEVs (Nissan Leaf and e-NV200) in operation in the city. The necessary charging infrastructure is planned to be expanded by 25 additional chargers each month and shall consist of 4,000 CSs in total by 2018. (Inside EVs, 2015) As of 2016, there are about 400 electric taxis in operation and all licensed taxi companies in Amsterdam have agreed to electrify the remaining 3,600 taxis until 2025. The country of the Netherlands and the city of Amsterdam strongly support this transition by providing purchase subsidies of 5,000 Euros for each BEV taxi. Besides, non-financial incentives such as free parking while charging and priority at the Central Station taxi rank are provided to taxi drivers. From 2018 on, only electric taxis are allowed there. Furthermore, fast-charging points (CPs) have been installed specifically for electric taxis at strategic locations around the city. (City of Amsterdam, 2016)

More examples of innovative policy approaches adopted by cities all around the world can be found in Urban Foresight (2014). However, our focal point in the following chapters will be the field of transit & fleets.

### 2.2.2 Advantages and dissemination of taxi fleet electrification

There are several advantages of electrifying taxi fleets. The most significant ones are listed in the following, sorted from most to least important:

1. Improvements in urban air quality: electric taxis have zero local emissions of GHG and PM, in contrast to conventional taxis. Thus, an introduction of electric taxis would improve urban air quality. While electricity generation does also generate emissions, it is beneficial for public health to have those emissions released into the atmosphere distant from large population centers. (NYC Taxi & Limousine Commission, 2013)

2. Reduction of noise pollution: electric taxis emit less noise than conventional taxis at typical urban travel speeds (see Figure 3, p. 9).

3. Reduction of carbon footprint: since the daily operational time of taxis in urban areas is a lot longer than of private vehicles (see e.g. Ajanovic and Haas 2016), the electrification of one taxi would have about the same impact as of eight private cars. Hence, this represents an effective way to reduce the carbon footprint of passenger transportation. (NYC Taxi & Limousine Commission, 2013)

4. Lower maintenance costs: taxi operators would benefit from significantly lower maintenance costs. Electric taxis do not have transmissions or cooling systems, thus do not need e.g. oil changes, and they rarely need replacement parts due to non-existence of e.g. spark plugs. These costs and the generally lower fuel respectively charging costs would need to be weighed against higher upfront battery and infrastructure investment costs. (Kettles, 2016)

5. Better resiliency: not depending on gasoline for their operation, electric taxis can make cities more resilient against natural hazards such as hurricanes causing, for example, fuel shortage. Also, by designing the electric taxis as mobile power storages, they could in cases of emergency keep many important devices running for days. (NYC Taxi & Limousine Commission, 2013)

6. Price consistency: prices for electricity are generally less volatile than for gasoline, as the latter depend on the oil price (see Figure 4). Thus, taxi operators would benefit from more stable and predictable operating expenses. (NYC Taxi & Limousine Commission, 2013)

7. Raising awareness: on top of the mentioned advantages, electrified taxi fleets are likely to raise awareness of EVs as taxis are highly visible in urban areas. Also, taxi customers will be able to have the experience of sitting in the back

seat of popular EV models. Thus, electric taxis could have an education impact on the population and encourage adoption by private vehicle owners. (NYC Taxi & Limousine Commission, 2013)

8. Potential for large-scale data analysis: by monitoring the movements and technical conditions of their cars, operators of large taxi fleets will be able to gather loads of data on issues such as range at different temperatures and number of battery life cycles in case of frequent recharging.

9. Lower heat emissions: electric taxis heat up the surrounding urban environment only 20% as much as conventional taxis. (Li and Mi, 2015)

For these reasons, experts, potential users and service companies have ranked taxis among the three ecologically most promising areas of application in an online survey conducted within the framework of the Showcase Program Electro-Mobility in Germany. (Harendt et al., 2017) Programs for electrification of their taxi fleets are planned, ongoing or finalized in the cities of Amsterdam (NL), Bangalore (IN), Beijing (CN), Bogotá (CO), Dundee (UK), Hangzhou (CN), Hongkong (HK), Loja (EC), London (UK), Madrid (ES), Montevideo (UY), Montreal (CA), Nagpur (IN), Nanjing (CN), New York City (US), Rotterdam (NL), Santiago (CL), Shenzhen (CN), Singapore (SG) and Taiyuan (CN). There may even be more such programs of which we are not aware at this point. The most popular EV models used in these programs are BYD e6, Nissan Leaf, Nissan e-NV200 and Tesla Model S. Nagpur and Bangalore also incorporated some models produced in India. Most of the largest fleet electrification programs are launched by Chinese cities, most notably Beijing. The government of China recently announced that the whole taxi fleet of 67,000 ICEVs would be replaced by BEVs, costing around 1.3 billion USD. (Electrek, 2017a) The two main incentives for large cities to pursue an electrification of their taxi sectors, the reduction of air and noise pollution, have been explained in Sections 2.1.1 and 2.1.2. In places where these pollution levels are worst, local governments are forced to quickly tackle the problem - and an apt starting point is to electrify the taxi fleets. This is also the case in Bejing, where the Chinese government hopes to significantly improve local air quality by implementing the complete overhaul of its taxi fleet. According to estimates, 30% of air pollution in Beijing is caused by vehicles. Local air quality may improve soon but the overall impact of their program on GHG emissions is unclear. This is due to China's continuing reliance on coal as major energy source for electricity generation (Cai et al., 2017). Therefore, the electrification of the transport sector needs to be accompanied by a de-carbonization of the energy sector in order to ensure positive effects on local and nation-wide air quality.

In Germany, few taxi companies already incorporate EVs in their fleets. For exam-

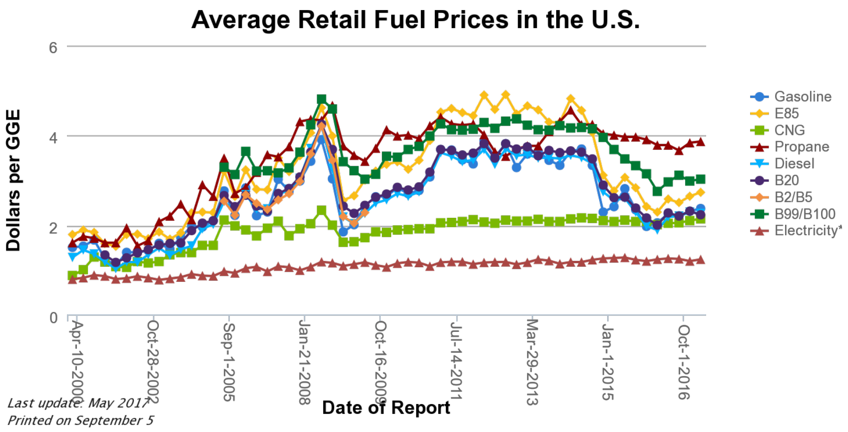


Figure 4: Development of retail prices in USD of common and alternative fuels from 2000 to 2017. Fuel volumes measured in gasoline-gallon equivalents (GGEs). Electricity prices reduced by factor of 3.4 as electric motors 3.4 times more efficient than ICEs. Based on US Department of Energy (2017).

ple, taxi companies in Hamburg (see Prima Clima Mobil, 2013) and Bochum (see Bednarz Elektro Taxi, 2017) each acquired four Nissan Leafs for their businesses. Mentionable support programs for the introduction of electric taxis only exist in the cities of Munich (two million Euros for support of taxi companies, 0.2 Euros for each kilometer traveled; see Muenchen.de, 2016) and Regensburg (0.25 million Euros for support of commercial fleets including taxi companies; see Stadt Regensburg, 2016). A major setback for electrification efforts of taxi fleets in German cities is that since November 2016 it has not been possible to use EVs as taxis which have not been equipped with a distance counter and a taximeter by the manufacturing company. (see e.g. Der Tagesspiegel, 2017). The German government is reportedly working on this issue. (Bundesministerium für Wirtschaft und Energie, 2017) Since only few EV models, not including e.g. Tesla Model S, are available as taxi versions so far, it is imperative that this be resolved so that taxi fleet operators in Germany may plan for electrification. The following chapter is meant to provide an overview of the technical background needed to take the necessary decisions before starting and while conducting a project on fleet electrification.

# 3 Technical background regarding fleet electrification

Among the most important decisions to take when starting to conduct a project on vehicle fleet electrification, aside from financing, are:

1. what EV technology (BEV, PHEV, etc.) to use,
2. what charging technology to use,
3. where to place the necessary CSs,
4. what business model to follow.

The following sections shall assist in taking these decisions by first explaining the different vehicle powertrains. The environmental impact of replacing conventional with EV taxis may then be assessed based on a comparison of emission footprints. In order to provide a basis for determining the necessary charging level and selecting the standard, these are reviewed and amended by an overview of installation costs and observations on battery degradation. Subsequently, the possibilities of implementing wireless power transfer or battery swapping instead of conventional technology are fathomed before the chapter is concluded by pointing out the technical and financial benefits of integrating the electrified fleet into the electricity grid. Especially the last aspect is of importance to the business model since power loads consumed by charging EVs are potentially large.

## 3.1 EV technologies and associated emission footprints

The practicality of EVs depends on their built-in battery packs as it does on fuel tanks in ICEVs. Although various other chemical compositions are being researched and some appear to be promising, the leading technology is based on lithium-ion. (Larcher and Tarascon, 2014) It is also used in a multitude of other products such as smartphones and tablets. The range of lithium-ion batteries built into vehicles is mainly determined by their energy density and size. Since the battery packs make up about 25% of vehicle prices (see e.g. Nykvist and Nilsson 2015), two developments are particularly relevant for the diffusion of EVs: the development of battery prices and energy density of battery packs. A compilation of cost statements and projections by International Energy Agency (2017) is displayed in Figure 5. As of 2016, major US car manufacturers report battery costs of below 200 USD/kWh, down from 900 USD/kWh in 2009. During the same timespan of seven years, energy density has increased from little more than 100 to over 600 kWh/L. The recent trend

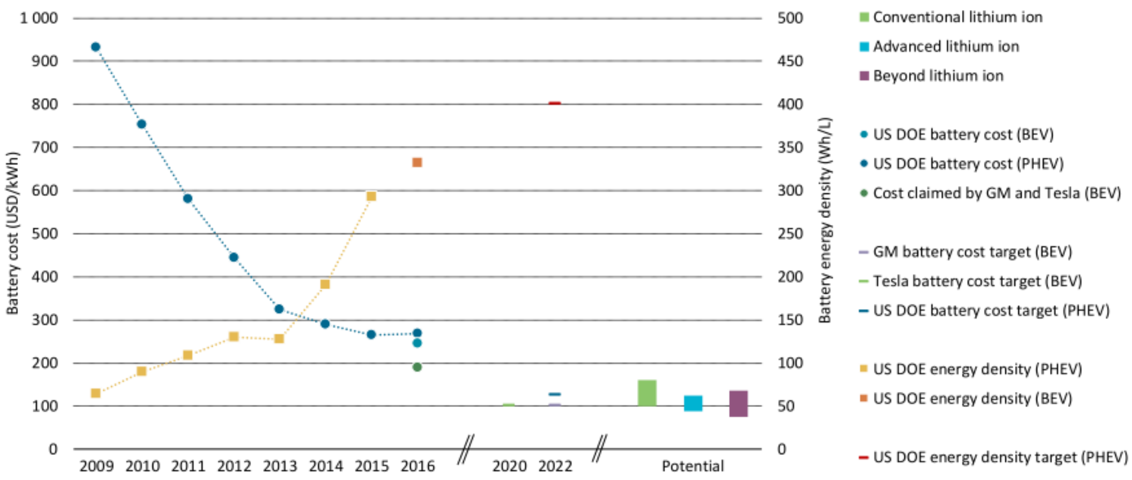


Figure 5: Evolution of EV battery prices and energy density. The x-axis represents a timeline from 2009 to 2022 and beyond, the left y-axis the battery costs in USD/kWh, and the right y-axis the battery energy density in kWh/L. The points in the diagram stand for cost and density reports and projections from the US Department of Energy and the major US car companies, General Motors and Tesla. Inserted from International Energy Agency (2017).

of rapidly falling battery prices is confirmed by Nykvist and Nilsson (2015). In their systematic review of battery pack costs, they look at data from multiple types of sources and conclude that battery costs of leading manufacturers are declining by 8% annually. Correspondingly, the learning rate (the cost reduction following a cumulative doubling of production) - is estimated between 6 and 9%. Based on these insights, we expect that generally BEVs will beat ICEVs in terms of TCO in the next five years.

### 3.1.1 Classes of EVs based on powertrain configurations

EVs are commonly classified based on their powertrain configurations, ranging from 0% electrification (ICEV) to 100% electrification (BEV), as illustrated in Figure 6. Their corresponding hybridization ratio is a quotient between maximum power of the electric motor and maximum power of power train. Six different vehicle classes (see Figure 7) will be distinguished in the following: ICEV, hybrid-electric vehicle (HEV), PHEV, range-extended electric vehicle (REEV) or serial HEV, BEV and fuel-cell electric vehicle (FCEV). The distinction between micro-, mild- and full-HEV only refers to the relative size of the electric motor and will henceforth not be made. Vehicles with hybrid electric powertrains (HEV and PHEV) are propelled via a combination of internal combustion engine (ICE) and electric motor. Their respec-

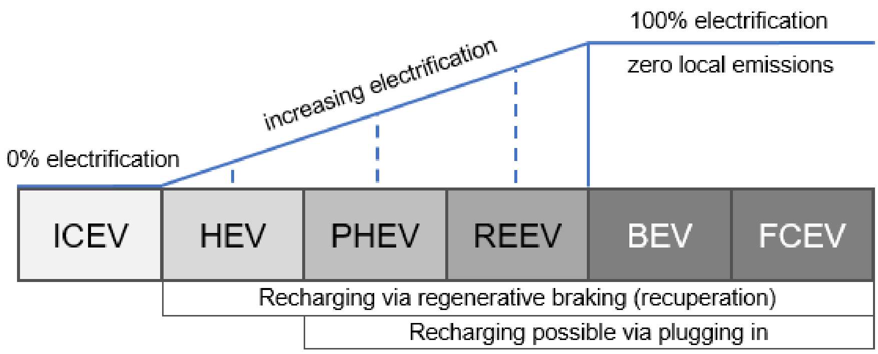


Figure 6: Main powertrain configurations and respective electrification ratios. Different EV types able to recharge their batteries via regenerative braking i.e. recuperation. All except HEV can also plug in for recharging. Only fully electrified vehicles with zero local emissions. Based on Ajanovic and Haas (2016)

tive energy sources are gasoline and electricity, to be stored in a connected fuel tank respectively battery. Battery and electric motor are added either to achieve better fuel economy or better performance than with internal combustion only. (Poullikkas, 2015) (Yong et al., 2015)

In a HEV, the battery is charged either by the ICE or through regenerative braking, also called "recuperation". In the first case, a generator and a power converter are installed between ICE and battery in order to convert the output of the ICE, thermal energy, to chemical energy, which is then stored in the battery. In the second case, recuperation allows the vehicle to use kinetic energy from deceleration, convert it to chemical energy and store it in the battery. Basically, the regenerative brakes put the electric motor into reverse mode during deceleration, thereby slowing the wheels down. This way, the electric motor turns into a generator and produces electricity to charge the battery. For situations in which this mechanism does not provide enough braking power, HEVs have friction brakes for back-up. Applying these two mechanisms, HEVs always operate in charge-sustaining mode, maintaining their batteries at nearly constant state of charge (SOC) while driving. (Poullikkas, 2015) The electric motor sources itself from the battery to propel the vehicle at startup and when accelerating. At these moments the electric motor can exert much higher torque[5] than an ICE. Therefore, overall vehicle efficiency is maximized by switching the engine on only for one of the following: higher speed levels, faster acceleration or charging the battery. (Poullikkas, 2015) The combination of ICE and electric motor can be realized in three different setups - series, parallel and series-parallel:

[5]In simple terms, "torque" is the engine's rotational force. Thus, it is measured in Nm. Torque refers to the amount of work an engine can deliver as opposed to horsepower (HP) which defines how quickly the work can be delivered. (Auto Express, 2017)

1. in a parallel HEV, ICE and electric motor are both mechanically coupled to the transmission. They simultaneously transfer power to the transmission turning the wheels, and propelling the vehicle,

2. a serial HEV or REEV is only propelled by its electric motor, which is attached to transmission and wheels. The connected battery cannot be recharged via plug but only by recuperation or a combination of ICE and generator. In this framework, the ICE is not directly connected to the transmission,

3. a series-parallel HEV can be operated in either mode, series or parallel. In order to enable that, the design is more complicated than with the other setups.

Depending on the exact configuration, HEVs can be up to 43% more fuel-efficient than ICEVs. (Tie and Tan, 2013) (Yong et al., 2015)

In a PHEV, the battery can also be connected to a charging station and charged from the electricity distribution grid via plug (in addition to charging via ICE and recuperation). Usually, PHEVs have larger battery packs than HEVs enabling them to stay in electric propulsion mode for larger fractions of their operating time. Since PHEVs are meant to cover the average daily driving distance of e.g. around 50km in the US, their battery packs should provide at least 12 kWh. (Kong and Karagiannidis, 2016) Using the ICE only at high vehicle speeds, where it is most efficient, potentially increases the total combined efficiency. PHEVs can operate either in charge-depleting or in charge-sustaining mode. (Emadi, 2011) The vehicle is usually started in charge-depleting mode. With the ICE being disabled, the vehicle's only propulsion source is the electric motor and the battery's SOC starts decreasing. Once the SOC reaches a certain lower threshold, representing the minimum amount of energy to be stored at all times, the vehicle switches to charge-sustaining mode. Being also powered by the ICE, the vehicle sustains the battery's SOC. Some vehicles also feature variations of the two described modes: the blended and the mixed mode. If the vehicle features a mixed mode, the vehicle can automatically switch to charge-sustaining mode once its electric range is exhausted. The blended mode is a variation of the charge-depleting mode so that the ICE is engaged even before reaching the predefined threshold for SOC. The latter is used in ICEVs, in which the electric motor is not able to reach or maintain desired speed levels on its own. The achieved increased fuel efficiency leads to higher vehicle ranges. (Poullikkas, 2015) (Yong et al., 2015) (Kong and Karagiannidis, 2016)

A BEV does not need an ICE, instead using an electric motor as its only propulsion and a battery as its sole power source. Their battery has multiple times the capacity of a PHEV's. Therefore, a BEV always operates in charge-depleting mode and needs

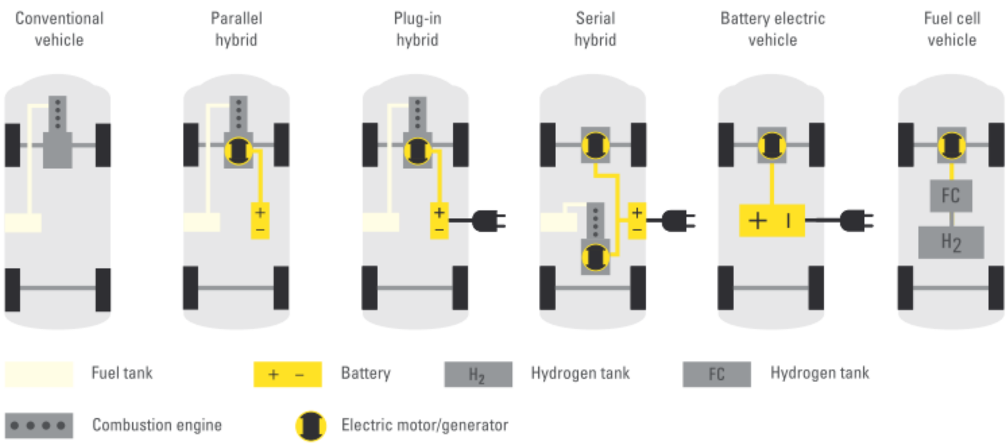


Figure 7: Visualization of powertrain configurations of ICEV and different EV types. Inserted from (BWe-Mobile, 2011)

to be recharged regularly. This can be done either via recuperation or externally. Its all-electric propulsion system enables the vehicle to exhibit much higher torque at low vehicle speeds than an ICE. That is why BEVs are able to accelerate better from a resting position than ICEVs. A FCEV is similar to a BEV regarding its powertrain configuration. However, instead of lithium-ion battery packs, the vehicle features a tank of hydrogen as its primary energy source and a fuel cell as device for energy conversion. The fuel cell either acts as primary or as secondary energy supplier, depending on the requirements and the technology. It utilizes an electrolysis process to convert thermal into electric energy, leaving the byproducts of heat and water. (BWe-Mobile, 2011) (Tie and Tan, 2013) (Poullikkas, 2015) (Yong et al., 2015)

### 3.1.2 Emission footprints of available vehicle classes

The five described EV classes use electricity as complementary (HEV and PHEV) or primary (REEV, BEV and FCEV) energy source. EVs can be compared to ICEVs regarding levels of tailpipe emissions by examining the origin of the used electricity. The G20 countries exhibit an electricity mix which is dominated by fossil fuels. In 2014, coal (44%), oil (3%) and natural gas (19%) together accounted for two thirds of total electricity generation. Renewable energy sources (22%) and nuclear energy (12%) represented the remaining third.[6] Due to the high emission intensity of fossil fuels consumed in the process of electricity production, it is therefore questionable whether BEVs can deliver on their promise of zero emissions. They do not have any tailpipe emissions, but if GHG and PM are emitted by conventional power plants instead, then replacing ICEVs with BEVs would already lead to a significant reduc-

[6] Other sources contributed less than 1% and were therefore disregarded.

tion of urban air pollution. The reason is that ICEVs are mainly responsible for PM emissions in the city (see e.g. Hooftman et al. 2016) and the vast majority of conventional power plants is located far from city centers. Therefore, goal # 3 of this project, reducing GHG emissions in order to mitigate climate change, will be the main focus in the following. A comparison of emission levels of state-of-the-art ICEVs, HEVs, PHEVs and BEVs shall help with clarification. Thereby, the varying composition of sources for electricity generation between countries needs to be taken into account. More specifically, the type of power plant which has generated the consumed electricity makes a great difference for the level of GHG emissions associated with BEVs (see e.g. Huo et al. 2015 and Rangaraju et al. 2015). (Greenpeace, 2017)

Life-cycle assessment (LCA) is a standardized method to assess the environmental performance and resource consumption of products including vehicles throughout their life cycles. (US Environmental Protection Agency, 2006) Two major types of LCAs can be distinguished depending on the system boundaries. (Nordelöf et al., 2014) Studies either perform a "complete" LCA on a vehicle, from raw material acquisition to recycling at end-of-life, or they focus on a "well-to-wheel" (WTW) assessment. (Rangaraju et al., 2015) Despite their claim, these studies usually do not take into account aspects such as differences in battery degradation through use of different charging modes (see e.g. Omar et al. 2014) or individual driving behavior (see e.g. Canals Casals et al. 2016) since they are hard to capture thoroughly in such analyses. The energy flow from mining (at the "well") the energy source to driving the vehicle ("wheel") differs between ICEV and BEV. Hence, the process steps differ as well. On te one hand the seven steps for ICEVs are extraction, transport, refining, distribution, engine combustion, power delivery system and wheel. The process of mining the energy, transporting it, and storing it in the car is summarized under the term "well-to-tank" (WTT) whereas the process of driving the car using the stored energy is called "tank-to-wheel" (TTW). On the other hand, the nine steps for BEVs are extraction, transport, refining, distribution, power generation, power transmission & distribution, charging, motor and wheel. The major processes are called "well-to-power-plant" (mining the energy source and transporting it to the plant) and "power-plant-to-wheel" (transmitting the electricity to the car and using it by driving). (Woo et al., 2017) A comprehensive well-to-wheel assessment for popular ICEV and BEV models is performed in Woo et al. (2017). In order to attain a global perspective and observe regional differences regarding the resulting $CO_{2eq}$ emissions[7], the researchers include the top 70 countries (covering more than 97%)

[7]The term $CO_2$-equivalent or $CO_{2eq}$ is generally used to bundle different GHG in a common unit. For any type and amount of GHG, x $CO_{2eq}$ states the amount of $CO_2$ which would have an equivalent impact on global warming. For example, 1kg of methane ($CH_4$) has the same impact as 25kg of $CO_2$ and thus gets multiplied by 25 when adding it up to $CO_{2eq}$.

| Region/country | Subcompact | Full-size luxury |
|---|---|---|
| Global | 78.1 | 99.3 |
| United States | 77.3 | 98.4 |
| China | 102.7 | 130.7 |
| Europe | 51.0 | 64.8 |
| Germany | 74.8 | 95.2 |
| Norway | 2.3 | 2.9 |
| Gasoline ICEV | 101.4 | 187.5 |
| Diesel ICEV | 89.8 | 143.1 |

Table 2: GHG emissions of BEVs in $gCO_{2eq}/km$ using median emission factors, considering electricity generation mix, calculated on well-to-wheel basis. Based on Woo et al. (2017).

in terms of $CO_{2eq}$ emissions. They add up fuel economy data and emission factors for ICEVs respectively GHG emissions data of each power source and electricity generation mix data for each country. The researchers work with four different vehicle categories: subcompact, compact, full-size luxury and SUV. Each category is represented by one to three BEVs, among them Tesla Model S and Nissan Leaf, and three corresponding ICEV models. The Nissan Leaf is currently popular with taxi companies in Europe. (Electrek, 2017b) This may be due to the relatively early introduction of the Leaf and it can be presumed that vehicle size requirements will lead to the adoption of larger models once they have proven to be fit. One promising candidate is the Nissan e-NV200. (NYC Taxi & Limousine Commission, 2013) Another one is the BYD e6, which has been in operation in Shenzhen since 2010 (see EV News 2015) and is on the verge of large-scale introduction to several other taxi markets (see e.g. Taxi Times 2016). Since the Nissan Leaf is in the subcompact category, and candidates for wide-spread adoption rather belong to full-size luxury, GHG emission levels of both categories are deemed relevant. Results show that GHG emissions of BEVs are strongly related to the electricity generation mix of the country in which they are charged. Countries with major shares of fossil fuels exhibit considerably higher GHG emissions than countries with large amounts of nuclear or renewable energy as part of their mix. Woo et al. (2017) show that, on a global level, BEVs of all categories have lower GHG emissions than their ICEV counterparts (see Table 2). The global average is 78.1 $gCO_{2eq}/km$ for the subcompact class and 99.3 $gCO_{2eq}/km$ for full-size luxury. In Germany, emissions are smaller than the global average but considerably higher than the European average, due to the remaining large share of coal. However, as of 2017 environmental organizations are urging the federal government to take the necessary steps for a gradual phase-out of coal in the near future. (Deutsche Welle, 2017) (Woo et al., 2017)

Similar conclusions have been reached by Ramachandran and Stimming (2015). Rangaraju et al. (2015) point to even lower life cycle emissions of $SO_2$, $NO_x$ and $PM$ in addition to $CO_2$. Rangaraju et al. base their analysis on the Belgian electricity mix, which consists of about 60% nuclear and 27% natural gas. Other recent studies supporting the finding that BEVs have lower well-to-wheel emissions of GHG than ICEVs are Wolfram, P. and Lutsey, N. (2016), Borén and Ny (2016), Canals Casals et al. (2016) and Moro and Helmers (2017). These studies calculate on the basis of the European electricity mix. Tagliaferri et al. (2016) find even lower GHG emissions of BEVs, covering the complete life cycle. Apparently, the significant savings from the use phase are able to offset the $CO_2$-intensive manufacturing of battery packs (see e.g. Plötz et al. 2017 and Bickert et al. 2015). These savings can already be achieved with low annual driving distances of 2500 to 5500 kilometers. Both vehicle types, ICEVs and BEVs, are projected to achieve further emission savings in the future: ICEVs may benefit from efficiency gains of combustion engines and BEVs may improve their production emissions through the increasing energy density of the used battery packs. (Bickert et al., 2015)

With these findings in mind, a replacement of ICEVs with BEVs in taxi fleets seems effective for reducing urban air pollution and GHG emissions. A majority of the mentioned studies point to lower life cycle emissions of BEVs compared to ICEVs even when the vehicles are only privately used. Therefore, due to the high daily mileage of taxis we can expect to see even greater savings for BEV taxis. Having discussed different powertrain configurations used in electric vehicles, the focus shifts to charging technologies in the following sections.

## 3.2 Charging infrastructure for EV taxi fleet in urban area

Fast-charging stations are mainly deployed along highways, connecting large cities. In these places, they serve as replacements for gasoline refueling stations, providing the possibility to quickly recharge EVs while taking long trips. Consequently, these stations can be expected to be sufficiently utilized once PEVs are widely adopted. (Jochem et al., 2016a) High investment and operating costs associated with fast-charging stations require an economical operation and adequately short amortization periods and thus make high utilization rates important. Deployment and operation of fast chargers in urban areas seems less sensible, as private EV owners should be able to meet their daily driving needs charging only at home. However, EV taxi fleets should provide the needed utilization levels to make the operation of a fast-charging infrastructure economically sound. The EVs must be recharged between or during drivers' shifts. From an economic point of view, in order to minimize the downtime, charging during shifts should be restricted to break times. As opposed to the charging infrastructure along highways, the deployment of which is under way (see e.g. EnBW 2017 for Germany), dedicated fast-charging infrastructure for EV taxi fleets is more likely to be planned and built from the ground up as demand will only increase with the share of electrified vehicles. In this respect, it is important that the number (and placement) of fast-charging stations be planned according to the size respectively daily movements of the EV taxi fleet in order to ensure sufficient utilization and therefore economic operation. Studies examining large datasets of taxi fleet movements point to average daily travel distances much higher than 200km (see e.g. Yang et al. 2016 for Nanjing, China and Asamer et al. 2016 for Vienna, Austria). The adoption of EVs as taxis and associated deployment of fast chargers can also be performed in incremental steps diminishing the risk of having mostly idle fast chargers due to a lagged adoption of EVs. Additionally, revenue streams other than from charging shall be explored in order to ensure financially stable operations.

Charging stations have three main characteristics: level, type and mode. The level describes the power output of an outlet, the type refers to the socket and the connector being used, and the mode defines the communication protocol being used between vehicle and charger. (International Energy Agency, 2017) Following the classification of the Society of Automotive Engineers (SAE) (see Green Transportation 2017), five charging levels can be distinguished: AC level 1, 2 & 3 and DC level 1 & 2.[8] The relatively slow AC chargers of level 1 and 2 are mainly used in private households and in office buildings. AC level 3 and DC level 1 chargers are mainly used in public areas, for example at urban parking spaces. DC level 2 chargers are typically installed along highways, where charging speed is most important. Their installation and operating costs are by far the highest, due to the relationship between installed charging power and installation costs, which can be approximated by a linear function. (Nie and Ghamami, 2013) The mentioned charging levels are displayed in Table 3, along with their maximum power levels, estimated charging times and the respective standards used in Europe. Since not all charging power can be directly transferred to battery energy, the charging efficiency of the connected vehicle also has to be considered when estimating the actual charging rate. Nie and Ghamami (2013), for instance, assume a charging efficiency of 1.3, meaning that with an input power of $x$ kW, the effective charging power would be $x$ kW divided by 1.3. As even the fastest available outlets, with an estimated charging time of 15 min are not able to compete with the speed of traditional gas refueling stations, which is around 5 min including payment, further improvements are nec-

[8] Other organizations e.g. IEA classify them differently. However, for the purpose of this thesis it is sufficient to gain insight into the practical aspects of installation & operating costs, and charging speeds rather than to dive deep into the technicalities.

| **Charging level** | AC level 1 | AC level 2 | AC level 3 | DC level 1 & 2 |
|---|---|---|---|---|
| **Max. power (kW)** | $\leq 3.7$ | $\leq 22$ | $\leq 43.5$ | $\leq 200$ |
| **Est. time (0-80%)** | 6-8 h | 1-2 h | 30-60 min | 15-20 min |
| **Standards in Europe** | None | IEC 62196 | IEC 62196 | CCS Combo 2, Tesla, CHAdeMO |

Table 3: Overview of charging levels for EVs, according to International Energy Agency. Rough approximations of charging times, based on battery capacity of 24 kWh. Stated numbers for charging from 80 to 100% roughly equal times for 0-80% as current is normally decreased after reaching 80% for topping off cells. IEC stands for International Electrotechnical Commission. Based on Shareef et al. (2016) and International Energy Agency (2017).

essary in order to make the system more convenient for long-distance trips. These improvements are necessary in order to enable the use of EVs in taxi fleets where charging during breaks and/or shift changes will be crucial. Additionally important are investment and operating costs associated with the deployment of strategically located fast-charging stations for EV taxi fleets. For the mentioned reasons, the next section will cover current developments in the field of fast charging in order to provide insight as to whether the transition from ICEVs to EVs in taxi fleets can be performed in an economically sound fashion. Besides the conventional charging technology, which is called conductive charging, power supply can also be handled differently. For this purpose, two other technologies are on the brink of market readiness: wireless power transfer (WPT) and battery swapping. These will be examined in detail in Section 3.2.2.

### 3.2.1 Most important fast-charging standards & battery degradation

The charging time for an EV is a function of its battery size (in kWh) and the amount of electric power (in kW) that the electrical circuit can deliver respectively the EV can accept: larger circuits provide higher drawing rates. So, it is the EV's capability that determines the ultimate maximum amount of power that can be charged. Hence, more powerful charging stations do not necessarily result in quicker charging operations. (Massachusetts Department of Energy Resources, 2014) In recent years, there has been a competition among three popular standards for fast charging (DC level 1 & 2): the Combined Charging System (CCS), CHAdeMO and Tesla Supercharger. (Jochem et al., 2016a) (Massachusetts Department of Energy Resources, 2014) In China, the State Grid Corporation has set GB/T 20234 AC & DC as the nationwide standards. Figure 8 shows the geometrical differences. Of the three main competitors, CCS seems most likely to emerge as the winner at least for Europe, since Tesla Motors Inc. joined the Charging Interface Initiative e.V. (in


Figure 8: Overview of charging systems being used in Europe, USA, Japan and China, according to CharIN. Inserted from CharIN (2017a).

short: CharIN, see CharIN 2017b). Established in 2015, their primary aim is to "develop and establish the Combined Charging Sytem (CCS) as the standard for charging battery-powered electric vehicles of all kinds." As of March 2017, 15 of the top 20 car brands by volume have already assumed membership of CharIN. (CharIN, 2017a) The European Union also supports this initiative. (European Union, 2014). As of August 2017, more than 3,200 fast-charging stations of this type are already in operation in Europe. (Kraus, M., 2017) CHAdeMO, on the other hand, is the trade name of a fast-charging method established by the Tokyo Electric Power Company (TEPCO) in 2009. It dominates the Japanese EV market, and major Japanese car companies such as Toyota, Nissan and Honda install the associated charging sockets in their cars. The standard has also been adopted by some French car companies such as Peugeot. However, Toyota, Peugeot and Honda are also members of CharIN. Only cars manufactured by Nissan, Mazda and Suzuki exclusively feature CHAdeMO charging sockets. (CharIN, 2017a) The third competitor, Tesla Supercharging, is part of a proprietary system developed by Tesla Motors, the American car company which has been dominating the EV Premium segment with their Model S. Interestingly, Tesla does not allow other brands to charge at their stations but they offer adapters for CHAdeMO chargers. Since Tesla has to comply with the rules set by the European Parliament and Council (see European Union 2014), they also joined CharIN in 2016. As of today, it is unclear whether one of these three competing technologies will emerge as a global standard in the near future and which one it may be.

The Combined Charging System features two different connectors, Combo 1 and Combo 2. The first one represents the charging solution for North America, featuring one plug according to SAE J1772 for AC slow charging and one plug according to CCS for DC charging. The second, Combo 2, has been developed for the European market and features IEC 62196 and also a CCS plug for DC charging. As of 2017, new CCS outlets are able to deliver a maximal charging power level of up to 200 kW. There are even plans to increase that level to 350 kW in the near future. Such an improvement would decrease the time needed to recharge a battery of 24 kWh (see Table 3) to approximately 5 to 10 min. (CharIN, 2017a) However, the most commonly installed fast-charging stations in recent years have featured outputs of 50kW. In Germany, for example EnBW, one of the four large electric utilities mainly operating in the south-west of the country, is currently expanding its fast-charging infrastructure network along highways in the state of Baden-Württemberg and neighboring states. Although their stations have the capability to be upgraded in order to deliver power levels of 150 kW in the near future, a popular charger in Germany is a so-called triplecharger produced by the company ABB, enabling charging with one of three standards: 50 kW (DC level 1), provided via CHAdeMO or CCS plug, and 43 kW (AC level 3) (for classification, see Table 3). (EnBW, 2017) A similar DC fast-charging station with only one charging point and a power output of 50 kW (see German National Platform for Electric Mobility 2015) featured the following investment costs in Euros in 2015 (projections for the year 2020 in brackets):

- Hardware incl. communication and smart meter: 25,000 (15,000)
- Grid connection: 5,000 (5,000)
- Authorization, planning, location search: 1,500 (1,500)
- Installation, building, signage: 3,500 (3,500)

Therefore, the total investment costs (or capital expenditure, CAPEX) amount to 35,000 Euros in 2015 respectively 25,000 Euros in 2020. For running costs (operating expenditure, OPEX), 3,500 respectively 1,500 Euros per year are estimated for 2015 and 2020, consisting of cost blocks for hotline, maintenance and disposal, communication, contract management/billing and the IT system. (German National Platform for Electric Mobility, 2015)

Despite the benefits of pushing the limits of fast-charging, the issue of battery degradation has to be taken into account when designing and implementing a system of EV taxis and accompanying fast-charging infrastructure. Omar et al. (2014) investigate aspects such as performance and lifespan of commonly used battery cells in EVs (lithium iron phosphate) based on different current rates, operating temperatures, and SOCs. They conclude that temperature strongly influences the performance and lifespan of the tested batteries and that high current rates are harmful to the battery cells. (Omar et al., 2014) Chacko and Chung (2012) find that Li-ion cells generate heat during both charge and discharge and are prone to overheating under

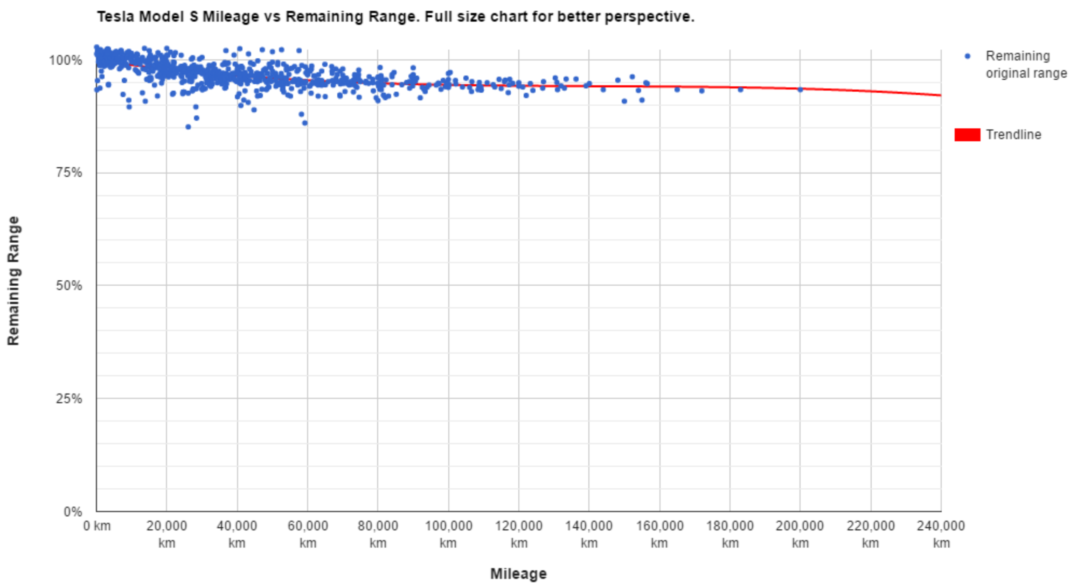


Figure 9: Remaining ranges of 286 Tesla Model S depending on mileage. Trendline illustrated in red, actual data points in blue. Inserted from Electrek (2017c).

stressful conditions such as high-power fast-charging or ambient heat. So, temperature influences performance, reliability, and durability of battery cells. Therefore, the researchers find that the temperature of battery cells needs to be effectively controlled to maintain optimal performance. In contrast to these results, a group of 286 Tesla Model S owners have been gathering data on the remaining ranges i.e. the battery capacities of their vehicles over the past years. These vehicle owners find that the battery packs lose only about 5% of their capacity after 100,000 km. The associated trend line suggests that the average battery pack could operate for another 241,000 km before reaching 90% of original capacity. The few observable outliers (see Figure 9) are explained by the frequency of operating at 100% SOC and deep discharge, as well as the regularity of using fast chargers. (Electrek, 2017c) In light of the inconclusive research on potential battery degradation, it should be examined whether moderate charging powers about 22kW could be sufficient for the application in an e-taxi environment before turning to 50 kW and more. If moderate charging powers were sufficient and requirements for installation of such stations were met, even home-charging of EV taxis could be considered. These aspects will be further discussed in Chapters 5 and 6.

### 3.2.2 Feasibility of wireless power transfer & battery swapping

Basically, instead of using conductive fast-charging stations, ”refueling” of EVs can also be handled through WPT or battery swapping. Therefore, the feasibility of these technologies for taxi operations will be examined. By weighing benefits and

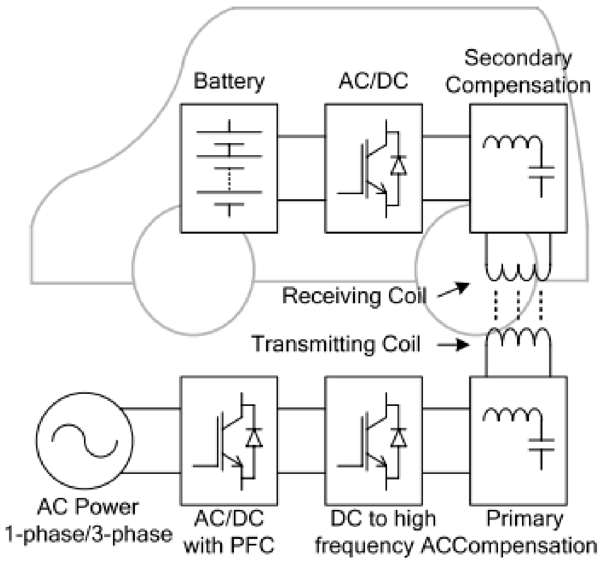


Figure 10: Schematic illustration of a wireless EV charging system. Inserted from Li and Mi (2015).

drawbacks against each other, a verdict will be reached as to whether either of those has already matured enough for deployment. For further observations it is assumed that EV taxis will need to be charged once between shifts and once during each shift. Wireless charging of EVs can be performed either in a stationary or dynamic fashion. (Jeong et al., 2015) Both technologies employ an electromagnetic field for transferring electricity to the battery. A typical wireless EV charging system is shown in Figure 10. First, the utility AC power is converted to DC by a converter with power factor correction. Second, the DC power is converted to high-frequency AC power in order to drive the transmission coil through a compensation network. An optional high-frequency isolated transformer may be inserted between DC-AC inverter and the primary side coil for extra protection against insulation failure. Third, the high-frequency current in the transmitting coil generates an alternating magnetic field, inducing an AC voltage in the receiving coil. The power transfer efficiency is significantly improved by resonating with the secondary compensation network. Fourth and last, the AC power is rectified in order to charge the battery. Summarized, the main parts of this system are the detached transmitting and receiving coils, the compensation network and the power electronics converters. (Li and Mi, 2015)

The company Qualcomm has developed an inductive charging system called Halo in which the energy is transferred from induction coils in a plate on the ground or under it to a plate on the underside of EVs. (Wards Auto, 2017) Using such a stationary WPT, drivers just need to park their vehicles instead of also plugging the EV in, and the charging process can be started. In this way, people do not need to remember to plug in, they are not exposed to tripping hazards due to charging cables on the floor or to leakage from cracked old cables. Also, they do not have to suffer the risk of an electric shock from plugging in under weather conditions such as wind, rain, ice or snow. However, stationary WPT cannot deliver power currents near as large as those of fast-charging stations, and therefore cannot charge as quickly. Although leading researchers in the field have successfully demonstrated a 20 kW system with 90% efficiency, 50 kW are not yet achieved. (Oak Ridge National Laboratory, 2016) Hence, the idea of using this technology for an EV taxi fleet, for which the speed of charging is crucial, can be discounted. (Li and Mi, 2015) In a dynamic WPT setting, the EV can be charged while in motion and run almost indefinitely without stopping. This is achieved through installation of power tracks under roads. Applying this strategy, researchers at the Korea Advanced Institute of Science and Technology (KAIST) have developed a dynamic charging transportation system called the Online Electric Vehicle. Its first commercial version has been in operation in the Seoul Grand Park since 2009, and on the KAIST campus since 2012. There are plans to extend operation of the Online Electric Vehicle to several other sites. As a consequence of more frequent charging events, battery sizes could be significantly reduced. (Jeong et al., 2015) Also, their lifetimes could be extended since shallow, frequent charging is better for lithium-ion batteries than deep, infrequent charging. (Omar et al., 2014) However, in order to fully exploit these advantages, power tracks would have to be embedded under a significant portion of urban roads so that EV taxis would be able to recharge frequently without making large detours. (Jeong et al., 2015) This requirement, together with the restrictions on maximal charging current, make this technology impossible for application in an EV taxi fleet setup. One of few commercial providers of such a system in Germany is the company Primove, a subsidiary of the company Bombardier. Even they do not provide charging currents above 22 kW for passenger cars. (Primove, 2013) Some additional projects in this field are described in Qiu et al. (2013). It is concluded that wireless power transfer is not fit for large-scale deployment as needed for an EV taxi fleet. At this stage, the technology is more suitable for home-charging of PHEVs, as recognized by BMW, Daimler and other major car companies. (Tech Crunch, 2017) (Green Tech Media, 2016)

As opposed to wireless charging, battery swapping has already been tried once for large-scale application by the company Better Place, which was founded in 2007 and went bankrupt six years after. They embraced a system in which the company would own the batteries in the EVs of their customers who would instead subscribe to an annual mileage plan. This was meant to relieve the customers from the financial burden of purchasing expensive battery packs for their EVs, effectively decoupling ownership of the battery and the EV. By building a network of chargers and battery swapping stations for their customers, Better Place aimed at reducing range anxiety, infrastructure concerns and charging times. The company started to build infrastructure in Israel before selling any vehicles and soon thereafter expanded to Denmark. It eventually failed due to a combination of over-investment in battery-swapping technology, mismanagement and misconception of its core markets. (Noel and Sovacool, 2016) EV batteries can be swapped in less than two minutes, which makes it the only technology up to this day which is able to compete with gasoline refueling in terms of speed (see Table 3, p. 24). However, tremendously high costs, about ten times as high as for fast chargers (see Baster et al. 2013), arise from storing and charging the batteries needed for the swaps. Since battery swapping stations also need storage facilities, they would be quite spacious and strict constructional safety rules would apply for the storage facility due to risk of fire. Therefore, these stations would probably need to be sited at the periphery of the city. This requirement would increase trip distance and travel time for EV taxis, and make battery swapping stations impractical for usage in EV taxi fleets. Furthermore, standardized batteries and vehicles capable of switching them are essential for operation of battery swapping stations. (Asamer et al., 2016) That car companies would not agree on a standardized design contributed to the fall of Better Place. It is even questionable whether EV taxis would actually need such rapid recharging. The assumed combination of one charging event between shifts, easily lasting for 15 minutes or longer, and one charging event during a mid-shift break would probably suffice for a conductive fast charger to regularly bring back the SOC of the EV taxi's battery to the necessary level. Therefore, swapping stations should only be located where charging stations are inferior due to longer charging times: outside of cities and along highways. (Baster et al., 2013) In fact, there are signs that the technology of battery swapping may already be obsolete. First, since the energy density of battery packs keeps on growing and costs are still declining (see e.g. International Energy Agency 2017) future EVs, including those suitable for taxi application, will feature such large battery packs that charging outside of home will rarely be necessary anymore. Second, as conductive charging technology continues to improve and becomes less expensive, the marginal benefit of battery swapping is reduced. (Noel and Sovacool, 2016) On top of all that, the logistical challenge of transporting batteries from the swapping stations to charging stations back in time and also holding enough spare batteries to satisfy demand peaks would further increase system costs (see Asamer et al. 2016) and might even prove insurmountable. It is concluded that the marginal benefits of quicker "refueling" through battery swapping is not worth the effort of setting up and operating a system of battery swapping and charging stations. Instead, an appropriate number of fast-charging stations should prove adequate.

### 3.2.3 Benefits of EV integration into the power grid

In order to illustrate the potential benefits of integrating EVs into the power grid, the basic workings of the latter will be explained first. In a conventional electricity market, end-users have contracts with retailers who buy the electricity from generators. These transactions are either brokered bilaterally or on a wholesale market. Most of the electricity is bought months in advance on the futures market as the aggregated energy demand of regions can be approximated well in advance. However, since its consumption heavily depends on the weather, energy is also traded 24 hours in advance on the day-ahead market and up to an hour ahead on the intraday market. (Shuai et al., 2016) Figure 11 illustrates a conceptual framework for the integration of PEVs through aggregators into the power system. The following three challenges arise from the integration and need to be met: first, deterioration of power quality, second, instability of electrical networks and, third, degradation of operating efficiency. (Kong and Karagiannidis, 2016) The mentioned suppliers, also called energy service providers, supply their portfolio of loads by contracting energy on the wholesale market. The distribution system operators (DSOs) plan, operate and maintain the distribution network (low and medium voltage), including the installation and operation of charging facilities for PEVs. Similarly, the TSO is responsible for developing, operating, and ensuring the maintenance of the transmission system (high voltage) in a specific area. Bessa and Matos (2010) Traders are active on the wholesale markets, buying and selling electricity in order to generate profit through arbitrage. Balancing group managers (BGMs), clustering loads and generators, submit energy schedules for their balancing groups to the TSO. The latter uses these forecasts on production and consumption during operational time steps e.g. 15 min to assess the security and operation of the power system. This is increasingly necessary since the volatile and unpredictable nature of PEV charging makes it difficult to match supply and demand in the power grid. (Kong and Karagiannidis, 2016)

In Germany, the power system is dominated by four large companies: E.ON, RWE, EnBW and Vattenfall, owning the majority of generation, distribution and retail assets. However, since Germany has unbundled generation, transmission, distribution and retail activities in the electricity sector in 2005, the corresponding TSOs are Amprion (formerly belonging to RWE), TransNet BW (EnBW), TenneT (E.ON) and 50Hertz Transmission (Vattenfall). There are only four TSOs but 900 DSOs, including about 700 municipally owned "Stadtwerke". However, major parts of the distribution grid are operated, again, by E.ON, RWE, EnBW and Vattenfall through concession contracts with the municipalities. The 900 DSOs serve 20,000 municipalities in the most complex distribution system in Europe. Moreover, generation

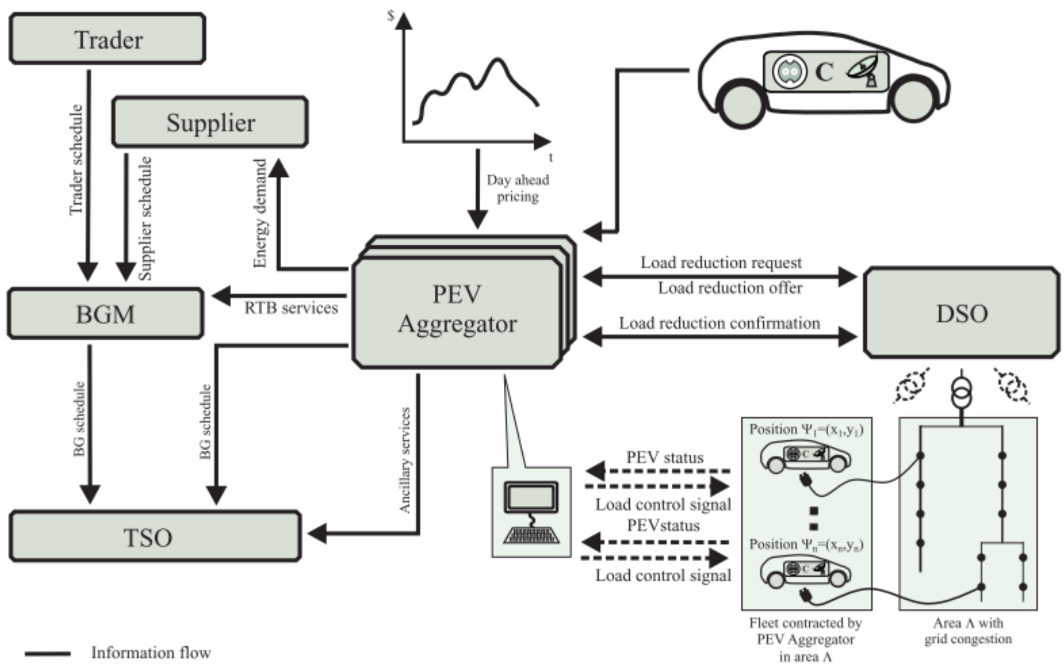


Figure 11: Conceptual framework for integration of PEV aggregators into power system. Inserted from Galus et al. (2013).

is handled by over 1000 producers, excluding individuals, and supply is handled by more than 900 suppliers. (Agora Energiewende, 2015)

Since single PEVs have relatively little capacity (most feature battery packs of around 24 kWh), PEV aggregators are needed in this power system to manage and control the charging and/or discharging of PEV fleets by communicating with all of the described entities. (Bessa and Matos, 2010)[9] DSOs may deliver information about the PEVs parked, plugged in and charging in their areas including spatial and temporal availability, battery energy levels and connection capacities of individual PEVs. This information is used to approximate energy demand and charging flexibility. It can be collected and clustered by managing devices, symbolized by a computer in Figure 11. PEV aggregators will also steer all market activities, similar to BGMs, related to their contracted PEVs. These include performing day-ahead energy demand forecasts, contracting energy service providers, and communicating with the DSOs, BGMs and the TSO. Using the spatial and temporal PEV availability and demand forecasts, they may either algorithmically minimize costs (see variable price curve in Figure 11) and purchase the necessary energy on the wholesale market, or they could acquire the energy directly from a supplier. Moreover, PEV aggregators may submit their forecasted energy supply schedules to the TSO

[9]The question of how flexible the electrified taxi fleet in Karlsruhe is regarding its charging will be discussed in Chapters 5 and 6 on the basis of a large-scale dataset.

for validation of feasibility. At least one DSO should supervise the activities of PEV aggregators in its region in order to ensure the security of the distribution and eventually the transmission system. For instance, by performing a day-ahead network security assessment based on the forecasted spatial and temporal consumption schedules submitted by the PEV aggregators, the DSO would be able to remove possible congestion in specific parts of the distribution network by using bidding algorithms if the load reduction request gets granted by the related PEV aggregator. The final energy consumption schedules will be submitted to the TSO and the PEV aggregators need to control the vehicles to be operated accordingly. Furthermore, if PEVs are equipped with vehicle-to-grid (V2G) technology, the fleet can also be used as a resource. (Bessa and Matos, 2010) For this, charging stations must function bi-directionally i.e. be able to charge the battery as well as discharge it by feeding the stored energy back into the grid. (Kempton and Letendre, 1997) (Kempton and Tomić, 2005) The grid operator or TSO may request power from a large number of BEVs and the fleet operators control the batteries of their plugged-in vehicles accordingly. Fleet operators could also submit bids for the provision of ancillary services to the TSO and/or of real-time balancing services to other BGMs, and subsequently control the charging and/or discharging of their virtual storages. They can be of local nature such as voltage or frequency control in isolated systems, or system-wide such as primary, secondary, or tertiary frequency control. Generally, they are needed to match supply and demand for electricity, as the frequency of the grid needs to be held constant at all times. This is becoming increasingly difficult due to the intermittent feed-in of renewable energy sources. Effectively, the fleet would form a virtual battery and function similarly to a virtual power plant. This concept is already used to cluster renewable energy sources and enable them to jointly operate on power and ancillary services markets.

Apart from the direct control approach to achieve desired EV operation functionalities in power systems, a decentralized approach would be another possibility. Generally, this approach would be based on exogenous price signals serving as input to individual multi-period optimizations minimizing the charging costs of each vehicle. However, the centralized approach seems more feasible. (Galus et al., 2013) In conclusion, PEV fleet operators should pursue at least one of these strategies: first, guarantee the driving needs of PEV owners through optimal charging management including cost minimization, second, provide peak power to the grid through provision of storage for RES suppliers or, third, provide ancillary services to grid operators (TSOs, DSOs) through optimal allocation of battery resources. (Hu et al., 2015) In order to reap all the mentioned benefits, the charging infrastructure must be located first, for which we select an appropriate optimization model in the following chapter.

# 4 Literature review on models for location of charging stations

Essentially, our case of optimally placing CSs for a fleet of BEV taxis is a facility location problem. Key questions addressed by location models are the following (see Daskin 1995):

- How many facilities should be sited?
  In our case, CSs represent the facilities. The decision to what degree demand peaks will be fully accommodated for depends on a variety of factors e.g. the financial budget and the expected revenue.

- Where should each facility be located?
  The CSs may be placed in the whole municipal area of Karlsruhe, but preferably at taxi stands. The exact locations may depend on e.g. taxi traffic flows.

- How large should each facility be?
  CSs may accommodate multiple CPs so as to serve more than one vehicle at once. More CPs may be added to the stations later in the electrification process.

- How should demand be allocated to the facilities?
  The issue of guiding BEV taxis, which are in need of charging, to idle CPs is an essential part of the problem, as well as the timing for aborting charging processes.

The following review will be structured along the chronology of the original publications. Mentioned studies will be fit into the following sequence: first, the study featuring the original problem will be presented and, second, extensions or applications of this problem will be reviewed. Thereby, a special focus will be set on applicability to our case of optimally locating charging stations for an electrified taxi fleet in the city of Karlsruhe. Of the basic facility location models, those with the best fit to this case will systematically be filtered out. Subsequently, these favorite candidates will be evaluated and compared in detail in order to arrive at one model as basis for further refinements which will be made in Chapter 5. At that point, it will also be discussed and illustrated how exactly the refined model differentiates from the basic model.

## 4.1 Node-based models

The covered node-based problem classes include the p-median model, the fixed-charge facility location model (FCFLM), the set-covering location model (SCLM) and the maximal-covering location model (MCLM). Subsequently, related flow-based models will be covered, such as the flow-capturing location model (FCLM) and the flow-refueling location model (FRLM). These five problem classes are the major ones combining two characteristics: they fit our problem setting and they originated from the p-median model. Therefore, and due to space restrictions, we focus on this selection. Studies featuring stochastic versions of these problem classes, e.g. Lee (2014) and Wu and Sioshansi (2017), incorporate a temporal dimension. For example, they would take into account at what point in time and in what order events representing potential demand, such as customer drop-offs, occur as opposed to just where. However, we will use the selected model solely for determining optimal locations and will address the issue of sizing the stations using a different approach. For these reasons, stochastic problem classes will not be considered for finding the best locations.

The study of location theory began in 1909 with Alfred Weber's approach on where to locate a single warehouse so as to minimize the total distance between a warehouse and its customers. (Weber and Friedrich, 1929) Following this kickoff, the theory was further developed by researchers from several different fields, who sought to apply it to their problems.

### 4.1.1 The p-median model

The first influencing work relevant to our case was published by Hakimi (1964). The author is examining the p-median problem, that is, to find the location of $P$ facilities so as to minimize the total demand-weighted travel distance between demands and facilities. The mathematical formulation is as follows (see Hakimi 1964):

$$\text{minimize} \quad \sum_{i\in I}\sum_{j\in J} h_i d_{ij} y_{ij} \tag{4.1a}$$

$$\text{subject to} \quad \sum_{j\in J} x_j = P, \tag{4.1b}$$

$$\sum_{j\in J} y_{ij} = 1 \quad \forall i \in I, \tag{4.1c}$$

$$y_{ij} - x_j \leqslant 0 \quad \forall i \in I, j \in J, \tag{4.1d}$$

$$x_j \in \{0,1\} \;\; \forall j \in J, \tag{4.1e}$$

$$y_{ij} \in \{0,1\} \;\; \forall i \in I, j \in J, \tag{4.1f}$$

where
$I$ = set of demand nodes, indexed by $i$,
$J$ = set of potential facility locations, indexed by $j$,
$h_i$ = demand at node $i$,

$d_{ij}$ = distance between demand node $i$ and potential facility location $j$,
$P$ = number of facilities to be located,
and

$$x_j = \begin{cases} 1 & \text{if facility is placed at potential site } j, \\ 0 & \text{otherwise,} \end{cases}$$

$$y_{ij} = \begin{cases} 1 & \text{if facility at site } j \text{ is assigned to demand node } i, \\ 0 & \text{otherwise.} \end{cases}$$

In the objective function, the demand-weighted travel distance is obtained by multiplying demands at nodes with the distances between these nodes and potential facility sites for all those facilities being assigned to demand nodes i. Equation 4.1b requires that exactly $p$ facilities be located, 4.1c ensures that each demand node is assigned to exactly one facility, and constraint 4.1d restricts assignments of demand nodes only to opened facilities. Hakimi applies the described model to the location of switching centers in a communications network and to the location of police stations in a highway system. The latter case is similar to our case of charging e-taxis. Siting stations so as to cover a network of roads being used by certain vehicles is what we would like to do. Hakimi's seminal work has represented an inspiring starting point for several streams of model families. It has been taken up by other researchers working on station siting problems in an urban context. The p-median model has been first applied by Goodchild and Noronha (1987), to the problem of optimally locating conventional gasoline refueling stations. For this, the researchers embed the model in a multi-objective setting. Nicholas and Ogden (2006) and Lin et al. (2008) applied a p-median optimization model to the case of siting hydrogen stations along highways in California. The model, which was developed in Nicholas and Ogden (2004), differs only little from Hakimi's. It optimizes the location of retail facilities for hydrogen such that the aggregate travel time for all consumers is minimized. Thereby, the locations of consumers and the number of facilities to be placed are fixed. These simplifications, inter alia ignoring the distance from a given location to a fuel station, rule out this model for our case. However, the modified approach of ReVelle (1986), who examined the p-median problem for locating retail facilities in the presence of competing firms, led to a different promising approach: maximum capture. The objective is to locate facilities so as to maximize the number of new customers captured, assuming that they choose the nearest firm. With his research, ReVelle contributed to the emergence of the flow-capturing models (see Hodgson 1990). Three other basic models inspired the mentioned stream of literature and are therefore discussed first.

### 4.1.2 The fixed-charge facility location model (FCFLM)

In the same year as Hakimi published his second paper on the p-median problem, Balinski (1965) presented a slightly different approach, the fixed charge facility location model (FCFLM). This approach relaxes three assumptions made by the p-median model: first, all potential sites have the same fixed location costs, second, facilities are uncapacitated i.e. there are no upper limits on the demand they can serve and, third, the number of facilities to be opened is known a priori. The objective function includes, in addition to the p-median formulation, the sum of the fixed facility location costs. The mathematical formulation of the capacitated version of the FCFLM is as follows:

$$\text{minimize} \quad \alpha \sum_{i\in I}\sum_{j\in J} h_i d_{ij} y_{ij} + \sum_{j\in J} f_j x_j \tag{4.2a}$$

$$\text{subject to} \quad \sum_{j\in J} y_{ij} = 1 \quad \forall i \in I, \tag{4.2b}$$

$$y_{ij} - x_j \leqslant 0 \quad \forall i \in I, j \in J, \tag{4.2c}$$

$$\sum_{j\in J} h_i y_{ij} - C_j x_j \leqslant 0 \quad \forall i \in I, \tag{4.2d}$$

$$x_j \in \{0,1\} \;\; \forall j \in J, \tag{4.2e}$$

$$y_{ij} \in \{0,1\} \;\; \forall i \in I, j \in J, \tag{4.2f}$$

where, in addition to the notation in the p-median,
$\alpha$ = cost per unit demand per unit distance,
$f_j$ = fixed cost of locating a facility at candidate site $j$,
$C_j$ = capacity of a facility at candidate site $j$.

The decision variables stay the same, whereas main differences to the p-median model beside the modified objective function are, first, the relaxation of not having to locate exactly P facilities and, second, the capacities $C_j$ imposed on the facilities in constraint 4.2d. If the latter is removed, the model becomes the uncapacitated FCFLM. However, setting capacities for facilities resembles the reality of charging BEV taxis more closely than the p-median formulation: enough charging points must be built so as to accommodate peaks in charging demand and taxis with low SOC need to be guided to the nearest idle charging point. Moreover, the fixed costs of locating facilities at candidate sites make an equally fine addition since purchase and installation costs are relatively high for fast-charging stations and should therefore not be disregarded when deciding on locations. Sankaran and Raghavan (1997) extend the capacitated FCFLM to incorporate endogenous[10] selection of fa-

[10] "Endogenous" means that something is caused by factors inside the system. (Merriam-Webster, 2017) The term is used by economists to illustrate that variables are the output of an optimization model rather than exogenously set or assumed by the modeler.

cility sizes, therefore making them also an output of the optimization. While this is a step in the direction of our case, the amendment made by Baouche et al. (2014) appears to be more relevant as the researchers use real-world data from a household travel survey in combination with a dynamic vehicle model for the evaluation of BEVs' energy consumption based on realistic trips as inputs of an optimization for the location of various types of charging stations including fast chargers. Their model incorporates a p-dispersion constraint. Dispersion models are related to the p-median approach. However, they differ from the latter in that it is their main objective to locate facilities so as to maximize the minimum distance between any pair of facilities. The dispersion constraint in Baouche et al. (2014) forces each pair of charging stations to be separated by a certain minimum distance, artificially making the distribution of fast-charging stations more uniform and costly since grid connection costs exhibit economies of scale for CSs within a certain area. This would also potentially avoid under-utilization of neighboring stations. While the model appears promising, the requirement to estimate energy needs of traveling BEVs could make it too difficult for us to implement. Ghamami et al. (2016) formulate a similar model for the installation of charging facilities in urban parking lots. The objective is to locate these facilities so as to minimize the total system cost, including a monetary approximation of the costs of walking to the nearest charging points, under charging capacity constraints. The objective function combines facility and user costs and is therefore equivalent to Balinski's. However, an additional constraint ensures that each parking lot/charging station has enough CPs to serve a fixed percentage (the so-called service level) of the BEVs assigned to it for charging. Since the model is quite tailored to the problem setting of private commute trips ending in an urban area, it would be difficult to transfer it to our case. However, the service-level constraint represents valuable input.

### 4.1.3 The set-covering location model (SCLM)

In order to understand the framework of "covering" location models, the notion of "coverage" has to be explained first. For example, the problem of locating outlets of a pizza delivery service so that the number of potential customers that can be reached within a certain period of time is maximized, illustrates that demand within the covering distance of the nearest facility is regarded as covered. On the other hand, if a customer orders pizza from the delivery service and cannot be reached within the required time, her demand is considered as not covered. Underlying is the assumption that a customer is either satisfied or not, there may not be any nuances. The literature on covering problems is divided into two segments, one in which coverage is required (see SCLM) and one in which it is maximized (see MCLM). The first publication about the set-covering problem is Toregas et al. (1971). The original formulation of the SCLM has been applied on the problem of optimally locating emergency service facilities so as to minimize the costs of facility placement, while covering all potential destinations within a fixed maximum response time. The mathematical formulation of the basic model is as follows:

$$\text{minimize} \quad \sum_{j \in J} x_j \tag{4.3a}$$

$$\text{subject to} \quad \sum_{j \in N_i} x_j \geqslant 1 \quad \forall i \in I, \tag{4.3b}$$

$$x_j \in \{0,1\} \;\; \forall j \in J, \tag{4.3c}$$

where, in addition to the previous notation,
$D_c$ = distance coverage,
$N_i = \{j | d_{ij} \leqslant D_c\}$ = set of candidate locations able to cover demand point $i$.

Constraint 4.3b ensures that each demand node is covered by at least one facility. This simple model does not have cost coefficients in its objective function since it assumes equal costs of facility location. However, it can be enhanced with minimal effort to incorporate different costs for opening each facility. For this, define $c_j$ as *fixed cost of siting a facility at node $j$* and add $c_j$ to the summation in the objective function. It must be noted that due to its simplicity, this model makes no distinction between nodes[11] meaning that each node is covered regardless of demand size or associated costs. The SCLM has been applied and tailored to the location of bus stops by Gleason (1975). It has been extended by Batta and Mannur (1990) in order to also cover emergency situations which require multiple response units. However, the underlying assumption of all these approaches, that all of the demand nodes must be covered, means the absence of any budget constraints. Since many facility planning situations including our case do need to consider budgetary restrictions, the SCLM is therefore not fit to be used.

### 4.1.4 The maximal-covering location model (MCLM)

The MCLM, first established in Church and ReVelle (1974), specifically addresses these planning situations featuring an upper limit on the number of facilities to be sited. Therefore, there may not be enough facilities to cover all demand and decision-makers must make compromises by considering trade-offs. Consequently, the objective of the MCLM is to locate the available number of facilities in such a

[11] In graph theory, a flow or transportation network is a directed graph with nodes and edges. These edges may represent roads, and they carry flows of e.g. passenger vehicles. The nodes are usually at the intersections but in our case they should coincide with the potential sites for charging stations.

way that the share of covered demand is maximized. The model can be formulated as follows:

$$\text{maximize} \quad \sum_{i \in I} h_i z_i \tag{4.4a}$$

$$\text{subject to} \quad \sum_{j \in N_i} x_j - z_i \geqslant 0 \quad \forall i \in I, \tag{4.4b}$$

$$\sum_{j \in J} x_j = P, \tag{4.4c}$$

$$x_j \in \{0,1\} \;\; \forall j \in J, \tag{4.4d}$$

$$z_i \in \{0,1\} \;\; \forall i \in I \tag{4.4e}$$

where, in addition to the previous notation,

$$z_i = \begin{cases} 1 & \text{if demand at node } i \text{ is covered,} \\ 0 & \text{otherwise.} \end{cases}$$

The objective function in this model includes an additional decision variable $z_i$. Constraint 4.4b makes sure that demand at node i is only seen as covered if a facility is placed at one or more of the candidate sites covering this node. Constraint 4.4c represents the upper limit on the facilities which distinguishes the MCLM from the SCLM, and 4.4e is the associated constraint for the decision variable $z_i$.

Typically, the set of potential facility sites coincides with a major share of the demand nodes. However, Church and Meadows (1979) have shown that even if facilities can be placed anywhere on the network, the problem can be reduced to one of finite selection. A variant of the original MCLM was presented by White and Case (1974). They weigh all demand points equally regardless of size. Therefore the objective turns to maximizing the number of covered demand nodes. Church and ReVelle (1974) formulate an amended model with a constraint ensuring mandatory closeness for planning scenarios in which demands up to a certain distance shall be covered but there also exists some maximum distance beyond which service is not accepted. Chung et al. (1983) add a capacity constraint to the MCLM i.e. define an upper limit on the number of demand points that may be covered by single facilities. As for the other presented models, capacity restrictions are considered as a way of making our model more realistic, should we choose to use the MCLM and tailor it to our needs. Adapting the notation to the previous model formulation, the additional constraint would read as $\sum_{i \in N_j} h_i x_j \leqslant w_j x_j \;\; \forall j \in J$, and restrict the demands $h_i$ covered by the stations to an upper limit $w_j$ equal to their capacities. ReVelle (1986) adapt the original model in order to optimize the siting of retail stores in the presence of competitors offering the same product. In this setting, customers i.e. demand points are served by the nearest facility. In contrast to the original MCLM, demand is captured instead by siting a facility closer to it than any of the existing facilities has been. However, since our project is of the nature of a public-private partnership, no competitive behavior is expected and therefore this model will not be needed. Current and Storbeck (1988) also formulate a capacitated MCLM. This model, however, can be discounted for application since the researchers relax the restriction that entire demands arising at nodes are covered by one facility. This relaxation would mean that taxi drivers would have to unplug their vehicles in the middle of charging processes and therefore need to resume charging somewhere else, which would supposedly prove impractical in reality. Pirkul and Schilling (1991) examine the previous capacitated modeling approaches and attempt to correct their deficiencies. The researchers find that coverage and the service level delivered to uncovered demand should simultaneously be considered in order to cover situations in which coverage of demand is desired but all demand will be served in the end. Therefore, they introduce a modified objective function which incorporates both of these objectives in a weighted linear combination. The described approach may lead into the right direction as we will also attempt to directly cover as many demand points as possible but the located charging stations will be used by the whole fleet in the end. Berman et al. (2003) challenge the underlying assumption of a critical distance within which demand points are covered by the nearest facility whereas they are not covered at all beyond this distance. The authors define two radii: one within which demand points are 100% covered and one outside of which they are 0% covered. Furthermore, they introduce a coverage decay function specifying the rate at which partial coverage decays for points between the two radii. Their model is a special case of an uncapacitated facility location model. Frade et al. (2011) apply their version of the MCLM in order to determine optimal locations for EV slow-charging stations in the urban area of Lisbon (Portugal). They optimize the demand covered while maintaining an acceptable level of service, and define the number and size of the located stations. However, since they only focus on nighttime demands associated with residences and daytime demands associated with workplaces, and both in the form of slow-charging, this approach shall not serve as basis for our work. In contrast to the previously mentioned approach, Asamer et al. (2016) focus on the optimal placement of fast-charging stations for the electrified taxi fleet in Vienna, Austria. They apply a slightly modified version of the basic MCLM in order to arrive at optimal regions in which to place charging stations.

## 4.2 Flow-based models

In the MCLM, demands are assumed to be located only at nodes on the network so that drivers would need to make specific trips to these facilities to be serviced, starting for example from home. Hence, this and the previous models can be described as node-based. However, for facilities such as automated teller machines, convenience stores, gasoline-refueling and charging stations this assumption may not hold in reality. Since these stations rather serve people or vehicles during their trips, it may be more realistic to model the demands as flows between pairs of origin (O) and destination (D) instead of only occurring at nodes on the network.

### 4.2.1 The flow-capturing location model (FCLM)

For the mentioned reasons, Hodgson (1990) and Berman et al. (1992) separately introduced the FCLM, which is essentially a flow-based maximal covering location model. It is the first model of those introduced so far that has been specifically developed for locating refueling stations on a road network. The FCLM locates a fixed number of facilities so as to maximize the flow volume "captured" or "intercepted" by facilities located along the paths of the flows. Taking up this idea for our case: since a major share of the taxi trips in urban areas such as Karlsruhe heavily operate on a certain set of roads (e.g. Kriegsstrasse), it might be efficient to locate charging stations along the most frequented ones of these roads. The FCLM is structurally similar to the MCLM and may be formulated as follows:

$$\text{maximize} \quad \sum_{q \in Q} f_q y_q \tag{4.5a}$$

$$\text{subject to} \quad \sum_{k \in N_q} x_k - y_q \geqslant 0 \quad \forall q \in Q, \tag{4.5b}$$

$$\sum_{k \in K} x_k = P, \tag{4.5c}$$

$$x_k \in \{0,1\} \ \forall k \in K, \tag{4.5d}$$

$$y_q \in \{0,1\} \ \forall q \in Q \tag{4.5e}$$

where
$Q$ = set of all O-D pairs (on the shortest paths), indexed by $q$,
$f_q$ = flow volume on shortest path between O-D pair $q$,
$K$ = set of all potential facility locations, indexed by $k$,
$N_q$ = set of nodes capable of capturing $f_q$,

and

$$y_q = \begin{cases} 1 & if\ f_q \text{ is captured,} \\ 0 & \text{otherwise,} \end{cases}$$

$$x_k = \begin{cases} 1 & \text{if a facility is located at } k, \\ 0 & \text{otherwise.} \end{cases}$$

In the MCLM, $N_i$ has represented the set of nodes capable of covering node i, meaning those nodes within the range of demand node i. In the FCLM, $N_q$ equals the set of nodes capable of capturing flow q, that is those nodes on the path taken by the flow $f_q$. The model has later been extended and applied to a number of different situations.

Hodgson and Rosing (1992) developed a hybrid model of p-median and FCLM in order to account for the observation that demands in the real world can be located at nodes or be represented by passing flows. Transferring this notion to our case would make it necessary to incorporate both as inputs to the optimization, pick-up and drop-off (DO) positions of customer trips and frequently taken paths by taxi vehicles. Combining the two might lead to a more efficient solution than just applying one of the models. Berman et al. (1995) turn the FCLM into several new directions, three of which are worth mentioning. Those are aimed at relaxing the flow capturing notion so as to allow flows to deviate from the shortest path by a certain maximum deviation. Intuitively, this observation makes sense since many drivers may take detours in order to refuel and therefore deviate from their shortest paths. Demand flows are, hence, also seen as captured if their paths pass within this maximum distance of the facility at the closest point. The second amendment considers the share of captured flows to decrease with the extent of the deviation. In a third extension, they minimize the sum of all deviations instead of imposing the maximum deviation. Hodgson and Rosing (1996) apply the FCLM to a real road network in Canada. Hodgson et al. (1996) focus on applying the FCLM to the location of inspection stations for dangerous vehicles (e.g. steered by drunk drivers). As opposed to the original model where facilities capture flows on complete paths, the researchers find that facilities may realistically only capture the downstream parts, that is from facility to destination. Hodgson and Berman (1997) reformulate the model with the objective of locating billboards for passing drivers. Unlike the original situation in the FCLM in which only one facility is needed to capture a complete flow, advertisements on billboards become more effective when shown to drivers multiple times. Shukla et al. (2011) modify the FCLM originally introduced in Berman et al. (1992) for application on a road network in Alexandria, US. They change the equal sign in constraint 4.5c into a less-or-equal sign to allow redundant (since already 100% of flow volume is covered) facilities not to be placed. They also add a constraint converting the maximum number of facilities to be placed into an investment budget. We find these adjustments not particularly useful since it is very likely that total flow volume will not be covered anyway, if we choose to implement the FCLM.

### 4.2.2 The flow-refueling location model (FRLM)

The FCLM approach depends on the assumption that if one facility is located on a node of a path, then all associated flows will be captured. This assumption may not hold for BEVs, since they have a much shorter range than ICEVs and therefore are likely to need multiple recharging stops in order to realize long-distance journeys. The FRLM, specifically designed by Kuby and Lim (2005) for alternative-fuel vehicles, considers a flow only as refueled if a necessary number of stations are located along its path. The notion of alternative fuels refers to all those which are not readily available at gasoline-refueling stations. Therefore, it covers a variety of technologies, besides electricity these are biodiesel, ethanol, hydrogen, natural gas and propane (see US Department of Energy 2017 for more information on these, and see Figure 4 in the Appendix for US prices). If the range of a vehicle is longer than any round-trip distance between O-D pairs, the FRLM imposes the same logic as the FCLM. Therefore, it is applicable to both, short- and long-distance trips. The model can be formulated as follows:

$$\text{maximize} \quad \sum_{q \in Q} f_q y_q \tag{4.6a}$$

$$\text{subject to} \quad \sum_{h \in H} b_{qh} v_h \geqslant y_q \quad \forall q \in Q, \tag{4.6b}$$

$$a_{hk} x_k \geqslant v_h \quad \forall h \in H, k \in K, \tag{4.6c}$$

$$\sum_{k \in K} x_k = P, \tag{4.6d}$$

$$x_k \in \{0,1\} \quad \forall k \in K, \tag{4.6e}$$

$$y_q \in \{0,1\} \quad \forall q \in Q, \tag{4.6f}$$

$$v_h \in \{0,1\} \quad \forall h \in H \tag{4.6g}$$

where, in addition to the previous notation,
$H$ = set of all potential facility combinations, indexed by $h$,

and

$$b_{qh} = \begin{cases} 1 & \text{if facility combination } h \text{ can refuel O-D pair } q, \\ 0 & \text{otherwise,} \end{cases}$$

$$v_h = \begin{cases} 1 & \text{if all facilities in combination } h \text{ are open,} \\ 0 & \text{otherwise,} \end{cases}$$

$$a_{hk} = \begin{cases} 1 & \text{if facility } k \text{ is part of combination } h, \\ 0 & \text{otherwise,} \end{cases}$$

The objective function maximizes the total flow possible to be refueled with $P$ facilities. Constraint 4.6b requires at least one eligible combination of facilities, consisting of at least one, $h$ to be opened for each path $q$. By constraint 4.6c, $v_k$ only turns 1 if all facilities in combination $h$ are opened. Constraint 4.6d sets the number of facilities to be built at $P$, and the remaining constraints set the binary variables. Many extensions and applications of the FRLM can be found in the literature.

Kuby and Lim (2007) extend the FRLM by addition of potential facility sites along edges using three different methods. Kuby et al. (2009) apply the model to a road network in Florida. Furthermore, they introduce weighting of trips by distance on the grounds that longer trips, replacing a larger amount of conventional by alternative fuel, should count for more than shorter trips. Upchurch et al. (2009) introduce a capacitated version of the FRLM, which limits the number of vehicles that can be refueled at each station by considering different numbers of charging points at each station. Their case study of a road network in Florida shows that the capacitated version may be superior to the original model. Therefore, since we explicitly expect high utilization rates of the CSs to be located at taxi stands in Karlsruhe, our approach could incorporate capacities in order to achieve more realistic results. Wang and Lin (2009) develop a set-covering approach to the FRLM in order to refuel the complete traffic while minimizing the cost of facility location. Thereby, they keep track of the remaining fuel of each vehicle at each node on its path. However, their focus on inter-city trips along highways as opposed to intra-city travel, and the assumption of a sufficient budget for deployment of CSs (see SCLM) disqualifies their model for application in our case. Wang and Wang (2010) further enhance this concept by introducing a second objective besides the minimization of costs: to maximize the covered flow. In addition to Wang and Lin (2009), they also cover short-distance trips within the city. Upchurch and Kuby (2010) compare the results of the FRLM and the p-median model on the same networks by applying the locations determined by each model to the objective function of the other. The p-median model appears to spread the facilities across the network by favoring denser population clusters. In contrast, the FRLM locates the facilities at intersections with large flow volumes so as to avoid cannibalizing flows intercepted by other facilities. Consequently, at the state-wide scale the FRLM first develops cluster of stations in large urban areas. Generally, the FRLM is found to perform better than the p-median model. The researchers find the solutions produced by the FRLM to remain quite stable with increasing the number of facilities to be located, in stark contrast to the facilities located by the p-median model. Lim and Kuby (2010) show that the FRLM is computationally very demanding and therefore may prove impractical for examining large-scale networks. That is due to the need to generate all combinations of facilities able to refuel a path in its first stage. For this reason, the researchers propose three heuristics, greedy-adding, greedy-adding with substitution and a genetic algorithm, for solving larger problems. These three do not require the generation of combinations and therefore enable solutions to problems which may not have been solved before. This finding will be taken into account when solving the location problem for Karlsruhe, if we choose to apply the FRLM. Capar and Kuby (2012) reformulate the model into an even more efficient form by including the model's underlying logics into its constraints and requiring them to check whether a path may be refueled by the located stations. Kim and Kuby (2012), similar to what Berman et al. (1995) did regarding the FCLM, relax the assumptions of the FRLM in order to account for the willingness of drivers to deviate from their shortest paths when they need to refuel. This willingness is modeled to decrease with the required deviation distance. Thus, the authors find their version to represent refueling behavior more accurately than the basic model especially with charging infrastructure being in such an early stage as it was at the time. Indeed, this consideration of deviations results in an increase of the objective function with the same set of facilities as the basic FRLM, which implies more accurate projection of covered demands and higher utilization. Capar et al. (2013) went further into the mentioned direction. Their version has been analyzed in great detail and applied to the case of locating fast-charging stations along German highways by Jochem et al. (2016a). However, it is questionable whether the same model could be successfully applied to an urban setting. More recent attempts to reduce the solution time of the FRLM by modifications have been made by MirHassani and Ebrazi (2013) and You and Hsieh (2014). Chung and Kwon (2015) extend the version of MirHassani and Ebrazi (2013) so as to cover a multitude of periods and apply myopic methods for solving this dynamic flow-based location model. However, since their approach also lacks the possibility to include capacities, they advise future research to incorporate just that, once EVs are more widely adopted, in order to achieve more realistic results. Huang et al. (2015) further develop the approach of Kim and Kuby (2012) to incorporate deviation paths. While Kim and Kuby (2012) located facilities so as to maximize the flow volume refueled on *up to one path* for each O-D pair contributing most to the objective, Huang et al enable drivers to use *multiple deviation paths* between all O-D pairs in the network. Hence, an O-D pair is already covered if there exists either a shortest path or one with reasonable deviation between the O-D pair by which drivers may finish a trip with refueling stops. Not incorporating capacities either, the researchers support the notion of Chung and Kwon (2015), that this will only be necessary once wide-spread adoption of EVs takes place. Li and Huang (2015) develop heuristics for efficiently solving the previous problem. Moreover, the researchers expand their approach in Li et al. (2016) to locate CSs so as to cover the growing number of EV trips between cities. However, since our case specifically aims at locating charging stations within the municipal boundaries, we suppose this approach would likely take us into a wrong direction. Hosseini et al. (2017) combine the two extensions of considering capacities of facilities and enabling deviations from shortest paths, and solve the resulting optimization problem with a greedy heuristic.

## 4.3 Reasoning behind model selection

In light of the findings, the favorite candidates for application are the MCLM and the FRLM. The other four problem classes are not seen as fit due to a variety of reasons which emerged from the conducted review. The p-median model minimizes the average distance traveled from demand points to the selected locations for charging stations. This is deemed inappropriate in an electric taxi environment since BEV taxis need to be able to reach one of the selected locations shortly after finishing their customer trips. In these situations, their potentially low SOCs force them to recharge before accepting the next customer trip. Thus, charging stations shall instead be placed so as to cover demand points up to a certain maximal distance which will allow taxis with low SOCs to quickly find the needed charging station at any point in time. Although the FCFLM provides potentially valuable additions e.g. through the inclusion of different fixed location costs in the objective function or through restriction on capacities, none of the relaxations made relative to the p-median model removes its previously described deficiency. Therefore, the FCFLM shall also be ruled out for further consideration.

The notion of covering demand points up to a certain distance is represented by the covering location models, SCLM and MCLM. The first of these requires complete sets of demand points to be covered, whereas the second one merely maximizes the coverage of demand points. Since the chosen model shall be used for locating CSs such that only the share of demand points is covered that makes sense from an economical standpoint, the MCLM is clearly preferred over the SCLM. It offers the flexibility to choose a level of demand coverage which can be afforded and therefore makes it possible to consider the trade-off between coverage and deployment costs. Thus, the point at which the marginal benefit of siting one more station is still significant can specifically be determined and implemented in the project realization phase. Naturally, the number of CSs deployed also unequivocally depends on the financial budget available to the charging infrastructure planner. Since the facility location model shall only be used for finding optimal locations of CSs, not for determining the necessary numbers of CPs at these locations, and on top of that after full deployment all vehicles will use the located charging stations, anyway, the option of capacitating the MCLM is disregarded at once.

The MCLM has one potential weakness: it concerns itself with demands arising from points, while the available data can actually also be regarded as trips. Following this logic, flows of vehicles could be covered instead of demand points/nodes, speaking for a flow-capturing approach such as taken in the FCLM and the FRLM. While the FCLM assumes that already the first facility which is located on a node of a path captures all its intercepting flows, BEVs do have a much shorter range than ICEVs and are therefore likely to need multiple recharging stops in order to realize long-distance journeys. Hence, the FRLM was specifically designed by Kuby and Lim (2005) to account for refueling processes of the emerging alternative-fuel vehicles. This model only considers a flow as refueled if a necessary number of stations are located along its path. However, the assumptions made by both, FCLM and FRLM, may not hold in reality. On the one hand, it is probably true that gasoline-refueling stations are typically visited en route since drivers would otherwise need to make specific trips just for refueling. On the other hand, taxi drivers definitely cannot seek out a charging station while serving a customer. In addition, taxi trips in the urban area of Karlsruhe are generally in the range of just a few kilometers for which battery capacities are sufficient. This means that one assumption underlying the FRLM, that vehicles need to refuel during some trips in order to finish them, does not hold. The FRLM is more fit for locating fast-CSs along highways (see e.g. Jochem et al. 2016a). There, the chargers serve the purposes of enabling long-distance trips and reducing waiting time compared to slow chargers while being sufficiently utilized to justify the high upfront investment and operating costs. Very practical reasons speaking against the FRLM as model of our choice are, first, that all O-D pairs would need to be extracted from the dataset and, second, that for each path all combinations of facilities able to refuel that path would need to be generated. Since Lim and Kuby (2010) show the mentioned processes to be computationally extremely demanding, the FRLM may prove impractical for examining large-scale networks such as the urban road network of Karlsruhe. Even if the applied version of the FRLM could be solved heuristically as proposed by Lim and Kuby (2010), an exact solution would be found for the MCLM. Instead of during, charging demand is most likely to occur at the end of customer trips respectively once vehicles are back at one of the TSs, which are regarded as superior charging locations due to several reasons. Foremost, waiting times between subsequent customer trips may just be long enough to recharge the in-built batteries without having any negative impact on taxi operations. While TSs represent the favorite locations, hot spots of high potential charging demand other than the TSs will also be identified by the MCLM. For these reasons, the node-based version of the MCLM provided in Asamer et al. (2016) will be used as a starting point for further refinements in Chapter 6.

## 4.4 Discussion of recent research on fleet electrification

In addition to Asamer et al. (2016), several other recent publications deal with the problem of optimizing locations for the charging infrastructure of an electrified taxi fleet. However, since the applied optimization models cannot be clearly assigned to one of the problem classes mentioned either in Section 4.1 or Section 4.2, these publications will be discussed in the following. Thereby, the present work will be located in the research landscape.

Cai et al. (2014) use large-scale trajectory data of 11,880 taxis (roughly 18% of the fleet) in Beijing, China, over a period of three weeks in order to find optimal locations for public charging infrastructure which may also be used by the taxi fleet. The researchers restrict the search to existing gas stations and evaluate by means of several criteria whether these locations may be expanded to charging stations. Specifically, they identify the worthiest locations by looking at the number of parking events nearby. Their results show that using travel patterns for determining optimal locations for CSs may improve the overall electrification rate of the taxi fleet and thereby significantly reduce gasoline consumption. Also, peak charging demand is found to occur at around 12 PM and coincide with peak power generation. Sellmair and Hamacher (2014) analyze trajectory data of five taxis operating in Munich over a period of five months. Deriving several histograms from the data, they find the waiting periods at TSs to be sufficient for fast-charging during shifts. However, they also admit that their sample size of five taxis most likely is not representative of the whole taxi fleet of 3,402 vehicles operating in Munich. In order to mimic a larger sample, they simulate driving profiles and analyze the economic impact of fleet electrification. They find that by increasing battery capacity, the efficient mileage of BEV taxis can be significantly improved. Based on their results, they propose a three-phase approach for deployment of CSs. Using the same dataset as Cai et al (2014), Shahraki et al. (2015) formulate a Mixed-Integer Linear Programming (MILP) model that minimizes the total travel distance that cannot be covered on electricity i.e. that maximizes electrified VKT. The existing 1,737 gas stations in Beijing serve as candidate locations for CS placement. The researchers find the impact of CSs to be installed additionally to the 40 existing to quickly diminish. The determined optimal locations for CSs at first concentrate in the inner city and only slowly expand to the suburban area. Their results critically depend on two assumptions: first, that taxi drivers do not alter their behavior when switching to PHEVs and, second, that the built charging infrastructure will, at least in the beginning, exclusively be used by electric taxis and not by the public. Asamer et al. (2016) use operational data of around 800 taxis, which represent 25 % of the taxi fleet in Vienna, Austria to find optimal locations for taxi-only charging infrastructure. They partition the map of Vienna into about 1500 hexagons and use the number of taxi trips starting or ending in all of these hexagons as input for their optimization model, which is based on Church and ReVelle (1974). In addition, they analyze the dataset with respect to distributions of taxi trip distances, total mileages per shift, waiting times between trips and mileages before first break. The researchers show that the taxi fleet could easily operate using existing BEV models, and that it would be economical to do so. Optimal locations, in the form of hexagonal areas, for the installation of CSs are found all over the city area, without restriction to existing TSs. Han et al. (2016) use GPS data from 1,000 taxis operating in Daejeon City, Korea, over a period of several days. They formulate two flow-based optimization models, an uncapacitated one and a capacitated one, minimizing the sum of fixed facility costs and opportunity costs associated with charging due to access to the respective station, operating and charging delay. The researchers conclude that chargers need to be installed intensively in specific regions, however, if they are concentrated in only few regions, the opportunity costs increase while costs associated with installation and operation of the CSs decrease. Tu et al. (2016) use GPS data of about 15,000 taxis operating in Shenzhen, China, over a period of one week. The researchers apply a spatial-temporal demand coverage location model maximizing both the taxi service level, measured by total distance traveled by EV taxis meeting existing demand, and the charging service level, measured by the reciprocal value of the total waiting time of EV taxis at all charging stations. Applying a genetic algorithm to solve the optimization problem, the researchers find their novel inclusion of a dynamic rather than only static demand to effectively improve the outcome of the optimization. Yang et al. (2016) use a dataset generated by 10,145 taxis operating in Nanjing, China over a period of two days. In addition to analyzing the data, the researchers also assess the market potential and the potential energy consumption of PEVs replacing the conventional taxi fleet. Dividing possible charging events into charging while dwelling e.g. at a TS on the one hand and charging instead of cruising (trips made solely to find customers) on the other, the researchers find that if BEV taxis are able to use the time they would normally spend on cruising for charging instead it will be much more feasible to use BEVs as taxis. This may be enabled through the use of taxi apps e.g. *taxi.eu* on the drivers' cell phones. Furthermore, it is concluded that although in the context of private use, the installation of more slow chargers is to be preferred, expensive fast chargers are necessary for taxi fleet electrification since operating time may not be wasted on charging. Regarding optimal placement of CSs, the researchers evaluate locations where many taxis choose to park and analyze the sensitivity of distributing different numbers of chargers on the percentage of feasible taxis. Li et al. (2017) also make use of trajectory data of 46,765 taxis operating in Beijing, China, over a period of two months. These researchers, as Shahraki et al do, focus on the implementation of PHEVs, assuming that driving behavior will not change. They apply a time-series simulation model for the optimization of slow charger locations and also design an intelligent charging guidance system. Assuming the adoption of this system, they quantify the achieved electrification rates of VKT by the taxi fleet e.g. to 54.3 % for a scenario with 500 deployed public CSs each featuring 30 slow chargers, battery ranges of 80 km, home charging available and no charging guidance system applied. They conclude that replacing all slow chargers with fast chargers may not necessarily increase the electrification rate of VKT.

# 5 Feasibility analysis of introducing BEV taxis in Karlsruhe

In Chapter 2 the topic of taxi fleet electrification has been motivated by pointing out how it can contribute to reducing air respectively noise pollution and ultimately to diminishing climate change. In Chapter 3, the technical and economic basics of electric vehicles and the associated fast-charging infrastructure have been explained. In Chapter 4, we have reviewed the relevant literature and selected a suitable model for optimally locating fast chargers in an urban road network. Hereinafter, a large-scale trajectory dataset for Karlsruhe (in Germany) will be analyzed regarding the following question: *can BEVs be integrated into the taxi fleet of Karlsruhe without imposing any significant restrictions on daily taxi operations or resulting in considerable revenue loss?* Considering the financial support available to taxi owners choosing to switch to BEVs, which is provided by the federal and the state government, BEVs may just perform better than ICEVs regarding their total costs of ownership (TCO). The question whether this additional benefit is likely to be realized will be revisited in Chapter 6.

Tian et al. (2014) conduct a study on the operational patterns of EV taxis. The researchers use GPS records of 600 taxis operating in Shenzhen, China during the time period of one week in March of 2014. They observe a number of undesirable effects: first, charging has a considerable negative impact on the operational time of EV taxis, second, drivers of EV taxis prefer to operate around charging locations, third, the number of CPs is a major factor for station preference and, fourth, battery capacity decreases over time leading to more frequent charging and less range per full charge. As the latter would likely lead to revenue losses due to rejected customer trips and therefore weaken the business case of the taxi fleet electrification it must be avoided. The second and third effect are suspected to be caused by prevalent range anxiety. BEV drivers fear running out of battery while on the road and potentially carrying customers. Therefore, they prefer to operate near CSs with many CPs in order to be able to recharge whenever needed. This effect may be mitigated by tuning the spatial distribution of CSs to the actual movements and potential charging demands of an existing fleet of ICEVs so that drivers do not need to adjust their behavior. The approximation of spatial charging demand should be reviewed and continually refined with every batch of BEVs that is deployed and in operation. The fourth observed effect of decreasing battery capacity, which was predicted in Chapter 5, can be mitigated by operating the BEV taxis only at SOCs of more than 20%, since deep discharging leads to higher degradation than frequent, shallow recharging of the lithium-ion batteries.

## 5.1 Process of extracting information about trajectories from dataset

Karlsruhe, the city in question, has a population of 307,755 (as of 2015) and ranks therefore 21. among the biggest cities in Germany. It is the second-most populated city in the state of Baden-Württemberg, next to Stuttgart. Its 27 districts cover an area of 173,46 $km^2$, setting the population density at 1,774 people per $km^2$, which is less than half the density of Berlin. Figure 12 illustrates the discussed area. In the West, it is bounded by the districts of Daxlanden and Knielingen, in the North by Neureut and Waldstadt, in the East by Grötzingen and Durlach and in the South by Rüppurr and Oberreut. Since 1980, the number of taxis operating in Karlsruhe has been constantly around 213. There are, however, currently 34 applications for concessions on the waiting list, which may be granted - there is a current lawsuit. Therefore, for every 1,000 citizens there are 0.7 taxis operating, which is relatively little compared to other large cities nearby such as Freiburg, Heidelberg and Mannheim. (Taxi Times, 2017) Historically, the taxi dispatch center *Taxi-Funk Zentrale Karlsruhe eG* has been coordinating all local taxi companies. However, a second dispatch center called *Taxi-Ruf Karlsruhe GmbH* went into operation in 2015, carving out 32 of the small companies, 53 of the taxis and around 100 drivers. (Taxi Heute, 2015) Thus, 128 small companies, 161 taxis and more than 300 drivers have remained at the first dispatch center, resulting in a share of taxis and drivers of around 75 %. (Taxi-Funk-Zentrale Karlsruhe eG, 2017) This center has, in collaboration with the end-to-end fleet management provider *Austrosoft Weiss*, provided us with a large-scale trajectory dataset. The set includes GPS data spread over the urban area of Karlsruhe including some outliers which are far outside of the present map section. The specific traffic volumes on the main roads are available in the Appendix. The dispatch center operates 24 taxi stands (TS) which are located at important sites along the road network (see Figure 12). Of the TSs, two important ones are located north and south of the main railway station. The first one of these is located between station building and station square and is thus expected to be frequented most of all TSs. Some of the TSs have been in motion during recent years in order to evade large construction sites, particularly the two at *Durlacher Tor* in the district *Oststadt*. For more information on traffic in Karlsruhe and interferences of construction with it, the interested reader may refer to the traffic development plan of the city (see Stadt Karlsruhe 2013).

### 5.1.1 Description of raw dataset

The dataset at hand covers the time period between 15/07/17 and 14/08/17 (inclusive) representing one month of data about taxi operations during summer. It has

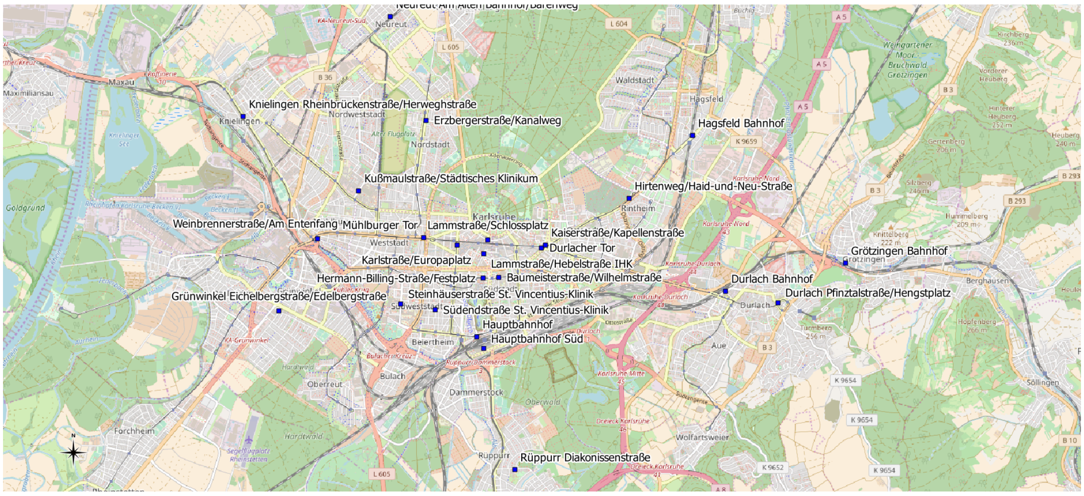


Figure 12: Map of Karlsruhe and surrounding area. The castle is located in the middle of a road network shaped similar to a hand fan. Thus, the city is also called "Fächerstadt" in German, which directly translates to hand fan city. The taxi stands in operation are represented by blue squares. Based on OpenStreetMap and exported from QGIS.

been recorded by *Austrosoft Weiss*, the fleet management provider of the taxi dispatch center in Karlsruhe. They continually store one month of data which is used by the center for coordinating the dispatch of their taxis. The exact composition of the data is illustrated in Table 4. Of the twelve data fields available, four were found useful for us: the x and y coordinates of the GPS points, the times of day and the operating status. The records of vehicle speed could have been valuable, however, a too large proportion of these fields was defective. Many of them displayed unrealistic measurements such as speeds far over 200 km/h and many others were just empty at times when the vehicle must have been in motion. For these reasons, the records of vehicle speed were found unreliable and therefore dismissed for application in our case. It is important to emphasize that we did not receive complete records of taxi trips, meaning from origin to destination (O-D trips). These would be needed as input to the FRLM. Instead, the fields contain GPS positions, which have been recorded at a rate of every few seconds to every few minutes. The rate of recording increased at times of higher vehicle speeds, and consequently decreased when the vehicle was not in motion. All in all, there are nearly 10 million data points. We have received the dataset in the form of delimited text (data format .csv) files, one file for each taxi. These strings of text have been converted by "text to columns" and joined to one large Excel (data format .xlsb) file in order to enable further processing via macros in Visual Basic for Applications (VBA). Date and time were separated into two cells, leading to the data points being displayed in a total of five columns: date, time of day, operating status, x and y coordinates. These columns

| Data field | Description | Used |
|---|---|---|
| ZEITPUNKT | Time of day of GPS record | Yes |
| VERMITTLUNGSSTATUS | Operating status e.g. customer on board | Yes |
| GEFAHRSTATUS | Verbatim: "risk status" | No |
| XKOORDINATE | Longitude of recorded GPS point | Yes |
| YKOORDINATE | Latitude of recorded GPS point | Yes |
| MESSUNGALTER | Verbatim: "age of record" | No |
| SATELLITEN | Verbatim: "satellites" | No |
| PDOP | Position dilution of precision | No |
| QUALITAET | Verbatim: "quality" | No |
| GESCHWINDIGKEIT | Vehicle speed | No |
| FAHRTRICHTUNG_WINKEL | Compass direction in deg. | No |
| FAHRTRICHTUNG_ANZEIGE | Compass direction in words | No |

Table 4: Data fields of the taxi trajectory dataset.

served as a basis for further extraction of useful information via the use of formulas. A text file has been attached to the dataset, explaining the different operating status messages. The most important of these are: 88 $\hat{=}$ taxi logged off from the system; 83 $\hat{=}$ taxi at a TS; 75 $\hat{=}$ taxi approaching a pick-up site; 70 $\hat{=}$ taxi in the area; 66 $\hat{=}$ customer on board and 65 $\hat{=}$ taxi logged into the system.

### 5.1.2 Assumptions made during the extraction process

During the extraction process some assumptions needed to be made. The logic behind these assumptions and the associated process steps of the extraction, which were performed in preparation of the subsequent visualization of the data, are explained in the following:

1. The gaps between any two consecutive time records were calculated. We had no information on the number of drivers for each taxi and shifts were not clearly identifiable. Furthermore, the law for regulation of working times of self-employed vehicle drivers (see German Bundestag 2012) did not offer sufficient orientation either since it gives the drivers considerable leeway with regards to daily working hours. Therefore, we assumed that any time gap of two hours meant that a new shift was started. Gaps under two hours were thus assumed to represent private time used for activities such as driving their children to school. Applying this assumption to the data points of the first taxi resulted in a reasonable number of shifts during the four weeks.

2. Since distances traveled were not part of the data a heuristic approach was

taken to generate those. Linear distances between all pairs of GPS positions were calculated applying the spherical law of cosines to determine the great-circle distance between two points on a sphere i.e. the shortest distance over the surface of the earth, given their latitudes and longitudes:

$$\begin{aligned}\text{linear distance} = &\arccos[\sin(x_1) * \sin(x_2) + \cos(x_1) * \cos(x_2) \\ &* \cos(y_1 - y_2)] * (\text{mean radius of the earth})\end{aligned}$$

where $x_i$ equal the latitudes, $y_i$ the longitudes of the two GPS positions and the mean radius of the earth equals 6371 km. We are aware of the inaccuracy arising from assumed straight lines between pairs of GPS positions instead of calculating shortest paths between them. However, first, the potential benefit would probably not justify the additional effort needed, second, the margin of error should be rather small since the median time gap between two recorded positions is only around nine seconds and, third, the distances traveled during customer trips and shifts suffice in the form of rough estimates. The distances calculated will henceforth be regarded and used as lower bounds while actual values are likely to be slightly higher.

3. The spherical law of cosines approach made heuristic distance calculations possible, enabling observations about potential energy consumption, if we assume that mostly Nissan Leafs will be purchased. The required rate of energy consumption is among the results of an EV pilot program, conducted by the New York City Taxi and Limousine Commission. They collected various data from data loggers installed in five Nissan Leafs, which have been taking part in normal taxi operations in New York City for more than two years. The resulting overall average electrical energy consumption in DC Wh per mile could easily be converted to DC kWh per km. (Idaho National Laboratory, 2016b) Based on these values, the potential total energy consumption of the taxi fleet may provide insight about the needed CS capacities to be installed.

4. Based on the operating status, the respective TSs were identified for all arrival times of taxis by using a list of the TSs in Karlsruhe and of the associated GPS points. Since the operating status already indicates arrival when the taxi is still approaching the TS, it was assumed to equal the nearest of the existing TSs at the time of arrival. Consequently, these events were assigned to time blocks of 1 min each, dividing each day into 1,440 and the whole week into 10,080 min. Based on these events, the continuous count of vehicles at each TS will provide guidance as to how many CPs need to be placed at each selected location.

5. Several types of trips are important for observations about the feasibility of BEV taxis regarding vehicle range. The trips from TS back to the same or

another TS (TS-TS trips) were extracted based on the changes in operating status. However, since many of those trips extend to two days, they needed to be restricted to a subset of trips starting and ending during the same shift. Another subset are the trips involving a customer order (TS-C-TS trips) since a considerable share of trips is spent cruising around the city without successfully picking up customers. Again, restricting this set of trips to the same shift is expected to deliver better insight. Comparing the histograms of the described trip types will help answer the question whether vehicle ranges of BEV candidates are sufficient to maintain normal driving behavior.

During the extraction process, it became apparent that many data points were incomplete in that for these times no records of associated GPS positions exist. Occurring mainly at the beginning of shifts, at these moments either the vehicle sent no signal or none was received by the associated GPS satellites. These incomplete data points were fixed by doing the following: for each data point, the chronologically closest of the respective two data points before and after was determined and its GPS position copied. Since most gaps between data points range between few seconds and several minutes, the arising degree of inaccuracy regarding the GPS positions is considered as limited and thus was accepted in order to maintain full accuracy regarding the recorded times. At the end, the single GPS recordings do not matter as much as total distances of trips, shifts and days, and are really only important for extracting arrivals at TSs and customer DOs. Having discussed the made assumptions, the information extracted on the basis of these assumptions will be illustrated in the following section.

## 5.2 Visualization of extracted information about trajectories

The two major questions to be addressed by the following dataset analysis are:

1. would the typical range of an available BEV model be sufficient to meet all requirements imposed by daily taxi operations?

2. do taxi drivers theoretically have enough spare time to recharge their vehicles during operating hours without disturbing operational patterns?

For the purpose of this analysis, BEV specifications are assumed to mimic those of the popular taxi model Nissan Leaf and those of the Nissan e-NV200, which is inter alia the choice made by NYC Taxi & Limousine Commission (2013). Eventually, the choice will be made by the taxi owners in coordination with the fleet operator in Karlsruhe. Since conversion of the whole fleet will take several years, battery

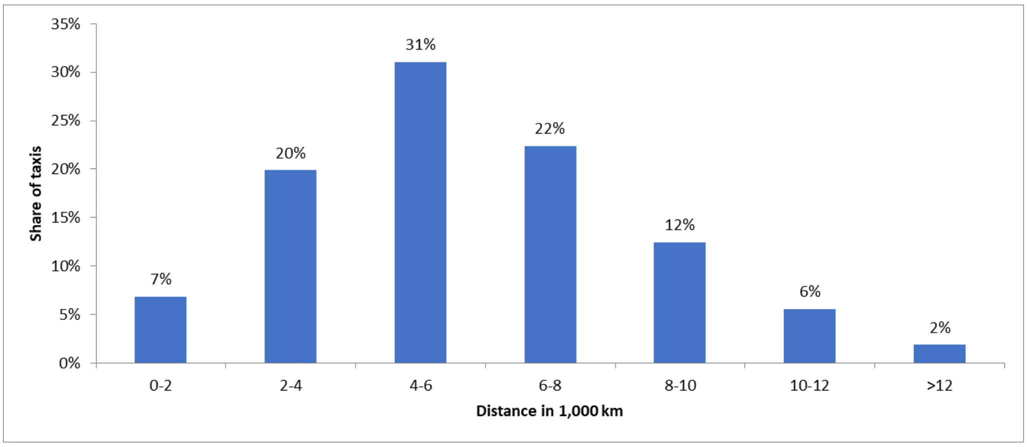


Figure 13: Frequency distribution of total distances covered by taxis during the sample time period. Average of 5179 km, median of 5444 km. See Appendix for distribution data.

technology can be expected to improve further adding to the range of available vehicle models.

### 5.2.1 Frequency distributions of data

During the examined time period of 15/07/2017 to 14/08/2017 (31 days), the fleet of 161 taxis has covered a total distance of 920,782 km converting to a fleet distance of 29,702 km per day. This information has been inferred from GPS data points (see first point on list in Section 5.1.1, p. 56). The associated frequency distribution (see Figure 13) illustrated that taxis covered an average distance of about 5719 km during the examined time period. If the vehicles had already been BEVs, they would have consumed approximately 109,280 kWh (or 109.28 MWh) of energy, calculated on the basis of field study results (see second point in 5.1.1). This value can be a reference point when deciding on the scale of the charging infrastructure to be installed. The average speed of taxis has been calculated to 14.74 km/h by combining covered distance with operating time. The frequency distribution (also called histogram) of times spent at TSs (see Figure 14) reveals that 51% of stays are shorter than five minutes. These stays are not long enough to warrant plugging in and out. The abundance of these short stays can be explained by all the re-parking happening at TSs. The remaining 49% may theoretically be used for charging. We assume that drivers would operate their vehicles exclusively above 20% and preferably higher SOC in order to limit battery degradation to a minimum. Also, they are likely not to recharge them to above 80% SOC since fast-charging speed declines to a minimum after this threshold. Furthermore, we assume a charging efficiency of 90%, which is in line with laboratory results on the efficiency of the popular charging

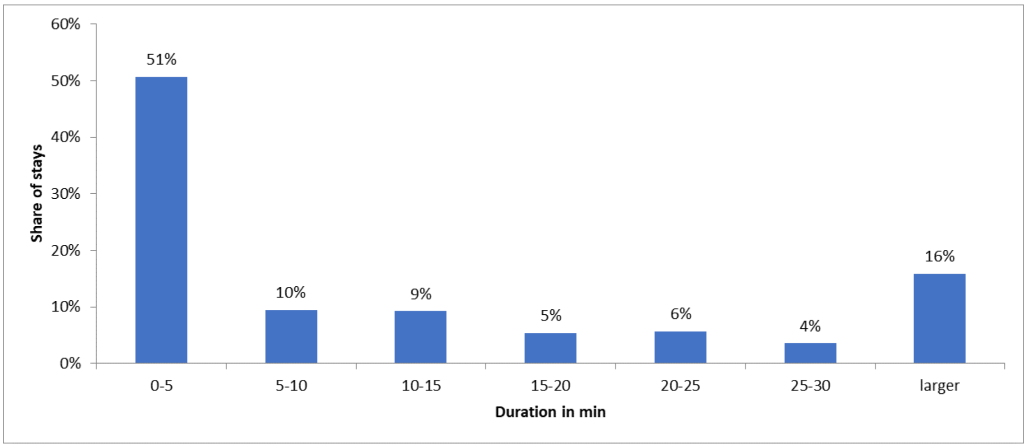


Figure 14: Frequency distribution of duration of stays at TSs. Sample size of 60,580. Average of 00:16:23, median of 00:04:30 (used format hh:mm:ss).

stations by ABB. (Idaho National Laboratory, 2016a) Based on these assumptions, the 16% of stays which are longer than 30 min are long enough for taxis to plug in, recharge from 10% to 80% corresponding to about 100km of range, plug out, and move a Nissan e-NV200 utilizing a fast-charger of DC 50kW. The longer-than-30-min stays are probably so numerous because they include (semi-)private break times. Another 15% of stays (of the eligible 49%) are 15 to 30 min long and therefore provide the opportunity of recharging one half of the battery. However, it is debatable whether the remaining 19% of 5-to-15-min stays should be used for charging. That is, because the associated coordination process can be arduous, depending on how many BEVs are involved.[12]

Although the stays at TSs are most relevant to our assessment, theoretically all time periods during operating hours in which taxis do not serve customers (see Figure 15) may be used for charging. These times should mainly encompass the times spent at TSs, the cruising trips made in search of a customer and the trips to pick-up respectively back from drop-off sites. Since the associated frequency distribution has a very long tail of increasingly less populated classes, the chart is cut off at 60 min. All time periods above 60 min, making up 15% of the sample, hypothetically provide enough time to recharge a range of about 200km, if a battery with such a capacity is used. Since the time periods are generally a lot longer than only those times spent at TSs, the fraction of periods usable for charging appears to be larger as well. However, since taxis drop off customers everywhere in the urban area, considerable times must be factored in for getting back to the TS/CS before plugging in. Moreover, in order to effectively use the times in which taxis are unoccupied, operational patterns would most likely need to be changed. This might make it more

[12] Mentioned percentage values are rounded and thus may not always add up to exactly 100%.

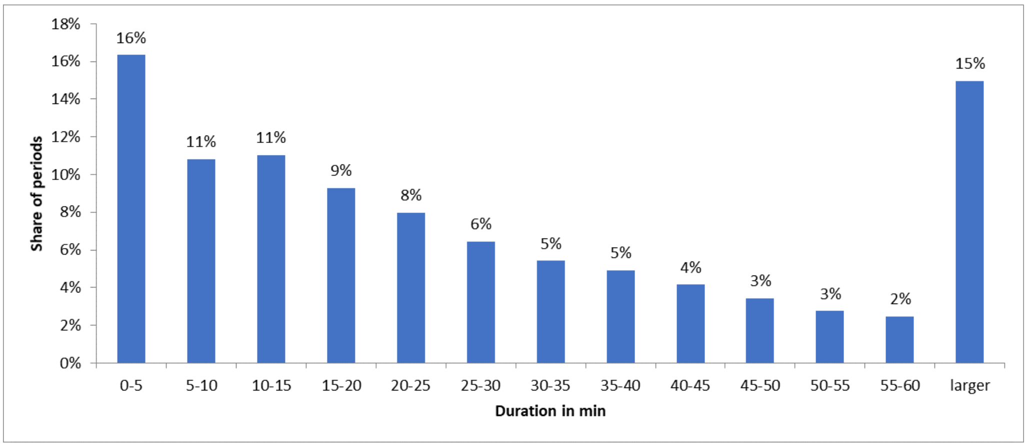


Figure 15: Frequency distribution of time periods during operations during which no customer is served. Sample size of 62,524. Average of 00:36:44, median of 00:21:25.

sensible to focus only on the times spent at TSs as a basis for further reflections. Based on these results, it is concluded that charging processes can be fit into regular operations. However, during most shifts taxis are likely to need two charging sessions.

In order to find out the amounts of energy needed to be recharged i.e. the range to be added, distances covered are analyzed in more detail in the following. Moreover, these observations will also address the question whether the typical range of an available BEV model would be sufficient to meet the requirements of daily taxi operations. For this purpose, the following definition of a taxi shift has been applied to the dataset in order filter out shifts: every distinct operating time period that is preceded and succeeded by a break of at least two hours. This was necessary since shifts have not been marked as such in the raw data. The application of the mentioned rule identifies the shift distances illustrated in Figure 16. The 16% share of shifts with less than 40 km and the extremely long tail of the distribution even with 20 values above 1,080 km can only be explained by a partial failure of the definition in reality. The small distances represent the many times in which drivers only briefly turn on their vehicle but do not start a shift, whereas the large distances are probably achieved by two drivers sharing one taxi and working their shifts in quick succession. However, the distribution may serve as an approximation. Moreover, it is assumed that the share of very small distances and the long tail of large distances cancel each other out nonetheless when calculating the average and especially the median value. Ignoring the weakness of the shift definition, these results indicate that in 69% of shifts the covered distance is less than 200 km. Thus, the needed energy for a vast majority of shifts could be recharged within 60 minutes (again employing a Nissan e-NV200). Moreover, the approach identified the average shift

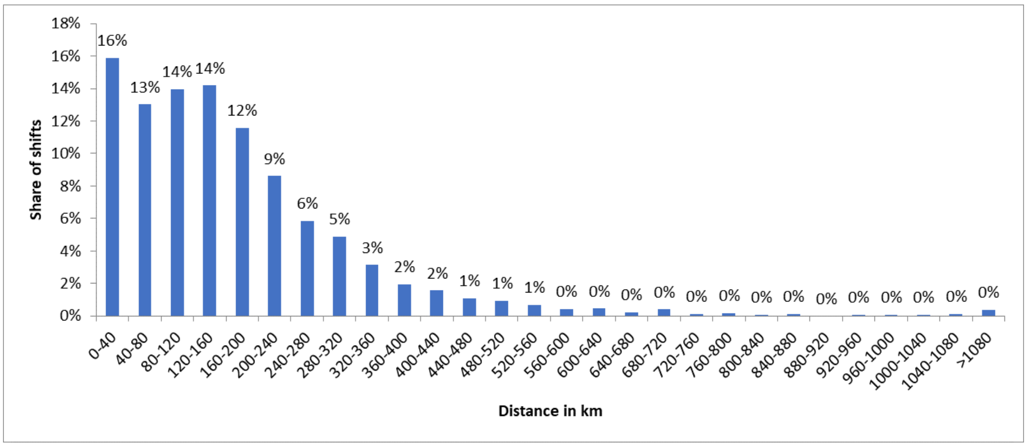


Figure 16: Frequency distribution of distances covered during shifts. Sample size of 5,286. Average of about 174 km, median of 140 km.

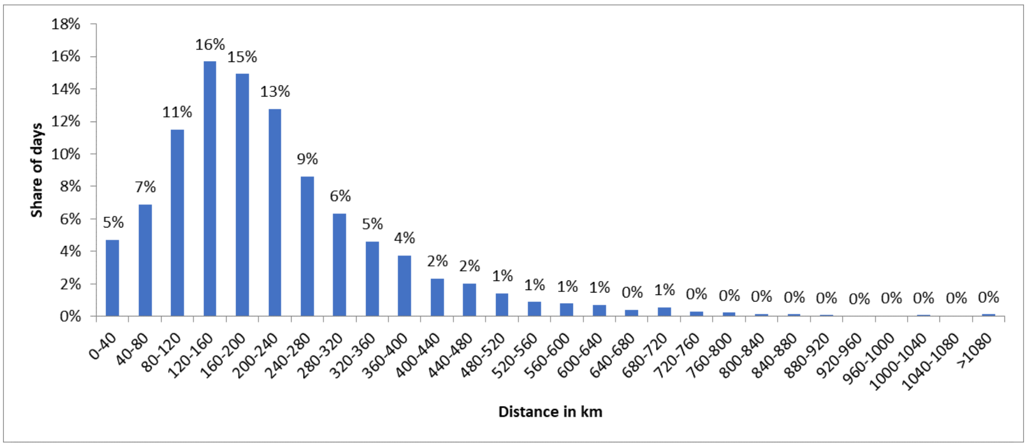


Figure 17: Frequency distribution of distances covered during 24 hours. Sample size of 4,076. Average of roughly 221 km, median of 191 km.

to last 8 hours and 5 minutes and the median shift to last 7 hours and 42 minutes.

In order to obtain a clearer picture of the covered distances, the observation period is extended to 24h in Figure 17. In this chart, the thickness of the right tail of the distribution is visibly reduced, as all classes above 720 km make up less than 1% each. 5% of days feature travel distances of less than 40 km, 12% of less than 80 km, 23% of less than 120 km, 39% of less than 160 km and 54% of less than 200 km. Hence, the energy needed on more than half of all days could be recharged within one 60-minute or two 30-minute sessions. Two 60-minute charging sessions during the day, providing 400 km of added range, would even cover 90% of days in the dataset. The distances covered during full days correspond to an average of 26.25 kWh respectively a median of 22.65 kWh of energy consumed. The associated operating hours during full days amount to an average of 15.0 hours and a median

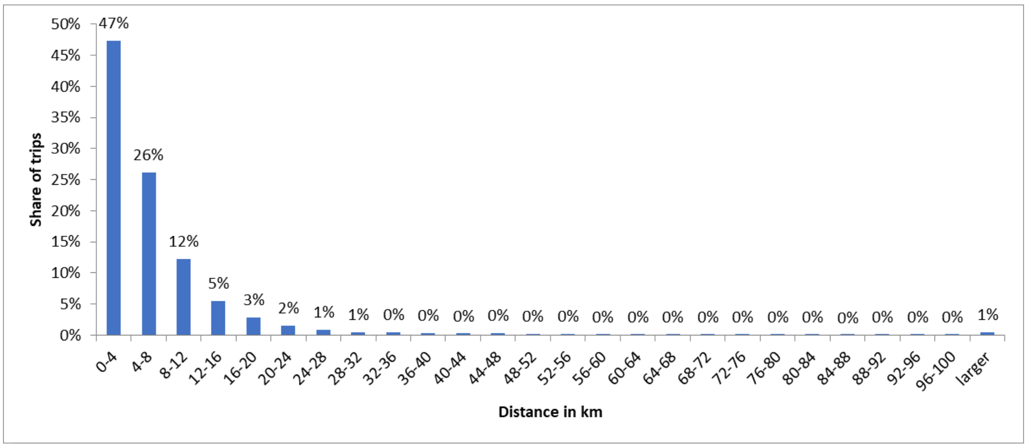


Figure 18: Frequency distribution of distances covered with customer aboard. Sample size of 52,077. Average of 7.55 km, median of 4.28 km.

of 14.25 hours. Combining median distance covered and operating time, a representative taxi covers 191 km during 14.25 hours on each full day. During 47% of days, the representative taxi is actually transporting customers for 0 to 2.4 hours whereas on another 40% of days it is doing so for 2.4 to 4.8 hours (and on 13% of days for longer). How these distances are distributed on single trips will be examined in the following. First, customer trips (only from pick-up site to drop-off), second, trips from TS to TS involving customer service and, third, all trips from TS to TS (irrelevant whether it is the same or not) will be distinguished in the following. The latter two types will subsequently be restricted to those taking place during operating hours.

Trip distances from TS to TS are distributed as in Figure 19. This distribution also features a long tail of very sparsely populated classes. The share of trips with distances of up to 8 km make up 54% of the whole sample, trips between 8 and 12 km add another 14% and the classes of up to 56 km contain nearly all remaining trips, except 5% of trips of which 2% are longer than 100 km. Only these 2% of trips may pose a problem to BEVs at nearly full SOC. The average trip from TS to TS during operating time took 26.6 minutes, the median trip took 16.1 minutes.

Since the trips from TS to TS also include cruising, that is, such trips that are made, without success, in order to find and serve those customers hailing a taxi from the roadside, a restriction of the aforementioned trips to those involving customer service should provide a clearer picture of the SOC that should be maintained in order to possibly serve all customers. The resulting frequency distribution (see Figure 20) shows, as opposed to the preceding chart, a clear peak at 4 to 8 km representing about 23% of trips. Around one sixth of all trips have distances under

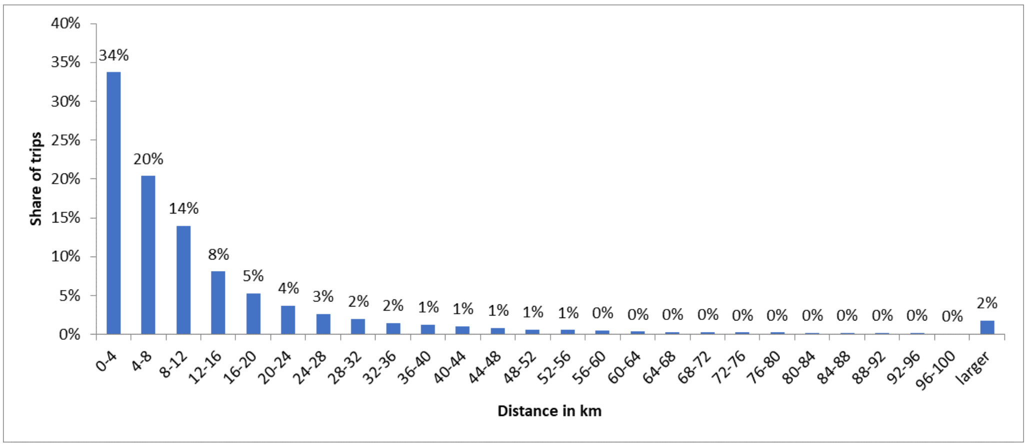


Figure 19: Frequency distribution of covered distances on trips from taxi stand back to the same or another taxi stand. Sample size of 60,125. Average of 15.16 km, median of 7.02 km.

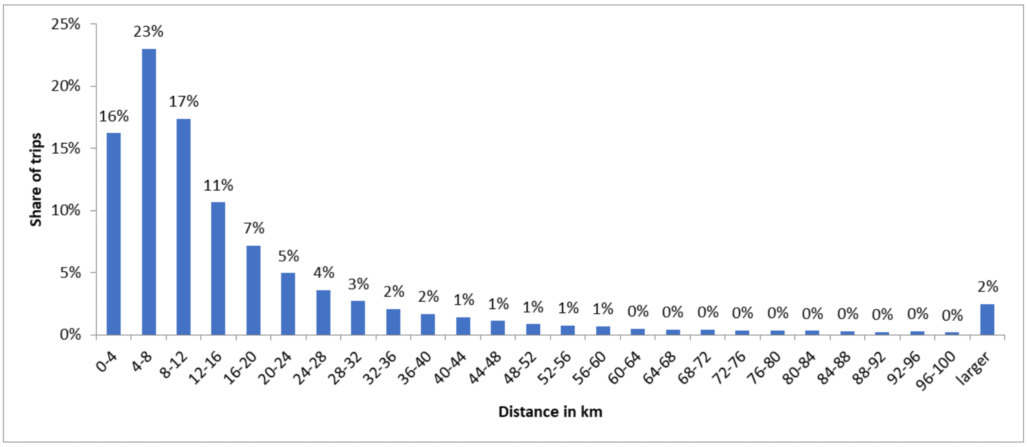


Figure 20: Frequency distribution of trip distances from TS to TS involving customer service. Sample size of 40,995. Average of 19.95 km, median of 10.29 km.

4 km and another sixth of trips are between 8 and 12 km, completing the 57% of trips under 12 km. As before, 2% of trips feature distances of more than 100 km and are therefore potentially challenging for BEVs and their limited range. 93% of trips can theoretically be covered by remaining ranges of 50 km. However, since deep discharging is harmful to the battery's technical condition including its capacity, BEV owners should refrain from exhausting their vehicles' batteries in such fashion. The average trip from TS to TS involving customer service took 33.6 minutes, the median trip took 21.8 minutes.

### 5.2.2 Conclusions from extracted information

In light of the results of this dataset analysis, the two main questions posed at the beginning of this section may be answered as follows:

1. would the typical range of an available BEV model be sufficient to meet all requirements imposed by daily taxi operations? Almost. It is clear that currently available BEVs will not be able to serve all customers at all times if drivers do not recharge during their shifts, since the trip distribution features a long tail of larger-distance trips. However, vehicles with a range of 100 km could cover 98% of the crucial type of trips i.e. those involving customer service.

2. do taxi drivers theoretically have enough spare time to recharge their vehicles during operating hours without disturbing operational patterns? On average, they do. 49% of all stays at TSs last longer than five minutes and thus enable a charging session. 15% of stays last for 15 to 30 min and can be used to add at least 50 km of range by recharging. One sixth of stays at TS are even long enough to recharge about 100 km of range. Hence, two of those stays during each fully day would suffice to cover the median distance of 191 km. With some operational changes, an even larger fraction of considerably longer operating time periods during which no customer is served could be exploited.

These statements should be taken with caution since the method applied for approximation of distances may understate them by up to a few percentage points. Interestingly, the issue of a possible lack of battery range may be greatly diminished once operators of electric taxi fleets start altering the assignment of customers to taxis so that different SOCs are taken into account. In such a scenario, fleet operators would always pick a BEV with sufficient range for the next job. However, such a system could only be put in place if customers hailed taxis using taxi apps and indicated their destinations while ordering. Now, that an electrification of the taxi fleet in Karlsruhe has been determined to be feasible, the next chapter will be dedicated to its implementation.

# 6 Optimization of charging station locations & economic analysis

The world's largest BEV taxi fleet in Shenzhen, China, has been in operation and growing since 2010. Therefore, local taxi drivers gathered large amounts of experience regarding the operation and recharging of BYD e6 vehicles. They report about three crucial issues: first, a limited charging infrastructure results in queues at CSs, second, inadequate spatial distribution of chargers increases the non-revenue mileage and, third, charging at relatively low outputs forces the drivers to make longer breaks at TSs between customer trips. (Shengyang et al., 2013) These and other issues shall be avoided through a holistic approach, outlined in the following:

1. formulation of a tailored optimization model for CS placement in Karlsruhe,
2. application of the model and calculation of results via sensitivity analysis,
3. illustration of results and systematic choice of sites,
4. assessment of weekly arrivals and departures at selected sites,
5. sizing of stations for achievement of reasonable utilization rates,
6. economic analysis of infrastructure and vehicles to be deployed.

Next, the implementation process will start with step one.

## 6.1 Modeling and application of the optimization model

Based on insights from the literature review in Chapter 4, two modifications of the node-based MCLM provided in Asamer et al. (2016) will be applied for the search of optimal locations. The objective is to locate $R$ charging stations on a grid of hexagons partitioning the urban road network of Karlsruhe so as to maximize the sum of covered trips. By using hexagons for this task we ensure complete, i.e. without gaps in between, coverage of the area of Karlsruhe specified in section 5.1. The utilized grid consists of 4760 regular-shaped hexagons with a center-to-center distance between neighboring hexagons of about 247.6 meters. Since potential CSs are assumed to be located in the center of hexagons, 247.6 meters represent a lower bound for the travel distance between hexagons. The associated travel time may be approximated to just over one minute by, first, using the average travel time from the dataset, second, assuming a Manhattan road network and, third, applying the law of Pythagoras. This approach accounts for the fact that vehicles nearly always need to take detours from the linear route on a real road network. However, the size and resulting amount of hexagons should not significantly change the optimization results.

### 6.1.1 Formulation and explanation of the model

The complete formulation of the modified model is as follows:

$$\text{maximize} \quad \sum_{i \in H} c_i x_i \tag{6.1a}$$

$$\text{subject to} \quad \sum_{i \in H} y_i \leqslant R, \tag{6.1b}$$

$$x_i \leqslant w_0 y_i + \sum_{j \in N_i} w_1 y_j + \sum_{k \in O_i} w_2 y_k + \sum_{l \in P_i} w_3 y_l \;\; \forall i \in H, \tag{6.1c}$$

$$0 \leqslant x_i \leqslant M \;\; \forall i \in H, \tag{6.1d}$$

$$D + (Z - d_{ij}) y_i + (Z - d_{ij}) y_j \leqslant 2Z - d_{ij} \, \forall i, j \in H, \, i \neq j, \tag{6.1e}$$

$$y_i \in 0, 1 \;\; \forall i \in H \tag{6.1f}$$

where
$c_i$ = amount of taxi trips ending in hexagon $i$,
$x_i$ = number of times that $i$ is covered in solution,
$R$ = number of stations to be built,
$H$ = set of all hexagons,
$w_0$ = weight of hexagon $i$ if station placed in i,
$w_1$ = weight of hexagon $i$ if station placed in first ring of adjacent hexagons $j$,
$w_2$ = weight of hexagon $i$ if station placed in second ring of adjacent hexagons $k$,
$w_3$ = weight of hexagon $i$ if station placed in third ring of adjacent hexagons $l$,
$N_i$ = set of first ring of hexagons around hexagon $i$,
$O_i$ = set of second ring of hexagons around hexagon $i$,
$P_i$ = set of third ring of hexagons around hexagon $i$,
$M$ = number of times that hexagon $i$ can be covered in solution,
$D$ = minimal distance to exist between each pair of charging stations,
$Z$ = largest of the pairwise distances between hexagons i.e. big number,
and

$$y_i = \begin{cases} 1 & \text{if station located in } i, \\ 0 & \text{otherwise.} \end{cases}$$

The objective function 6.1a maximizes the sum of numbers of taxi trips ending in one of the hexagons multiplied with the number of times that the respective hexagon is covered in the solution. Constraint 5.1b limits the number of CSs to be built to

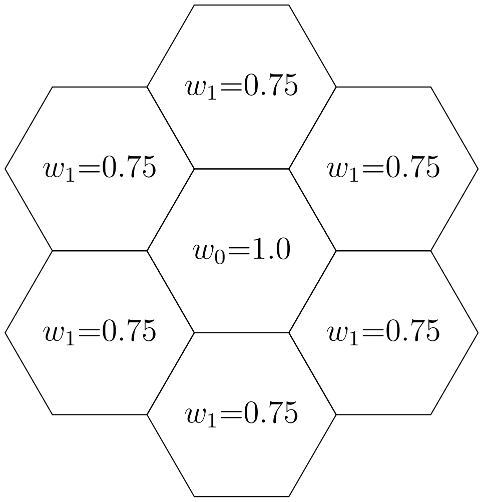


Figure 21: Illustration of weighted coverage of hexagons. Only first ring of hexagons depicted. Weights decrease with distance from center hexagon $i$.

$R$, while hexagons containing already existing CSs could theoretically be accounted for by setting their respective $y_i$ to 1. However, since we know that until today no fast chargers have been installed in the examined area, no such statement is needed and we recommend this possibility for later stages of the electrification project. Constraint 5.1f is restricting the decision variable for locating CSs to binary values. The two restrictions 5.1c and 5.1d represent a variation of the basic model, which is inspired by the coverage decay function introduced in Berman et al. (2003) (see Section 4.1.4, p. 42, for details). The motivation behind it is to consider not only the taxi trips ending in hexagon $i$ itself when deciding on the optimal locations for CSs but also consider the DOs made in nearby hexagons. It is assumed that after finishing their trips taxi drivers will also seek out the specific CS in hexagon i if they are within a certain distance of it i.e. in one of the rings of hexagons encircling it. The probability of this outcome shall decrease with the distance between DO and CS. In case the vehicle is roughly in the middle between two CSs, the situation is unclear. Then, other criteria might influence the decision, for example one might pick the CS with the smaller queue of vehicles and therefore shorter expected waiting time. Constraint 5.1c implements that the coverage value $x_i$ of each hexagon $i$ be a sum of the weighted number of hexagons selected for CS placement in $i$ itself as well as in the first, second and third ring of hexagons around $i$. This decaying coverage is illustrated for the center and the first ring around it in Figure 21. Constraint 5.1d limits the coverage value $x_i$ for each hexagon $i$ and therefore its influence on the objective function value. There might be several clusters of DOs in Karlsruhe e.g. in front of the main railway station or near the main shopping street of sizes much bigger than one hexagon. Since the model is supposed to select hexagons for placement so as to lend the high weights assigned to surrounding hexagons to those hexagons with the highest trip counts, this approach of capturing all the DOs in the nearby area is expected to result in a more efficient placement of CSs. Larger permitted values of $x_i$ theoretically lead to a higher density of CSs near hexagons with many DOs. However, our second modification is expected to prevent this. Hence, a limitation is not needed and thus we set the upper bound to its theoretical maximum of 16 which is occurring if all hexagons displayed in Figure 21 are selected for placement. The second modification to the basic model, a dispersion constraint inspired by Baouche et al. (2014), is implemented in restriction 5.1e. It forces each pair of hexagons selected for CS placement to be separated by at least a distance of $D$. As a consequence, CS locations will be considerably dispersed in every part of Karlsruhe, thus moderating the impact of the coverage decay constraint by preventing a clustering of CSs in areas of high demand. Moreover, under-utilization of single stations will be avoided. This uneconomical situation could occur if two stations were located near to each other and one exhibited a minor advantage over the other. This could be for example a toilet or a convenience store located nearby. If the taxi drivers were free to chose then, they might often prefer the one with the facilities, leaving the other one under-utilized. Therefore, we choose a value for $D$ of 1000 meters so as to ensure a minimal distance equivalent to at least four hexagons or at least three minutes. In order to enable an optimization with this additional constraint, a matrix of distances between each pair of hexagons is generated and stored in an array.

For comparison, our modified model, once with coverage decay and once also with dispersion, will be benchmarked against the basic model of Asamer et al. (2016) in the subsequent section.

### 6.1.2 Optimization of charging station locations in Karlsruhe

Several software have been used for the optimization. For example, the software have been used for the following tasks: Microsoft Excel 2016 (64 Bit) for extracting the GPS positions of the DOs from the dataset and generating frequency distributions for a variety of data; QGIS Desktop 2.18.12 for plotting the GPS points on a map of Karlsruhe, generating the grid of hexagons, counting the number of DOs in each hexagon and illustrating the results; CPLEX Studio IDE 12.7.1 for modeling and solving the resulting problems. The optimization runs with CPLEX have been made on a computer with the following specifications: Microsoft Windows 10 Home (64 Bit), Intel Core i5-5200U CPU and 8 GB RAM. The runtime for the runs performed for the sensitivity analysis varied between 1 minute 4 seconds and 32 minutes 18 seconds. We would prefer to see only hexagons with pre-existing TSs as clear result of the optimization runs, since the placement of CSs in other places would strategically be inferior. That is, because we aim at enabling BEV taxis to charge during waiting times at TSs. However, our approach is designed to identify additional hot spots e.g. large shopping malls which can subsequently be presented as potentially promising locations for new TSs. Optimization runs were performed for three model versions: first, the basic formulation (leaving out the two last terms in constraint 5.1c), second, additionally with coverage decay (now including the aforementioned terms) and, third, additionally with dispersion (also with 5.1e). An analysis of the sensitivity of optimization results to variations of R shall deliver insight regarding the issue of how to accomplish the most efficient amount and spatial placement of CSs, efficient in the sense of how many demand points can be covered and how the coverage increases per CS deployed. Six different configurations have been calculated:

1. basic model (Basic),
2. basic model with coverage decay (Decay),
3. coverage decay and dispersion, D=1, weights 1,0.75,0.5,0.25 (Dispersion 1),
4. coverage decay and dispersion, D=1, weights 1,0.5,0.25,0.125 (Dispersion 2),
5. coverage decay and dispersion, D=2, weights 1,0.75,0.5,0.25 (Dispersion 3),
6. coverage decay and dispersion, D=2, weights 1,0.5,0.25,0.125 (Dispersion 4).

Table 5 summarizes the results of the sensitivity analysis. Two different metrics are calculated for each model variant and R-values from 1 to 10. The first is the share of demand points covered by the located CSs: *number of covered demand points / all demand points*. It is important to note that absolute coverage values (the first column in each of the three sections) are not comparable for the basic model on the one hand and the other variants on the other, since selected hexagons in the basic model do not extend their reach as far. The second metric is the $\Delta$ in coverage delivered by each additional CS: *(coverage by current R) - (coverage by previous R)*. We anticipate one of the following strategies to be pursued when deciding on the combination of locations, ranked in decreasing order after potential financial exposure: first, settle on deploying solely one CS and choose its location so as to maximize the coverage of demand points, second, aim for maximal coverage of demand points regardless of budget constraints and choose accordingly, third, balance out budget constraints on the one hand and the aspiration for maximal coverage on the other hand, hence include CSs as long as the marginal benefit is reasonable or, fourth, decide later, on the basis of on-site assessments of feasibility and installation costs, bearing the displayed results in mind.

| | Basic | Decay | Disp. 1 | Disp. 2 | Disp. 3 | Disp. 4 | Basic | Decay | Disp. 1 | Disp. 2 | Disp. 3 | Disp. 4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| R | Cov. | Cov. | Cov. | Cov. | Cov. | Cov. | Δ Cov. | Δ Cov. | Δ Cov. | Δ Cov. | Δ Cov. | Δ Cov. |
| 1 | 12.82 | 14.58 | 14.58 | 14.58 | 14.58 | 14.58 | 12.82 | 14.58 | 14.58 | 14.58 | 14.58 | 14.58 |
| 2 | 17.29 | 14.72 | 25.48 | 23.90 | 22.73 | 22.73 | 4.48 | 0.14 | 10.89 | 9.31 | 8.15 | 8.15 |
| 3 | 17.87 | 15.25 | 31.13 | 30.43 | 27.83 | 27.36 | 0.58 | 0.53 | 5.65 | 6.53 | 5.10 | 4.63 |
| 4 | 20.37 | 15.32 | 35.95 | 35.06 | 33.80 | 31.99 | 2.50 | 0.07 | 4.82 | 4.63 | 5.97 | 4.62 |
| 5 | 21.79 | 15.76 | 41.05 | 39.91 | 37.03 | 34.44 | 1.42 | 0.45 | 5.10 | 4.86 | 3.22 | 2.45 |
| 6 | 23.62 | 16.30 | 44.48 | 43.40 | 40.98 | 37.44 | 1.83 | 0.53 | 3.43 | 3.49 | 3.95 | 3.00 |
| 7 | 26.08 | 16.31 | 47.46 | 47.07 | 43.44 | 41.40 | 2.45 | 0.01 | 2.98 | 3.67 | 2.45 | 3.95 |
| 8 | 27.52 | 16.41 | 51.87 | 49.53 | 45.91 | 44.35 | 1.44 | 0.10 | 4.41 | 2.45 | 2.47 | 2.95 |
| 9 | 28.52 | 16.52 | 55.10 | 52.53 | 47.92 | 45.71 | 1.01 | 0.12 | 3.22 | 3.00 | 2.01 | 1.37 |
| 10 | 30.27 | 16.58 | 56.60 | 56.89 | 49.26 | 46.49 | 1.75 | 0.06 | 1.51 | 4.35 | 1.34 | 0.78 |

Table 5: Sensitivity analysis of optimization results applying the basic and the enhanced models. All stated values are in % and rounded to two decimals, thus some do not exactly add up. Coverage refers to the amount of DOs made whereas, since the objective function values are distorted by the weighting approach, DOs in all hexagons that are at least assigned weights of 0.25 are counted. Due to the distortion, this approach is the only way to sensibly compare the results of the different configurations. As hexagons weighted with 0.25 are third-degree neighbors, potential charging sites can be reached from any covered demand point in less than three minutes, counting one minute for each crossed hexagon. The covered share of points thus represents the moments in which drivers can plug in to charge almost immediately after finishing a trip, without considerable detours. The term Δ coverage describes the marginal additional amount of coverage realized by each placed station.

| | Disp. 1 | Disp. 1 | Disp. 2 | Disp. 2 |
|---|---|---|---|---|
| R | Index | Nearest TSs | Index | Nearest TSs |
| 1 | 2076 | Hauptbahnhof | 2076 | Hauptbahnhof |
| 2 | 2012/2013 | Karlstraße | 2013 | Karlstraße |
| 3 | 2187 | Baumeisterstraße | 2186 | Baumeisterstraße |
| 4 | 1838 | Mühlburger Tor | 1632 | Kußmaulstraße |
| 5 | 1596 | Kußmaulstraße | 1838 | Mühlburger Tor |
| 6 | 2362 | Durlacher Tor-Kaiserstr. | 2363 | Durlacher Tor-Kaiserstr. |
| 7 | 1904/1939 | Südendstraße | 1904 | Südendstraße |
| 8 | 1453 | Weinbrennerstraße | 2855 | Hirtenweg |
| 9 | 3234 | Durlach Bahnhof | 3235 | Durlach Bahnhof |
| 10 | 1764 | Steinhäuserstraße | 1419 | Weinbrennerstraße |

Table 6: Comparison of sites and nearby TSs selected for placement of CSs.

Evaluating the respective achieved coverage, Dispersion 1 and 2 perform best, with 56.60% and 56.80% for ten placed CSs. Dispersion 3 and 4, with double the minimal distance between CSs, perform significantly worse in terms of covered DOs. Dispersion 1 and 2 choose nearly the same hexagons in nearly the same order, hence the different weights assigned to nearby hexagons had a very limited effect on the outcome. Figure 6 illustrates that nine of the hexagons chosen by Dispersion 1 and 2 point to the same set of TSs. Hence, no other hot spots are identified as could have been anticipated. All these nine TSs are selected for the following assessment of arrivals and departures in order to infer the necessary dimensions of the CSs to be placed. As most facility location problems, the problem at hand is also multi-objective in nature, considering both at once, cost minimization and demand orientation (cf. Current et al. (1990)). Proceeding according to the third strategy, seeking the point until which marginal improvements of additional CSs are high and from which improvements are low, does not appear to be of much value as the growth curves of Dispersion 1 and 2 are both close to linear. In case of the first strategy, all models point to the same hexagon, making this one the clear choice. The second strategy would be equally easy to implement, as you would only need to find the point that delivers the highest coverage: for all models, this is achieved for R=10. The fourth strategy may not be evaluated at this point.

Figures 22 to 27 illustrate the optimization results for the described combinations of different minimal distances between stations (D) and weights. In order to see whether the assumption that CSs would be placed near TSs holds true, the positions of these are represented by blue squares. The figures also feature heat maps of the demand points: hexagons are colorized in different shades of blue according

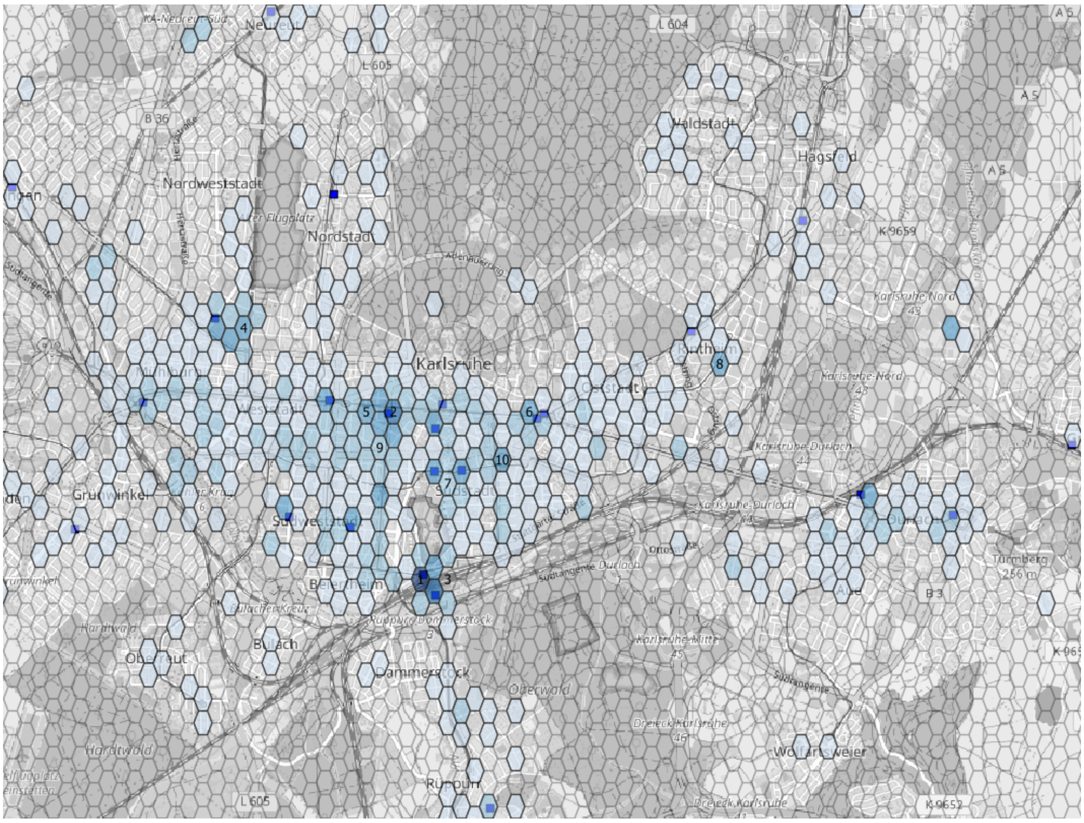


Figure 22: Results of Basic.

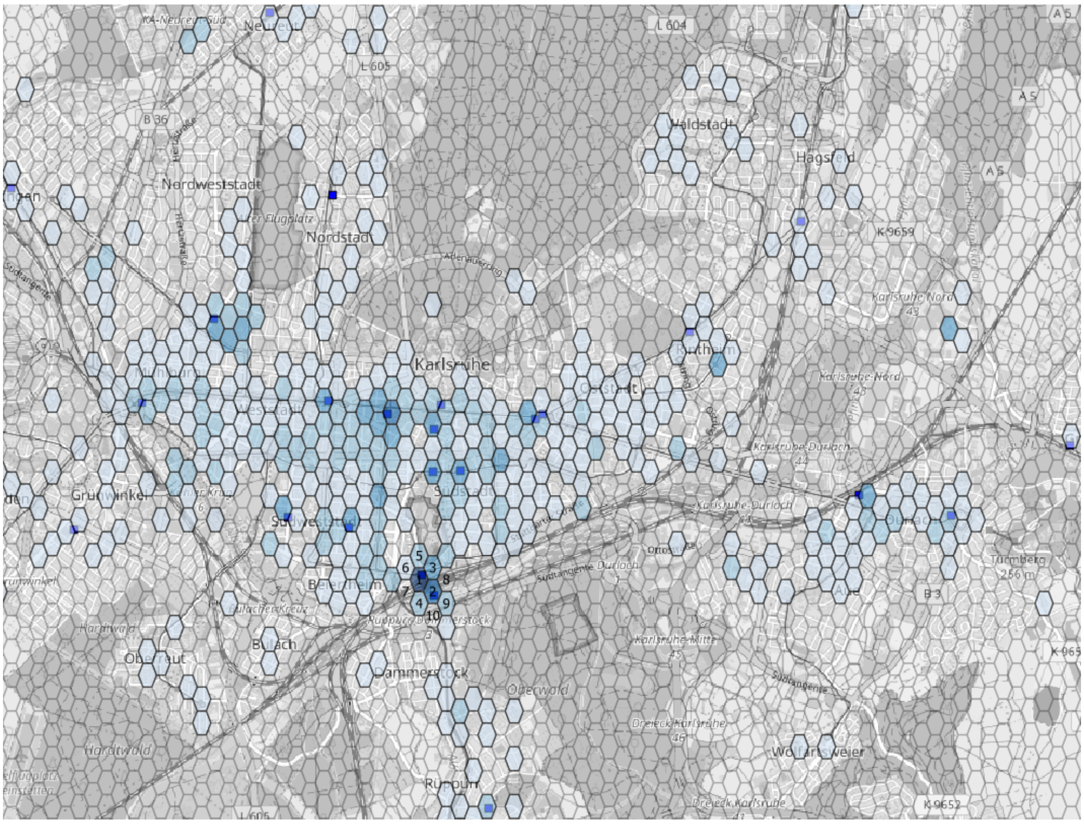


Figure 23: Results of Decay.

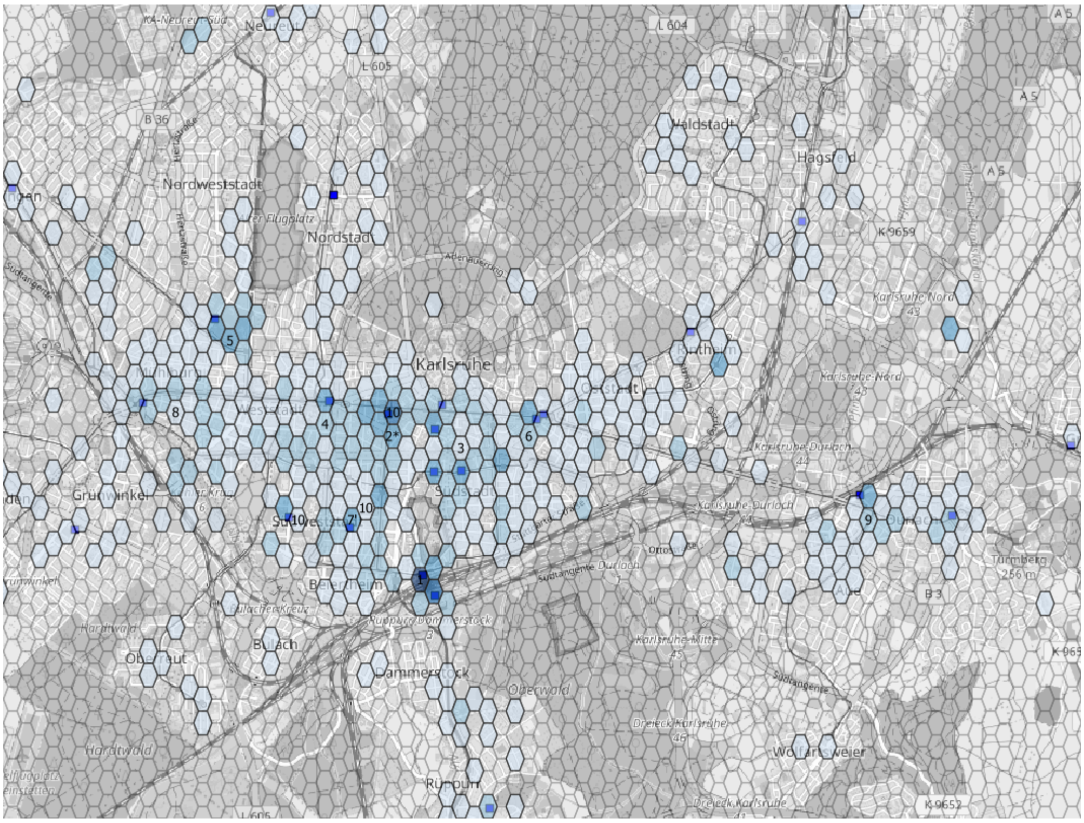


Figure 24: Results of Dispersion 1. D=1km, weights 1,0.75,0.5,0.25.

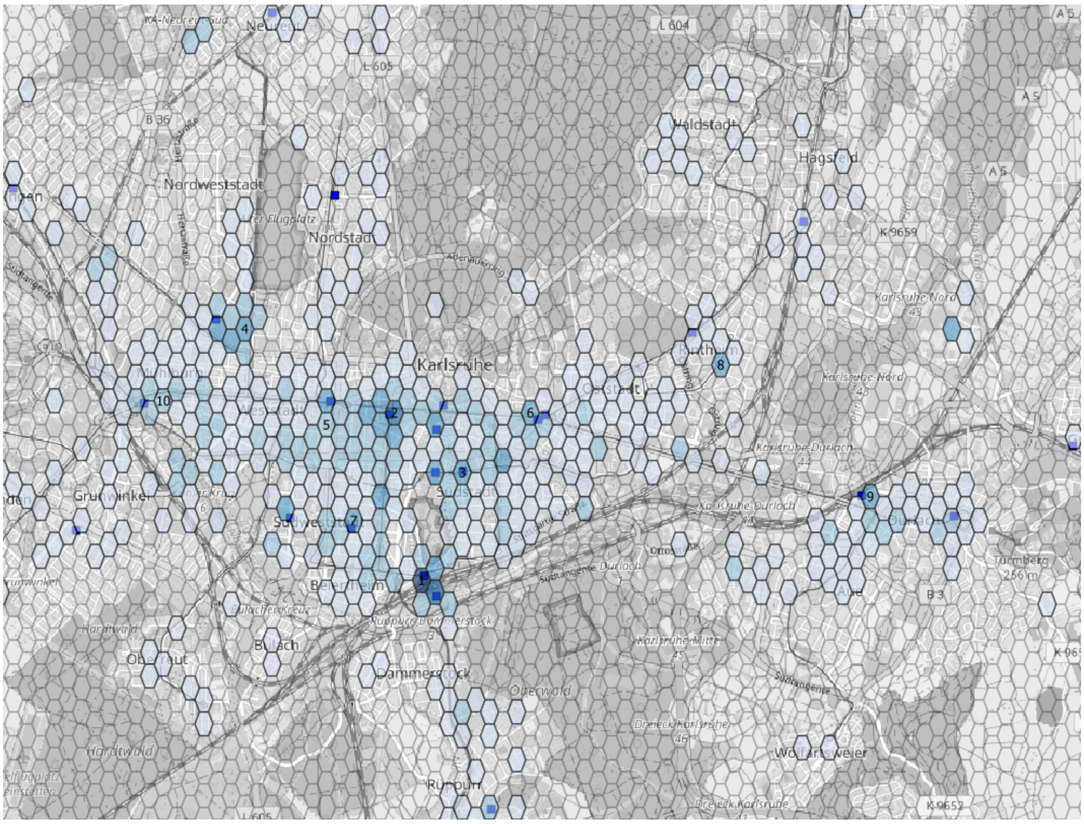


Figure 25: Results of Dispersion 2. D=1km, weights 1,0.5,0.25,0.125.

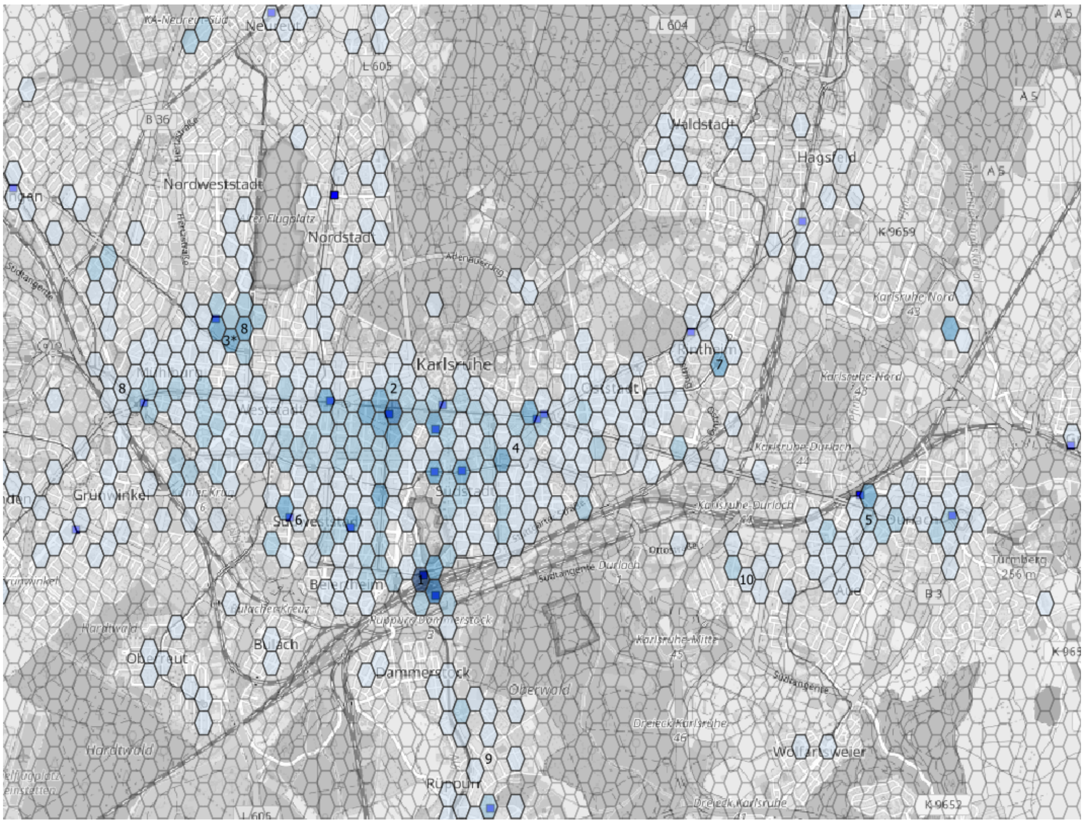

Figure 26: Results of Dispersion 3. D=2km, weights 1,0.75,0.5,0.25.

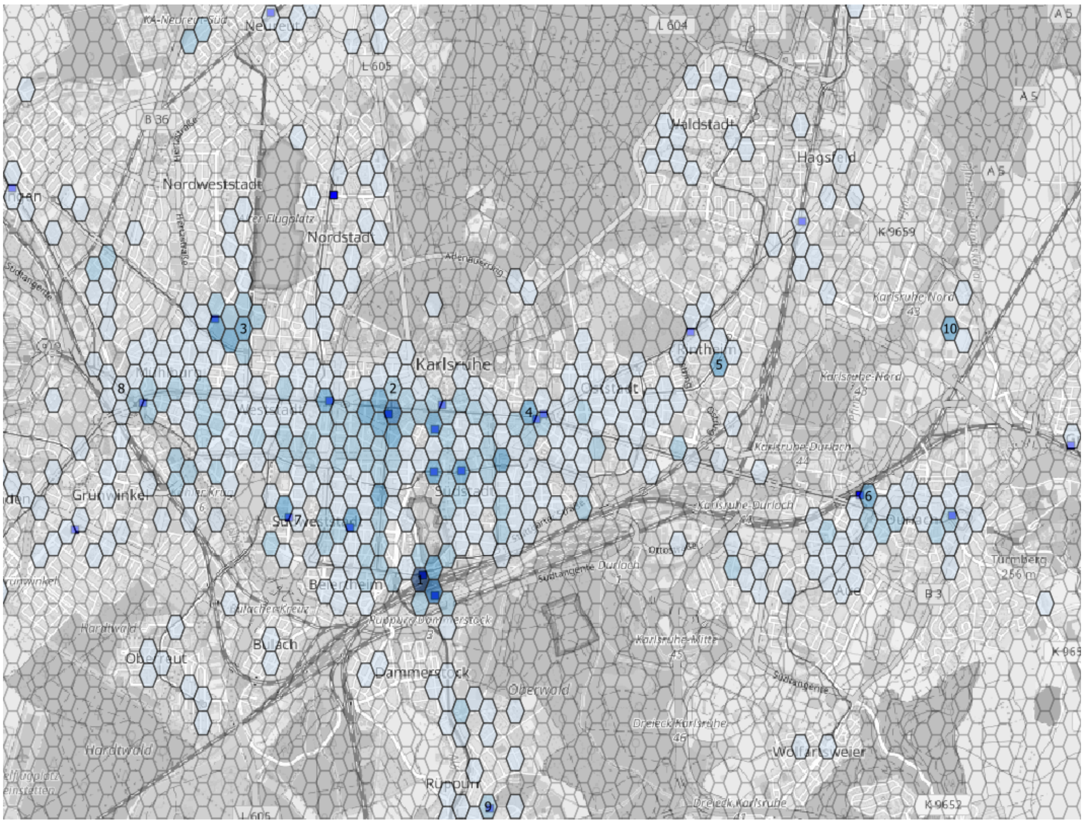

Figure 27: Results of Dispersion 4. D=2km, weights 1,0.5,0.25,0.125.

to the amount of DOs made during the period of four weeks. The following classes are thereby distinguished: 0-23, 23-82, 82-204, 204-538, 538-1849 and 1849-3964. Since 0-23 trips per hexagon amount to less than one visit per day and are therefore negligible, these hexagons are not colorized. Moreover, only the map sections with relevant hexagons are presented. Applying this method, the logic behind the spatial placement of CSs is made transparent. The order in which the CSs are chosen by the respective configurations is written inside the hexagons. Numbers of positions that are being replaced by other positions with increasing R are amended by a symbol. It is apparent that Basic essentially chooses the ten hexagons with the most DOs i.e. the darkest ones (see Figure 22). Decay, on the other hand, chooses the most populated one first and subsequently places CSs around it due to the weighting approach multiplying the impact of a sited CS through the overlap of several layers as in Figure 21. This tendency to concentrate the CSs is only counteracted by the dispersion constraint, implemented in Dispersion 1 to 4. Consequently, those four configurations produce the most useful results. The previously mentioned selection of hexagons appropriate for CS placement is near the respective following TSs (for exact locations, see Figure 12, p. 55): "Hauptbahnhof", "Karlstraße/Europaplatz" (only referred to as "Karlstraße"), "Baumeisterstraße/Wilhelmstraße" ("Baumeisterstraße"), "Kußmaulstraße/Städtisches Klinikum" ("Kußmaulstraße"), "Mühlburger Tor", "Durlacher Tor" & "Kaiserstraße/Kapellenstraße" ("Kaiserstraße")[13], "Südendstraße/St. Vincentius-Klinik" ("Südendstraße"), "Weinbrennerstraße/Am Entenfang" ("Weinbrennerstraße") and "Durlach Bahnhof". Since it is not possible to reasonably narrow down the selection at this point, the whole selection is used as input for the next step.

### 6.1.3 Determination of suitable capacities

The selection of TSs further to be evaluated represents only 41.7% of all TSs in Karlsruhe, however, they account for 66.7% of vehicle arrivals. The objective in the following will be to systematically deduct the number of CPs needed to be installed at each selected TS in order to simultaneously cover as much demand as possible and ensure economical utilization rates. One cannot simply install so many CPs as to cover all peak demands since this would certainly result in abysmal utilization rates and consequently unprofitable operation. In order to calculate and visualize the arrivals at and departures from the selected TSs, the associated data series of times have been matched, so that each data point contains the date, the arrival time, the departure time and the duration of stay. For each TS, a counter beginning

[13]These two TSs will be merged in the following as they are very close to each other. "Hauptbahnhof" and "Hauptbahnhof Süd" are, however, distinctly spatially separated from each other and it takes about five minutes to get from one to the other by car.

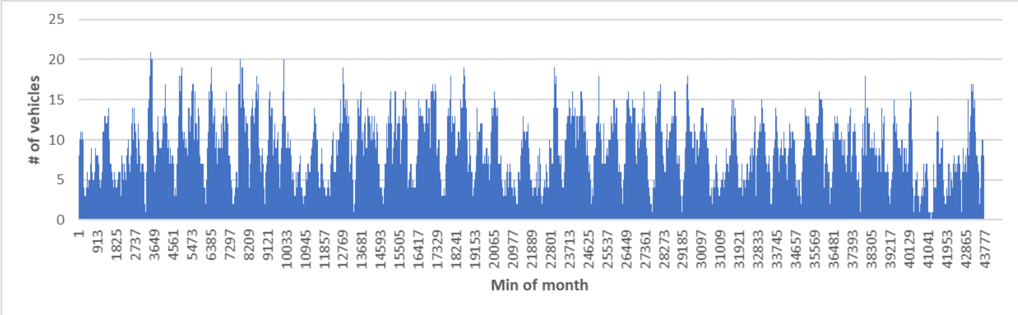


Figure 28: Pattern of arrivals and departures at the TS "Hauptbahnhof" during the whole month covered by the data.

with zero calculates the number of vehicles present in any given minute. Illustrating the pattern of arrivals and departures at "Hauptbahnhof" during the whole month (see Figure 28) and comparing it to the pattern of only the first complete week from 17/07/17 to 23/07/17 (see Figure 29), demonstrates that the chart for one week is superior in terms of clarity. For example, the weekly pattern can be recognized with peaks during the days and valleys during the nights. Moreover, the peak number of vehicles only varies slightly from week to week. On these grounds, further observations will be limited to the mentioned week from 17/07 to 23/07. Hence, arrivals for which the respective departures only happen after 00:00:00, and thus on the 24/07/17, are left out.

On every chart, the x-axis denotes the minute of the week, ranging from 1 to 10,080 minutes, each day containing 1,440 minutes. The maximum for "Hauptbahnhof" is at 21 vehicles, the average at 7.00 and the median at 6 vehicles. The frequency distribution of minutely vehicle counts supports the assessment of how many CPs are advisable, whereas a benchmark of about 80%, meaning that in four or out five minutes all present vehicles may be connected to a CP, appears sensible. Applying this rule to the distribution for "Hauptbahnhof" results in 10 CPs, well above the average of seven vehicles, covering 79% of minutely demands. The resulting utilization rate is obtained by, first, deleting all data points with stays shorter than five minutes since re-parking and plugging in and out consumes too much of these stays, second, rounding down values to the 30-minute mark since vehicles leave once fully charged and, third, subtracting one minute from each stay for plugging in and out. In a fourth step, the resulting stay durations are summed up in order to arrive at the total needed charging time during the week and, fifth, dividing this sum by the determined number of CPs multiplied with the 168 hours of a week gives out the theoretical utilization rate of each CP. For "Hauptbahnhof", this value is 43% translating to about 10.3 hours of charging time per day as well as average values of 258 charges per day, 26 charges per CP per day and stay lengths of about 24

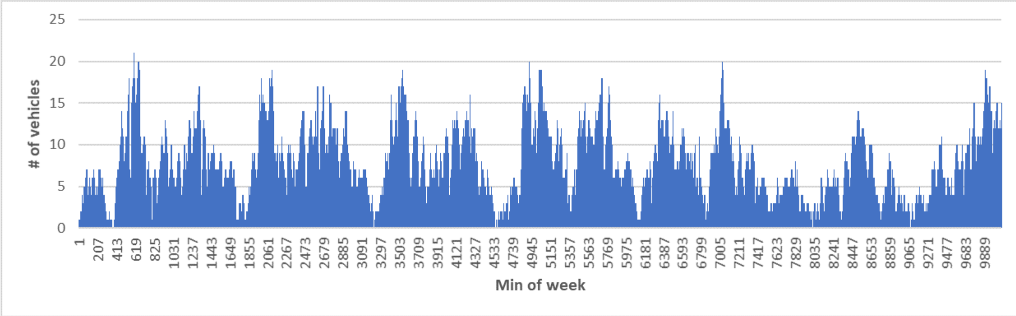


Figure 29: Pattern of arrivals and departures at "Hauptbahnhof" during first week.

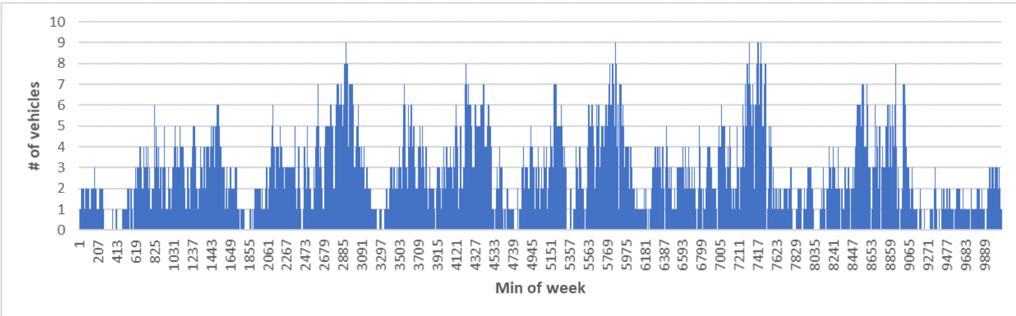


Figure 30: Pattern of arrivals and departures at "Karlstraße".

minutes.

The procedure of determining the number of CPs is repeated for the other eight sites (see Figures 30 to 37), leading to the results summarized in Table 7. This table lists the CS respectively TS, the number of CPs to be deployed there, the share of minutes of the week during which all vehicles may be plugged in for charging, the number of charges per CP per day, the average stay duration and the resulting average utilization rate of CPs at the respective CS. As CSs usually feature two CPs each, CPs are advised to be deployed in multiples of two, hence also the displayed

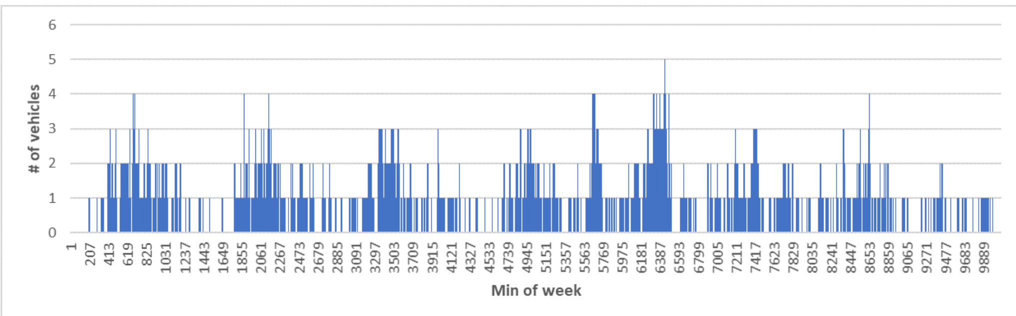


Figure 31: Pattern of arrivals and departures at "Baumeisterstraße".

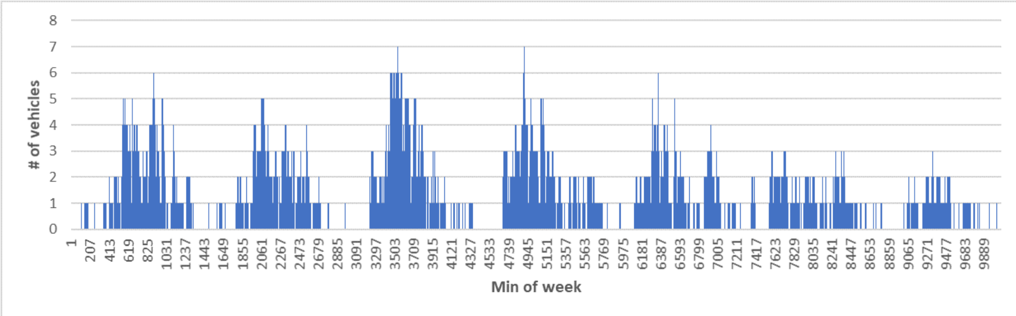


Figure 32: Pattern of arrivals and departures at "Kußmaulstraße".

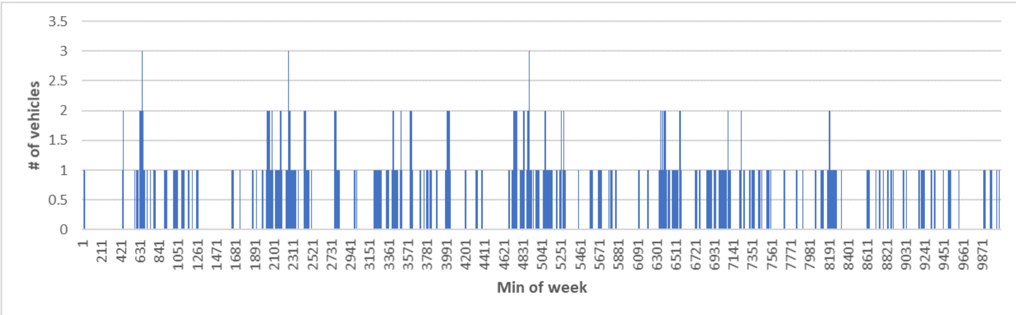


Figure 33: Pattern of arrivals and departures at "Mühlburger Tor".

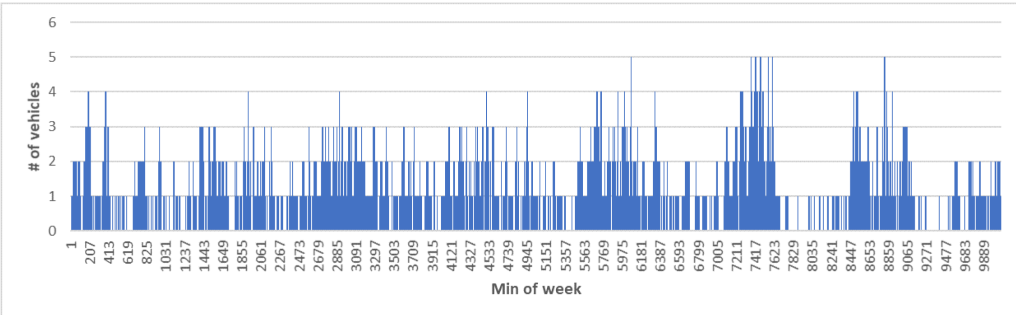


Figure 34: Pattern of arrivals and departures at "Durlacher Tor" & "Kaiserstraße".

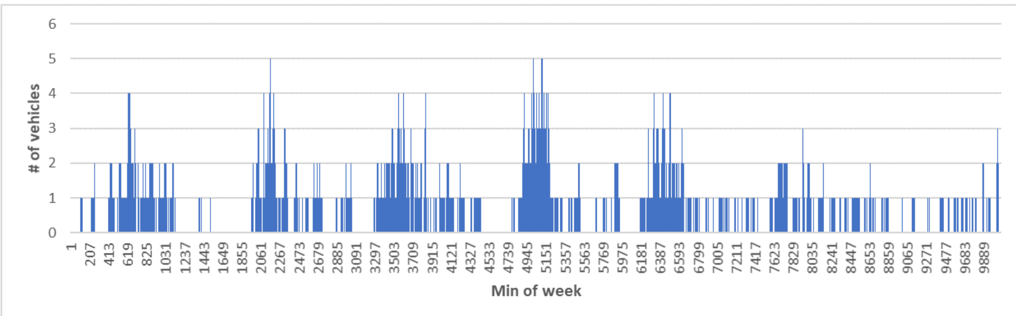


Figure 35: Pattern of arrivals and departures at "Südendstraße".

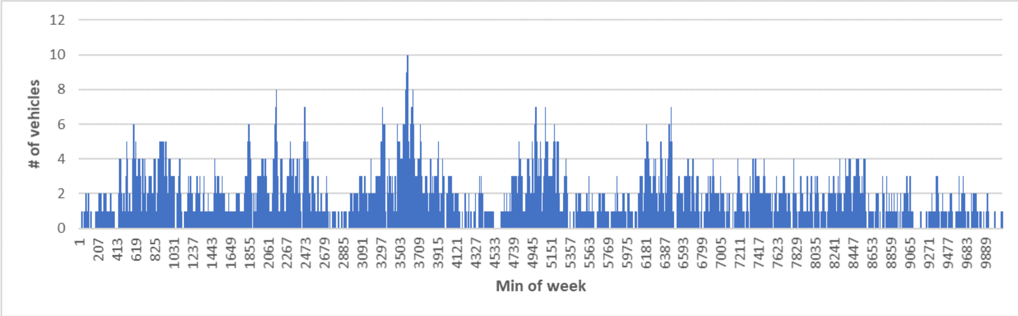


Figure 36: Pattern of arrivals and departures at "Weinbrennerstraße".

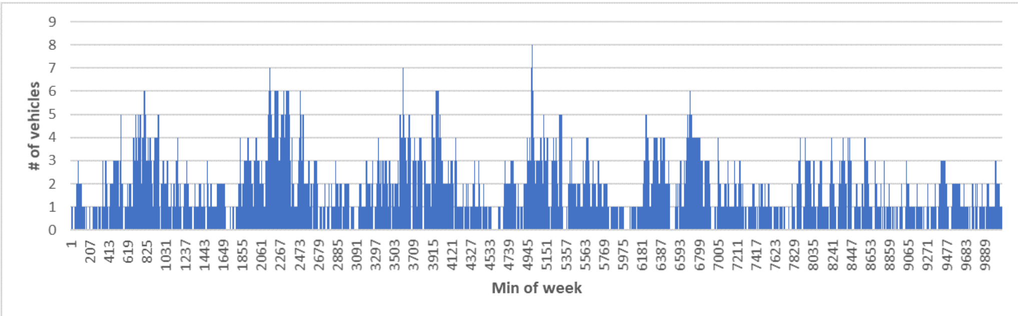


Figure 37: Pattern of arrivals and departures at "Durlach Bahnhof".

distribution of CPs. The order in which TSs shall be deployed (see Table7) has been set by the optimization model and thus represents the theoretically optimal approach. However, the installation of the minimum possible number of two CPs at four of these sites would produce utilization rates clearly below 20% and, as observed earlier, coverage grows in nearly linear fashion, permitting a slight deviation of the suggested order without losing too much value. Therefore, the four mentioned TSs shall be skipped and only the five in italics be equipped with CPs. With the recommended distribution of CPs, the following average values are obtained: coverage of 90%, 26 charges per CP per day, average stay duration of 18 minutes 19 seconds and a utilization rate of 34%. It is expected that taxi drivers will alter their driving patterns so as to even out the charging demands at the different TSs where CPs are installed. That is, they are likely to evade crowded charging sites and steer their vehicles to one of the other five charging sites instead. Consequently, demand peaks would be noticeably shaved and valleys filled. The finding that about 22 CPs are needed for a fleet of 161 BEV taxis (making it 7.3 taxis per CP) is quite consistent with the view of Sellmair and Hamacher (2014) that each CP can supply around 7.6 BEV taxis. This observation was made for the city of Munich for which travel patterns of taxis should not be too different from those in Karlsruhe. Henceforth, the approximated number of 22 needed CPs will be used as input for the following outline of a possible project schedule and the associated economic analysis.

| CS/TS | # CPs | Cov. | Ch./CP/day | ∅ stay | Util. |
|---|---|---|---|---|---|
| *Hauptbahnhof* | 10 | 79% | 26 | 00:24:02 | 43% |
| *Karlstraße* | 4 | 88% | 34 | 00:16:54 | 40% |
| *Baumeisterstraße* | 2 | 97% | 21 | 00:15:27 | 22% |
| *Kußmaulstraße* | 2 | 89% | 27 | 00:18:11 | 34% |
| Mühlburger Tor | 2 | 89% | 9 | 00:15:42 | 10% |
| Durlacher Tor | 2 | 95% | 21 | 00:09:47 | 14% |
| Südendstraße | 2 | 97% | 17 | 00:15:38 | 19% |
| *Weinbrennerstraße* | 4 | 96% | 24 | 00:17:02 | 29% |
| Durlach Bahnhof | 2 | 83% | 21 | 00:08:59 | 13% |
| Total | | 90% | 22 | 00:15:45 | 25% |
| *Selection* | | 90% | 26 | 00:18:19 | 34% |

Table 7: Results of procedure to find the optimal number of CPs per CS so as to cover demand and ensure adequate utilization. Selection written in italics.

## 6.2 Economic analysis of taxi fleet electrification

The resulting investment sum needed for the installation of the composition of CPs per site previously determined will be obtained by taking into account the scaling effects brought about by the deployment of more than one CS per site. That is, since every CS after the first one benefits from the already installed connection to the grid its installation will be less costly. Assuming costs of 50,000 for the first CS at a site and 30,000 for every additional one at the same site[14], it is concluded that the amount needed to be invested into the charging infrastructure would be about 430,000 Euros, that is, five times 50,000 (for first CSs) plus six times 30,000 (for additional CSs). This sum translates to 19,545 Euros per CP and needs to be invested over the course of several years. The time period during which the whole fleet may be converted from ICEV to BEV taxis is estimated on the basis of the average total distance covered by a taxi during one month (see Figure 13). This covered distance of 5,719 km per month converts to 68,628 km per year. According to the CEO of the *Taxi-Funk Zentrale Karlsruhe eG*, these taxis are replaced every four to five years. That is, when they reach mileages of 200,000 to 300,000 km, where taxis used jointly by two drivers exhibit the higher mileages. Since our estimation of annual mileage results in a 4-year mileage of around 274,000 and a 5-year mileage of 343,000 km, a value of 300,000 km is expected to represent a reasonable benchmark. It can be assumed that taxis are not bought in large quantities but instead

[14]Due to a lack of reliable, available data, we depend on expert knowledge for this approximation. Some of these experts are directly involved in installing charging infrastructure for electric vehicles and some are frequently managing projects in the field of hybrid and electric vehicles.

replaced continuously since this fleet is owned by a lot of small businesses making their own decisions. Consequently, the whole fleet may theoretically be converted to BEV taxis within a time period of five years without any negative effects on taxi businesses.

In order to ensure a smooth transition, the first CS must be installed prior to the introduction of the first BEV taxi. Since this step needs to be taken by another party, either by the local public utility *Stadtwerke Karlsruhe* or by the utility company *EnBW*, the project needs a lead time of at least one year dedicated to e.g. negotiations and coordination, raising the project horizon to six years. The preparation year will henceforth be denoted as year 0, and the years used for deployment as 1 to 5. It is recommended that the installation of the eleven CSs be conducted within three to five distinct construction phases so as to ensure economical utilization rates of the installed CPs at any point in time. These phases may be evenly distributed over the five years, for example one at the beginning of each project year. The points in time at which CSs are planned to be installed shall be aligned with the progress on fleet conversion. Through coordinated purchasing of BEVs and installation of charging infrastructure, the chicken-and-egg conundrum mentioned in section 2.2 can be avoided. If the fleet conversion does not move forward quickly enough, the installation of additional CSs must be postponed in order to prevent situations in which CSs are not frequented regularly enough i.e. under-utilization. The first construction phase shall be focused on "Hauptbahnhof" since this TS accounts for 19% of all arrivals, and possibly also on "Karlstraße/Europaplatz" which accounts for another 12%. However, it is recommended that the five respectively two CSs not be installed at once but in separate construction phases. During the five years, the expected amount of charges per CP per day (see Table 7) may be calculated for varying shares of BEVs in the fleet by factoring in that only every x-th arriving vehicle is in fact a BEV. Combining the frequency distribution resulting from this correction with a sensitivity analysis on the corresponding utilization rate may then point to the appropriate number of CPs. Two aspects are essential for an economic assessment of the CPs to be deployed at the selected sites: can the expected utilization rates support an economic installation and operation? And can the investment be financed at reasonable interest rates? In order to answer these questions, a comprehensive investment analysis (see Table 8) is performed on a worst-case basis. That is, we assess the potential CS at "Baumeisterstraße" with a utilization rate of 22%, translating to 5.28 charging hours daily, as if it was to be built already at the beginning of the fleet conversion. This action might be advantageous for the project since if all CSs are built at once construction might become less expensive. The objective of the net present value (NPV) calculation is to see how low the customer price for charging can be set so that the investment is still NPV neutral. In preparation of the calculation, the following assumptions have been made:

- Revenues and expenses accrue at the beginning of each year.
- One CS incorporates two CPs.
- A CS can stay in operation for ten years. No salvage value can be realized.
- The conversion of the whole fleet from ICEVs to BEVs takes five years.
- The financing institution can raise funds at an interest rate of 5%. This will therefore be the discount rate for the cash flows.
- The rate at which BEVs can be charged is 0.77 kWh/min. This is the rate for a Nissan e-NV200 being charged from 0 to 80% SOC. (Zap Map, 2017)
- Electricity can be purchased for 0.15 Euros per kWh (incl. VAT, see Destatis (2017)) and be sold at a mark-up. Both rates are to grow at 5% annually.
- The charging tariff is variable-only, without any fixed component.
- The corporate tax rate is set at 30%, the value-added tax rate at 19%.
- The Mercedes C Class serves as benchmark for charging, with a fuel consumption of 7 liters per 100 km and an average Diesel price of 1.15 Euros per liter, translating to about 8 Euros per 100 km.
- The inflation rate is set at 2% annually for all prices except for electricity.
- As mentioned earlier, the first CS to be built shall cost 50,000 Euros.
- Costs for planned maintenance are set at 3% of charger purchase & delivery costs, for unplanned maintenance at 4% (see Serradilla et al. (2017)). Charger purchase % delivery costs itself make up about 50% of total installation costs.
- A management fee is set at the same price as costs for planned maintenance.
- Since the fleet is assumed to convert to BEVs within five years, BEV stock is to grow at 32 vehicles annually. Charging demand reflects that growth rate.

| Year | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Revenue** | | 8,757 | 19,389 | 28,962 | 40,547 | 53,551 | 56,229 | 59,040 | 61,992 | 65,092 | 68,346 |
| **Expenses** | | | | | | | | | | | |
| CAPEX | | | | | | | | | | | |
| Initial outlay | 50,000 | | | | | | | | | | |
| Depreciation | | 5,000 | 5,000 | 5,000 | 5,000 | 5,000 | 5,000 | 5,000 | 5,000 | 5,000 | 5,000 |
| OPEX | | | | | | | | | | | |
| Electricity consumption | | 5,574 | 11,706 | 18,438 | 25,813 | 34,091 | 35,795 | 37,585 | 39,464 | 41,438 | 43,509 |
| Maintenance (planned) | | 765 | 780 | 796 | 812 | 828 | 845 | 862 | 879 | 896 | 914 |
| Maintenance (unplanned) | | 1,020 | 1,040 | 1,061 | 1,082 | 1,104 | 1,126 | 1,149 | 1,172 | 1,195 | 1,219 |
| Management fee | | 765 | 780 | 796 | 812 | 828 | 845 | 862 | 879 | 896 | 914 |
| Total | 50,000 | 13,124 | 19,307 | 26,091 | 33,519 | 41,851 | 43,611 | 45,457 | 47,393 | 49,425 | 51,557 |
| **Pre-tax Δ operating income** | (50,000) | (9,368) | (5,919) | (2,128) | 2,029 | 6,700 | 7,618 | 8,583 | 9,599 | 10,666 | 11,789 |
| **Tax on Δ operating income** | 0 | 0 | 0 | 0 | 609 | 2,010 | 2,285 | 2,575 | 2,880 | 3,200 | 3,537 |
| **Net Δ operating income** | (50,000) | (9,368) | (5,919) | (2,128) | 1,420 | 4,690 | 5,330 | 6,008 | 6,719 | 7,467 | 8,253 |
| **Add depreciation expense** | 0 | 5,000 | 5,000 | 5,000 | 5,000 | 5,000 | 5,000 | 5,000 | 5,000 | 5,000 | 5,000 |
| **Net cash flow** | (50,000) | (4,368) | (919) | 2,872 | 6,420 | 9,690 | 10,333 | 11,008 | 11,719 | 12,467 | 13,253 |
| **PV of net cash flow** | (50,000) | (4,160) | (833) | 2,481 | 5,282 | 7,592 | 7,710 | 7,823 | 7,932 | 8,036 | 8,136 |
| **Cumulative present values** | (50,000) | (54,160) | (54,993) | (52,512) | (47,230) | (39,638) | (31,928) | (24,104) | (16,172) | (8,136) | 0 |
| **Internal rate of return** | | (108%) | (110%) | (105%) | (94%) | (79%) | (64%) | (48%) | (32%) | (16%) | 0% |
| **Price incl. VAT per kWh** | | 0.29 | 0.31 | 0.32 | 0.34 | 0.36 | 0.38 | 0.39 | 0.41 | 0.43 | 0.46 |
| **Price for 100 km of range** | | 5.65 | 5.94 | 6.23 | 6.54 | 6.87 | 7.21 | 7.58 | 7.95 | 8.35 | 8.77 |

Table 8: Investment analysis of charging stations. CAPEX stands for capital, OPEX for operational expenditure. All values in Euros and rounded to integers.

With these assumptions as input, the calculation in Table 8 has been performed so that the NPV and hence the internal rate of return after ten years will exactly be 0 respectively 0%. This would mean that each CS finances itself by offsetting its annual capital costs of 5% (implicitly considered via the discount rate). The rates at which taxi drivers will be able to charge are attached to the bottom of the table, showing an increase from 0.28 Euros per kWh in year 0 to 0.46 Euros per kWh in year 10. These convert to 5.65 Euros per 100 km of range in year 1 increasing to 8.77 Euros per 100 km of range in year 10. As the results depend on some critical assumptions, they should be taken with caution and only be regarded as approximation: the price forecast for electricity is quite uncertain since for example the further development of the power grid will need to be financed once BEV sales increase and will therefore put an upward pressure on electricity prices. However, the purpose of this economic analysis is to illustrate that and how the charging infrastructure needed for a complete electrification of the Karlsruhe taxi fleet can be financed in an economically sound fashion and not to go into details about determinants of electricity prices. Regarding project funding, green bonds might be worth exploring. The interested reader may refer to OECD (2015) for general information on green bonds and to Milken Institute (2017) for insights from application in California. Regarding the total costs of ownership of ICEVs and BEVs, the financial incentives offered both by the state and the federal state should be looked into. Excellent up-to-date research on this issue can be found e.g. in Baek et al. (2016), Hagman et al. (2016) and Riesz et al. (2016).

# 7 Conclusion & outlook on future research

The objective of this thesis was to assess and illustrate how the taxi fleet in Karlsruhe may be fully electrified over the coming years in an economically sound fashion. In doing so, three goals shall be achieved: first, reduce urban air pollution, second, reduce urban noise pollution and, third, serve as a flagship project by contributing to the fight against climate change via greenhouse gas emissions reduction. Regarding the third goal, we count on both politicians, to lead the de-carbonization of the energy sector, and on automobile manufacturers to do the same with their production processes. Furthermore, the success of the project critically depends on its sound research foundation, of which this study shall represent a key cornerstone. The combination of an optimization of locations via a tailored model with a data-based approximation of needed capacities so as to ensure sufficient utilization resulted in a set of twenty-two charging points distributed over five locations which equal the positions of heavily frequented taxi stations. The model has been tailored by varying its parameters and analyzing its sensitivity so as to find the configuration delivering the highest coverage of immediately covered drop-off points: a Maximum-Covering Location Model with a coverage decay as well as a dispersion constraint, whereas the minimal distance between locations has been set to one kilometer. For the nine best-performing locations, the needed capacities have been determined to a total of 22 charging points by analyzing weekly arrival patterns at taxi stands and setting the number of charging points so that the final selection of five locations would ensure average utilization rates of 34% and cover all occurring charging demand 90% of the time. The subsequent investment analysis demonstrated that the charging infrastructure could be installed and operated so as to stay profit-neutral or even -positive while providing beneficial charging costs to taxi drivers. Thereby, the total investment sum for the charging infrastructure is estimated to about 430,000 Euros, to be invested over the project duration of five years.

In spite of the obstacles that had to be overcome while e.g. extracting accurate information from the dataset which exhibits a fair amount of incorrect data points, the optimal placement of charging stations is hereby deemed to have been sufficiently covered. As the data used in this study has been recorded in summer, whereas the batteries of electric cars exhibit noticeably less range in winter, a follow-up study on the question of whether this range reduction would decrease the feasibility of fleet electrification may be conducted shortly. Moreover, since the results of the approximative approach taken especially in the context of how many charging points to build shall only serve as first reference point. Therefore, follow-up research is planned to be conducted on the issue of determining the necessary capacities of charging stations by simulating the respective arrival processes. Once the installed batch of charging stations has completed their life cycle, it may be replaced by a more technologically advanced charging infrastructure featuring either battery swapping and/or wireless charging technology. Since the potential demand for a renewed batch of charging stations crucially depends on the vehicles' inability to perform complete shifts without recharging their batteries, it remains to be seen whether the plethora of new vehicle models that automobile manufacturers have announced to bring to market until 2020 respectively 2025 incorporating the projected improvements in battery technology, e.g. facilitating higher ranges at the same weight, will provide taxi drivers with suitable vehicle models to choose from. Once this development occurs, the option of recharging electric taxis at lower power levels and in-between shifts e.g. at parking lots should be re-evaluated. In doing so, drivers might bypass potential battery degradation caused by fast charging. Until then, used batteries of those vehicles that have lost too much of their original range might be sold and replaced by new ones. The company BMW, for example, is making efforts to use old batteries from their electric car models in a storage facility in Leipzig, Germany. (Clean Technica, 2017) Moreover, the participation in balancing markets, may provide additional revenue once vehicle-to-grid technology is ready for implementation.

# References

Agora Energiewende (2015). Report on the german power system. https://www.agora-energiewende.de/fileadmin/downloads/publikationen/CountryProfiles/Agora_CP_Germany_web.pdf. Last accessed on 19/09/17.

Ajanovic, A. and Haas, R. (2016). Dissemination of electric vehicles in urban areas: major factors for success. *Energy*, 115:1451–1458.

Asamer, J., Reinthaler, M., Ruthmair, M., Straub, M., and Puchinger, J. (2016). Optimizing charging station locations for urban taxi providers. *Transportation Research Part A*, 85:233–246.

Auto Express (2017). What is torque? All about torque: definition, equations, and units). http://www.autoexpress.co.uk/car-news/95110/what-is-torque-all-about-torque-definition-equations-and-units. Last accessed on 27/07/17.

Baek, S., Kim, H., and Chang, H. (2016). A feasibility test on adopting electric vehicles to serve as taxis in Daejeon metropolitan city of South Korea. *Sustainability*, 8(9).

Balinski, M. (1965). Integer programming: methods, uses, computation. *Journal of Management Science*, 12:253–313.

Baouche, F., Billot, R., Trigui, R., and El Faouzi, N.-E. (2014). Efficient allocation of electric vehicles charging stations: optimization model and application to a dense urban network. *IEEE Transactions on Intelligent Transportation Systems*, 6(3):33–43.

Baster, H., Bentzen, K., Laugesen, M., Kapitanovic, E., Mø ller, M., and Gvozdareva, I. (2013). Danish experiences in setting up charging infrastructure for electric vehicles with a special focus on Battery Swap Stations. http://e-mobility-nsr.eu/fileadmin/user_upload/downloads/info-pool/Acitivty_5.2_report_FDT.pdf. Last accessed on 05/09/17.

Batta, R. and Mannur, N. (1990). Covering-location models for emergency situations that require multiple response units. *Journal of Management of Science*, 36(1):16–23.

Bednarz Elektro Taxi (2017). Sauber durch den Pott! http://www.bednarz-elektrotaxi.de/. Last accessed on 25/07/17.

Berman, O., Hodgson, M., and Krass, D. (1995). Flow intercepting models. In Drezner, Z., editor, *Facility location: a survey of applications and methods*, pages 389–426.

Berman, O., Krass, D., and Drezner, Z. (2003). The gradual covering decay location problem on a network. *European Journal of Operational Research*, 151:474–480.

Berman, O., Larson, R., and Fouska, N. (1992). Optimal location of discretionary service facilities. *Journal of Transportation Science*, 26(3):201–211.

Bessa, R. and Matos, M. (2010). The role of an aggregator agent for EV in the electricity market. Proceedings of Seventh Mediterranean Conference and Exhibition on Power Generation, Transmission, Distribution and Energy Conversion.

Bickert, S., Kampker, A., and Greger, D. (2015). Developments of $CO_2$-emissions and costs for small electric and combustion engine vehicles in Germany. *Transportation Research Part D*, 36:138–151.

Bjerkan, K., Norbech, T., and Nordtomme, M. (2016). Incentives for promoting battery electric vehicle adoption in norway. *Transportation Research Part D*, 43:169–180.

Borén, S. and Ny, H. (2016). A strategic sustainability analysis of electric vehicles in EU today and towards 2050. *International Journal of Environmental, Chemical, Ecological, Geological and Geophysical Engineering*, 10(3):294–302.

Bubeck, S., Tomaschek, J., and Fahl, U. (2016). Perspectives of electric mobility: total cost of ownership of electric vehicles in germany. *Transport Policy*, 50:63–77.

Bundesministerium für Wirtschaft und Energie (2017). Zypries: 'Einsatz von E-Taxis wird erleichtert'. `https://www.bmwi.de/Redaktion/DE/Pressemitteilungen/2017/20170802-zypries-einsatz-von-e-taxis-wird-erleichtert.html`. Last accessed on 17/11/17.

BWe-Mobile (2011). Structure study BWe-Mobile 2011. `http://www.e-mobilbw.de/en/publications.html?file=files/e-mobil/content/DE/Publikationen/PDF/e_mobil_structure_study_en.pdf`. Last accessed on 26/07/17.

Cai, H., Jia, X., Chiu, A., Hu, X., and Xu, M. (2014). Siting public electric vehicle charging stations in Beijing using big-data informed travel patterns of the taxi fleet. *Transportation Research Part D*, 33:39–46.

Cai, Y., Applegate, S., Yue, W., Cai, J., Wang, X., Liu, G., and Li, C. (2017). A hybrid life cycle and multi-criteria decision analysis approach for identifying sustainable development strategies of beijing's taxi fleet. *Energy Policy*, 100:314–325.

Canals Casals, L., Martinez-Laserna, E., Amante García, B., and Nieto, N. (2016). Sustainability analysis of the electric vehicle use in Europe for CO2 emissions reduction. *Journal of Cleaner Production*, 127:425–437.

Capar, I. and Kuby, M. (2012). An efficient formulation of the flow refueling location model for alternative-fuel stations. *IEE Transactions*, 44(8):622–636.

Capar, I., Kuby, M., Leon, V., and Tsai, Y.-J. (2013). An arc-cover-path-cover formulation and strategic analysis of alternative-fuel station locations. *European Journal of Operations Research*, 227:142–151.

Car and Driver (2017). Everything you need to know about the VW Diesel-emissions scandal. `http://blog.caranddriver.com/everything-you-need-to-know-about-the-vw-diesel-emissions-scandal/`. Last accessed on 17/07/17.

Carsalesbase (2016). China car sales analysis 2016. `http://carsalesbase.com/china-car-sales-analysis-2016/`.

Center for Strategic & International Studies (2017). Urbanization, opportunity, and development. `https://www.csis.org/analysis/urbanization-opportunity-and-development`. Last accessed on 16/07/17.

Chacko, S. and Chung, Y. (2012). Thermal modelling of Li-ion polymer battery for electric vehicle drive cycles. *Journal of Power Sources*, 213:296–303.

CharIN (2017a). Document, Flyers etc. concerning CharIN e.V. `http://www.charinev.org/media/association-infos/`. Last accessed on 30/07/17.

CharIN (2017b). Members of CharIN e.V. `http://www.charinev.org/members/`. Last accessed on 30/07/17.

Chung, C.-H., Schilling, A., and Carbone, R. (1983). The capacitated maximal covering problem: a heuristic solution. *xxxxxxxxxxxxxxxxxxxxxxxxx*, 14:1383–1388.

Chung, S. and Kwon, C. (2015). Multi-period planning for electric car charging station locations: a case of Korean expressways. *European Journal of Operations Research*, 242(2):677–687.

Church, R. and Meadows, M. (1979). Location modeling utilizing maximum service distance criteria. *Journal of Geographical Analysis*, 11(4):358–373.

Church, R. and ReVelle, C. (1974). The maximal covering location problem. *Papers in Regional Science*, 32(1):101–118.

City of Amsterdam (2016). Electric mobility is here. `https://www.amsterdam.nl/publish/pages/799470/planam-03-2016_art1.pdf`. Last accessed on 23/07/17.

City of Oslo (2017). The electric vehicle capital of the world. `https://www.oslo.kommune.no/english/politics-and-administration/green-oslo/best-practices/the-electric-vehicle-capital-of-the-world/`. Last accessed on 22/07/17.

Clean Technica (2016). Will electric cars make traffic quieter? Yes & no. `https://cleantechnica.com/2016/06/05/will-electric-cars-make-traffic-quieter-yes-no/`. Last accessed on 19/07/17.

Clean Technica (2017). BMW Group officially commissions battery storage farm Leipzig). `https://cleantechnica.com/2017/10/30/bmw-group-officially-commissions-battery-storage-farm-leipzig/`. Last accessed on 09/01/18.

Comodi, G., Caresana, F., Salvi, D., Pelagalli, L., and Lorenzetti, M. (2016). Local promotion of electric mobility in cities: guidelines and real application case in italy. *Energy*, 95:494–503.

Current, J., Min, H., and Schilling, D. (1990). Multiobjective analysis of facility location decisions. *European Journal of Operations Research*, 49:295–307.

Current, J. and Storbeck, J. (1988). Capacitated covering models. *Environment and Planning B*, 15(2):153–163.

Daskin, M. (1995). *Network and discrete location: models, algorithms and applications*. John Wiley & Sons, Inc.

Der Tagesspiegel (2017). Regierung löst Problem mit der Eichverordnung). `http://www.tagesspiegel.de/wirtschaft/zulassung-von-elektrotaxis-regierung-loest-problem-mit-der-eichverordnung/19377764.html`. Last accessed on 25/07/17.

Destatis (2017). Preise - Daten zur Energiepreisentwicklung). `https://www.destatis.de/DE/Publikationen/Thematisch/Preise/Energiepreise/EnergiepreisentwicklungPDF_5619001.pdf;jsessionid=D70474F7861A2942353D35E9BA8095C5.InternetLive2?__blob=publicationFile`. Last accessed on 09/01/18.

Deutsche Welle (2016). Stuttgart: Germany's 'Beijing' for air pollution? `http://www.dw.com/en/stuttgart-germanys-beijing-for-air-pollution/a-18991064`. Last accessed on 18/07/17.

Deutsche Welle (2017). Wann schafft Deutschland den Kohleausstieg? http://www.dw.com/de/wann-schafft-deutschland-den-kohleausstieg/a-38267535. Last accessed on 29/07/17.

Earth Journalism Network (2014). Noise pollution: managing the challenge of urban sounds. http://earthjournalism.net/resources/noise-pollution-managing-the-challenge-of-urban-sounds. Last accessed on 18/07/17.

Electrek (2017a). Beijing wants to replace its 70,000 taxis with electric vehicles to fight local air pollution. https://electrek.co/2017/02/28/beijing-electric-taxis-air-polution/. Last accessed on 24/07/17.

Electrek (2017b). Nissan's all-electric Leaf is becoming increasingly popular with taxi companies. https://electrek.co/2017/05/30/nissan-leaf-all-electric-taxi/. Last accessed on 29/07/17.

Electrek (2017c). Tesla battery data shows path to over 500,000 miles on a single pack. https://electrek.co/2016/11/01/tesla-battery-degradation/. Last accessed on 08/11/17.

Emadi, A. (2011). Transportation 2.0. *IEEE Power and Energy Magazine*, 9(4):18–29.

EnBW (2017). E-Mobilitätsprojekte: aktuelles Projekt: Tank & Rast. https://www.enbw.com/privatkunden/energie-und-zukunft/e-mobilitaet/projekte/. Last accessed on 18/09/17.

European Automobile Manufacturers Association (2015). Average vehicle age. http://www.acea.be/statistics/tag/category/average-vehicle-age. Last accessed on 12/01/18.

European Commission (2015). Urban air pollution - what are the main sources across the world? https://ec.europa.eu/jrc/en/news/what-are-main-sources-urban-air-pollution. Last accessed on 17/07/17.

European Environment Agency (2017). Noise. https://www.eea.europa.eu/themes/human/noise. Last accessed on 18/07/17.

European Environmental Agency (2016). Air quality in Europe - 2016 report. https://www.eea.europa.eu/publications/air-quality-in-europe-2016. Last accessed on 18/07/17.

European Union (2014). Directive 2014/94/EU of the European Parliament and of the Council of 22 October 2014 on the deployment of alternative fuels infrastructure. http://www.charinev.org/fileadmin/Downloads/Papers_and_Regulations/022_Doc_Directive_CELEX_32014L0094_EN.pdf. Last accessed on 31/07/17.

EV News (2015). 800+ BYD e6 Blue Taxi in Shenzhen. http://evnews.net/800-byd-e6-blue-taxi-in-shenzhen/. Last accessed on 29/07/17.

Frade, I., Ribeiro, A., Gonçalves, G., and António, P. A. (2011). Optimal location of charging stations for electric vehicles in a neighborhood in Lisbon, Portugal. *Transportation Research Record: Journal of the Transportation Research Board*, 2252:91–98.

Galus, M., González Vayá, M., Krause, T., and Andersson, G. (2013). The role of electric vehicles in smart grids. *Wiley Interdisciplinary Reviews: Energy and Environment*, 2(4):384–400.

German Bundestag (2012). Gesetz zur Regelung der Arbeitszeit von selbständigen Kraftfahrern vom 11. Juli 2012 (BGBI. I S. 1479). http://www.bgl-ev.de/images/downloads/service/gesetze/selbstaendige_kraftfahrer.pdf. Last accessed on 15/10/17.

German National Platform for Electric Mobility (2015). Charging infrastructure for electric vehicles in germany: progress report and recommendations 2015. http://nationale-plattform-elektromobilitaet.de/fileadmin/user_upload/Redaktion/AG3_Statusbericht_LIS_2015_engl_klein_bf.pdf. Last accessed on 18/09/17.

Ghamami, M., Nie, Y., and Zockaie, A. (2016). Planning charging infrastructure for plug-in electric vehicles in city centers. *International Journal of Sustainable Transportation*, 10(4):343–353.

Gleason, J. (1975). A set covering approach to bus stop location. *Omega: The International Journal of Management Science*, 3(5):605–608.

Goodchild, M. and Noronha, V. (1987). Location-allocation and impulsive shopping: the case of gasoline retailing. In Ghosh, A. and Rushton, G., editors, *Spatial analysis and location-allocation models*, pages 121–136.

Green Tech Media (2016). Wireless charging: coming soon to an electric vehicle near you. https://www.greentechmedia.com/articles/read/wireless-charging-coming-to-an-electric-vehicle-near-you. Last accessed on 15/08/17.

Green Transportation (2017). EV DC fast charging standards - CHAdeMO, CCS, SEA Combo, Tesla Supercharger, etc. `https://greentransportation.info/ev-charging/range-confidence/chap8-tech/ev-dc-fast-charging-standards-chademo-ccs-sae-combo-tesla-supercharger-etc.html`. Last accessed on 31/07/17.

Greenpeace (2017). G20 climate profiles: a country-by-country review). `https://www.greenpeace.de/sites/www.greenpeace.de/files/publications/20170705-greenpeace-scorecard-g20-climate-profiles.pdf`. Last accessed on 28/07/17.

Hagman, J., Ritzén, S., Stier, J., and Susilo, Y. (2016). Total cost of ownership and its potential implications for battery electric vehicle diffusion. *Research in Transportation Business & Management*, 18:11–17.

Hakimi, S. (1964). Optimum locations of switching centers and the absolute centers and medians of a graph. *Journal of Operations Research*, 12(3):450–459.

Han, D., Ahn, Y., Park, S., and Yeo, H. (2016). Trajectory-interception based method for electric vehicle taxi charging station problem with real taxi data. *International Journal of Sustainable Transportation*, 10(8):671–682.

Harendt, B., Schumann, D., and Wirth, M. (2017). Abschlussbereicht der Begleit- und Wirkungsforschung 2017. `http://schaufenster-elektromobilitaet.org/media/media/documents/dokumente_der_begleit__und_wirkungsforschung/EP30_Abschlussbericht_2017_der_Begleit-_und_Wirkungsforschung.pdf`. Last accessed on 09/11/17.

Hennessy, D. A. and Wiesenthal, D. L. (1999). Traffic congestion, driver stress, and driver aggression. *Aggressive Behavior*, 25:409–423.

Hodgson, J. (1990). A flow capturing location-allocation model. *Journal of Geographical Analysis*, 22(3):270–279.

Hodgson, M. and Berman, O. (1997). A billboard location model. *Geographical and Environmental Modelling*, 1(1):25–45.

Hodgson, M. and Rosing, K. (1992). A network location-allocation model trading off flow capturing and p-median objectives. *Annals of Operations Research*, 40:247–260.

Hodgson, M. and Rosing, K. (1996). Applying the flow-capturing location-allocation model to an authentic network: Edmonton, Canada. *European Journal of Operations Research*, 90:427–443.

Hodgson, M., Rosing, K., and Zhang, J. (1996). Locating vehicle inspection stations to protect a transportation network. *Journal of Geographical Analysis*, 28(4):299–314.

Hooftman, N., Oliveira, L., Messagie, M., Coosemans, T., and van Mierlo, J. (2016). Environmental analysis of petrol, diesel and electric passenger cars in a Belgian urban setting. *Energies*, 9. article nr. 84.

Hosseini, M., MirHassani, S., and Hooshmand, F. (2017). Deviation-flow refueling location problem with capacitated facilities: model and algorithm. *Transportation Research Part D*, 54:269–281.

Hu, J., Morais, H., Sousa, T., and Lind, M. (2015). Electric vehicle fleet management in smart grids: a review of services, optimization and control aspects. *Renewable and Sustainable Energy Reviews*, 56:1207–1226.

Huang, Y., Li, S., and Qian, Z. (2015). Optimal deployment of alternative fueling stations on transportation networks considering deviation paths. *Networks and Spatial Economics*, 15:183–204.

Huo, H., Cai, H., Zhang, Q., Liu, F., and He, K. (2015). Life-cycle assessment of greenhouse gas and air emissions of electric vehicles: a comparison between china and the u.s. *Atmospheric Environment*, 108:107–116.

Idaho National Laboratory (2016a). DC Fast Charging Infrastructure 50 kW to 350 kW). `https://avt.inl.gov/sites/default/files/pdf/presentations/INL_DCFastChargerInfrastructure.pdf`. Last accessed on 04/01/18.

Idaho National Laboratory (2016b). New York City Electric Taxi Demonstration Results). `https://avt.inl.gov/pdf/fsev/NYCElectricTaxiFactSheetJan2016.pdf`. Last accessed on 15/10/17.

INRIX Research (2016). Global traffic scorecard. `http://inrix.com/scorecard/`. Last accessed on 16/07/17.

Inside EVs (2015). Amsterdam is electric taxi capital of the world. `http://insideevs.com/amsterdam-is-electric-taxi-capital-of-the-world-wvideo/`. Last accessed on 23/07/17.

International Council on Clean Transportation (2017). Electric vehicle capitals of the world. `http://www.theicct.org/EV-capitals-of-the-world`. Last accessed on 19/07/17.

International Energy Agency (2017). Global EV outlook. https://www.iea.org/publications/freepublications/publication/GlobalEVOutlook2017.pdf. Last accessed on 22/07/17.

International Gas Union (2015). Case studies in improving urban air quality. http://www.igu.org/research/case-studies-improving-urban-air-quality. Last accessed on 17/07/17.

Jeong, S., Jang, Y., and Kum, D. (2015). Economic analysis of the dynamic charging electric vehicle. *IEEE Transactions on Power Electronics*, 30(11):6368–5377.

Jochem, P., Brendel, C., Reuter-Oppermann, M., Fichtner, W., and Nickel, S. (2016a). Optimizing the allocation of fast charging infrastructure along the German autobahn. *Journal of Business Economics*, 86:513–535.

Jochem, P., Doll, C., and Fichtner, W. (2016b). External costs of electric vehicles. *Transportation Research Part D*, 42:60–76.

Kempton, W. and Letendre, S. (1997). Electric vehicles as a new power source for electric utilities. *Transportation Research Part D*, 2:157–175.

Kempton, W. and Tomić, J. (2005). Vehicle-to-grid power fundamentals: calculating capacity and net revenue. *Journal of Power Sources*, 144(1):268–279.

Kettles, D. (2016). Electric vehicle fleet implications and analysis. http://evtc.fsec.ucf.edu/publications/documents/FSEC-CR-2031-16.pdf. Last accessed on 24/07/17.

Kim, J.-G. and Kuby, M. (2012). The deviation-flow refueling location model for optimizing a network of refueling stations. *International Journal of Hydrogen Energy*, 37(6):5406–5420.

Kong, P.-Y. and Karagiannidis, G. (2016). Charging schemes for plug-in hybrid electric vehicles in Smart Grid: a survey. *IEEE Access*, 4:6846–6875.

Kraus, M. (2017). CCS Charge Map - Europe. http://ccs-map.eu/. Last accessed on 14/08/17.

Kuby, M. and Lim, S. (2005). The flow-refueling location problem for alternative-fuel vehicles. *Socio-Economic Planning Sciences*, 39:125–145.

Kuby, M. and Lim, S. (2007). Location of alternative-fuel stations using the flow-refueling location model and dispersion of candidate sites on arcs. *Networks and Spatial Economics*, 7(2):129–152.

Kuby, M., Lines, L., Schultz, R., Xie, Z., Kim, J.-G., and Lim, S. (2009). Optimization of hydrogen stations in Florida using the flow-refueling location model. *International Journal of Hydrogen Energy*, 34:6045–6064.

Larcher, D. and Tarascon, J.-M. (2014). Towards greener and more sustainable batteries for electrical energy storage. *Nature Chemistry*, 7:19–29.

Lee, Y.-G. (2014). UE-based location model of rapid charging stations for EVs with batteries that have different states-of-charge. `http://docs.trb.org/prp/14-3809.pdf`. Presentation at the 93rd Transportation Research Board Annual Meeting in 2014.

Li, M., Jia, Y., Shen, Z., and He, F. (2017). Improving the electrification rate of the vehicle miles traveled in Beijing: A data-driven approach. *Transportation Research Part A*, 97:106–120.

Li, S. and Huang, Y. (2015). Development of electric vehicle charging corridor for South Carolina. *International Journal of Transportation Science and Technology*, 4(4):395–412.

Li, S., Huang, Y., and Mason, S. (2016). A multi-period optimization model for the deployment of public electric vehicle charging stations on network. *Transportation Research Part C*, 65:128–143.

Li, S. and Mi, C. (2015). Wireless power transfer for electric vehicle applications. *IEEE Journal of Emerging and Selected Topics in Power Electronics*, 3(1):4–17.

Lim, S. and Kuby, M. (2010). Heuristic algorithms for siting alternative-fuel stations using the flow-refueling location model. *European Journal of Operations Research*, 204:51–61.

Lin, Z., Ogden, J., Fan, Y., and Chen, C.-W. (2008). The fuel-travel-back approach to hydrogen station siting. *International Journal of Hydrogen Energy*, 33:3096–3101.

Madina, C., Zamora, I., and Zabala, E. (2016). Methodology for assessing electric vehicle charging infrastructure business models. *Energy Policy*, 89:284–293.

Massachusetts Department of Energy Resources (2014). Installation guide for electric vehicle supply equipment (EVSE). `http://www.mass.gov/eea/docs/doer/clean-cities/ev-charging-infrastructure-manual.pdf`. Last accessed on 30/07/17.

Medicine Net (2016). Medical definition of cardiopulmonary. `http://www.medicinenet.com/script/main/hp.asp`. Last accessed on 18/07/17.

Merriam-Webster (2017). Definition of ”endogenous”. https://www.merriam-webster.com/. Last accessed on 24/09/17.

Mersky, A., Sprei, F., Samaras, C., and Qian, Z. (2016). Effectiveness of incentives on electric vehicle adoption in norway. *Transportation Research Part D*, 46:56–68.

Milken Institute (2017). Financing models to expand access to electric vehicles in California). http://assets1c.milkeninstitute.org/assets/Publication/InnovationLab/PDF/AccessToElectricVehiclesCA-LowRes26July.pdf. Last accessed on 09/01/18.

Mimi (2017). The World Hearing Index. https://mimi.io/en/hearingindex/. Last accessed on 18/07/17.

MirHassani, S. and Ebrazi, R. (2013). A flexible reformulation of the refueling station location problem. *Transportation Science*, 47(4):617–628.

Moro, A. and Helmers, E. (2017). A new hybrid method for reducing the gap between WTW and LCA in the carbon footprint assessment of electric vehicles. *International Journal of Life Cycle Assessment*, 22:4–14.

Muenchen.de (2016). München baut Förderung von Elektromobilität weiter aus. http://www.muenchen.de/aktuell/2016-12/muenchen-schreibt-foerderprogramm-fuer-e-mobilitaet-fort.html. Last accessed on 25/07/17.

Newman, D., Wells, P., Donovan, C., Nieuwenhuis, P., and Davies, W. (2014). Urban, sub-urban or rural: where is the best place for electric vehicles? *International Journal of Automotive Technology and Management*, 14(3, 4):306–323.

Nicholas, M. and Ogden, J. (2004). Using geographic information systems to evaluate siting and networks of hydrogen stations. *Transportation Research Record: Journal of the Transportation Research Board*, 1880:126–134.

Nicholas, M. and Ogden, J. (2006). Detailed analysis of urban station siting for California hydrogen highway network. *Transportation Research Record: Journal of the Transportation Research Board*, 1983:121–128.

Nie, Y. and Ghamami, M. (2013). A corridor-centric approach to planning electric vehicle charging infrastructure. *Transportation Research Part B*, 57:172–190.

Noel, L. and Sovacool, B. (2016). Why did Better Place fail?: range anxiety, interpretive flexibility, and electric vehicle promotion in Denmark and Israel. *Applied Energy*, 94:377–386.

Nordelöf, A., Messagie, M., Tillman, A.-M., Söderman, M., and van Mierlo, J. (2014). Environmental impacts of hybrid, plug-in hybrid, and battery electric vehicles - what can we learn from life cycle assessment? *International Journal of Life Cycle Assessment*, 19:1866–1890.

NYC Taxi & Limousine Commission (2013). Take charge: a roadmap to electric New York City taxis. `http://www.nyc.gov/html/tlc/downloads/pdf/electric_taxi_task_force_report_20131231.pdf`. Last accessed on 24/07/17.

Nykvist, B. and Nilsson, M. (2015). Rapidly falling costs of battery packs for electric vehicles. *Nature Climate Change*, 5:329–332.

Oak Ridge National Laboratory (2016). ORNL surges forward with 20-kilowatt wireless charging for vehicles. `https://www.ornl.gov/news/ornl-surges-forward-20-kilowatt-wireless-charging-vehicles`. Last accessed on 15/08/17.

OECD (2015). Green bonds: mobilising the debt capital markets for a low-carbon transition). `https://www.oecd.org/environment/cc/Green%20bonds%20PP%20%5Bf3%5D%20%5Blr%5D.pdf`. Last accessed on 09/01/18.

Omar, N., Monem, M., Firouz, Y., Salminen, J., Smekens, J., Hegazy, O., Gaulous, H., Mulder, G., van den Bossche, P., Coosemans, T., and van Mierlo, J. (2014). Lithium iron phosphate based battery - assessment of the aging parameters and development of cycle life model. *Applied Energy*, 113:1575–1585.

Piketty, T. and Goldhammer, A. (2014). *Capital in the twenty-first century*. Cambridge Massachussetts: The Belknap Press of Harvard University Press.

Pirkul, H. and Schilling, D. (1991). The maximal covering location problem with capacities on total workload. *Journal of Management Science*, 37(2):233–248.

Plötz, P., Funke, S., and Jochem, P. (2017). Empirical fuel consumption and $CO_2$ emissions of plug-in hybrid electric vehicles. *Journal of Industrial Ecology*. forthcoming.

Poullikkas, A. (2015). Sustainable options for electric vehicle technologies. *Renewable and Sustainable Energy Reviews*, 41:1277–1287.

Prima Clima Mobil (2013). Hamburgs neue Elektro-Taxi-Flotte. `http://pcm.com.de/`. Last accessed on 25/07/17.

Primove (2013). Introducing true electric mobility for a sustainable future. `http://primove.bombardier.com/fileadmin/primove/content/MEDIA/Publications/BT_Brochure_PRIMOVE_210x280_2013_final_upd_110dpi_SP.pdf`. Last accessed on 05/09/17.

PwC (2016). 2016 auto industry trends. `https://www.strategyand.pwc.com/media/file/2016-Auto-Trends.pdf`.

Qiu, C., Chau, K., Liu, C., and Chan, C. (2013). Overview of wireless power transfer for electric vehicle charging. Proceedings of the World Electric Vehicle Symposium and Exhibition 2013 (EVS27).

Ramachandran, S. and Stimming, U. (2015). Well to wheel analysis of low carbon alternatives for road traffic. *Energy & Environmental Science*, 8:3313–3324.

Rangaraju, S., de Vroey, L., Messagie, M., Mertens, J., and van Mierlo, J. (2015). Impacts of electricity mix, charging profile, and driving behavior on the emissions performance of battery electric vehicles: a belgian case study. *Applied Energy*, 148:496–505.

ReVelle, C. (1986). The maximum capture or "sphere of influence" location problem: Hotelling revisited on a network. *Journal of Regional Science*, 26(2):343–358.

Riesz, J., Sotiriadis, C., Ambach, D., and Donovan, S. (2016). Quantifying the costs of a rapid transition to electric vehicles. *Applied Energy*, 180:287–300.

Rogers, E. M. (1962). *Diffusion of innovations*. The Free Press.

Sankaran, J. and Raghavan, S. (1997). Locating and sizing plants for bottling propane in South India. *Interfaces*, 27(6):1–15.

Sellmair, R. and Hamacher, T. (2014). Optimization of charging infrastructure for electric taxis. *Transportation Research Record: Journal of the Transportation Research Board*, 2416:82–91.

Serradilla, J., Wardle, J., Blythe, P., and Gibbon, J. (2017). An evidence-based approach for investment in rapid-charging infrastructure. *Energy Policy*, 106:514–524.

Shahraki, N., Cai, H., Turkay, M., and Xu, M. (2015). Optimal locations of electric public charging stations using real world vehicle travel patterns. *Transportation Research Part D*, 41:165–176.

Shareef, H., Islam, M., and Mohamed, A. (2016). A review of the stage-of-the-art charging technologies, placement methodologies, and impacts of electric vehicles. *Renewable and Sustainable Energy Reviews*, 64:403–420.

Shengyang, S., Eekhoff, I., and Borowski, D. (2013). Electric taxis in Shenzhen. `http://www.sutp.org/files/contents/documents/resources/E_Fact-Sheets-and-Policy-Briefs/GIZ_SUTP_FS_`

Good-Practice-in-China-Electric-taxi-in-Shenzhen_EN.pdf. Last accessed on 18/10/17.

Shuai, W., Maillé, P., and Pelov, A. (2016). Charging electric vehicles in the smart city: a survey of economy-driven approaches. *IEEE Transactions on Intelligent Transportation Systems*, 17:2089–2106.

Shukla, A., Pekny, J., and Venkatasubramanian (2011). An optimization framework for cost effective design of refueling station infrastructure for alternative fuel vehicles. *Computers and Chemical Engineering*, 35:1431–1438.

Sierzchula, W., Bakker, S., Maat, K., and van Wee, B. (2014). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, 68:183–194.

Stadt Karlsruhe (2013). Verkehrsentwicklungsplan Karlsruhe. https://www.karlsruhe.de/b3/verkehr/verkehrsentwicklung/vep_plaene. Last accessed on 14/10/17.

Stadt Regensburg (2016). Elektromobilitätsförderung. http://www.regensburg-effizient.de/foerderprogramme/elektromobilitaets-foerderung/. Last accessed on 25/07/17.

Tagliaferri, C., Evangelisti, S., Acconcia, F., Domenech, T., Ekins, P., Barletta, D., and Lettieri, P. (2016). Life cycle assessment of future electric and hybrid vehicles: a cradle-to-grave systems engineering approach. *Chemical Engineering Research and Design*, 112:298–309.

Taxi-Funk-Zentrale Karlsruhe eG (2017). Herzlich Willkommen bei der Taxi-Funk-Zentrale Karlsruhe. https://taxi-zentrale-karlsruhe.de/. Last accessed on 14/10/17.

Taxi Heute (2015). Taxi-Ruf Karlsruhe startet mit modernem Vermittlungssystem. https://www.taxi-heute.de/Taxi-News/News/11585/Taxi-Ruf-Karlsruhe-startet-mit-modernem-Vermittlungssystem. Last accessed on 14/10/17.

Taxi Times (2016). BYD and HDT are launching e-fleet of 100 e6-cabs in Singapore. http://www.taxi-times.com/byd-and-hdt-are-launching-e-fleet-of-100-e6-cabs-in-singapore/. Last accessed on 29/07/17.

Taxi Times (2017). Richterin entscheidet: Stadt Karlsruhe muss weitere Taxis genehmigen. http://www.taxi-times.com/

richterin-entscheidet-stadt-karlsruhe-muss-weitere-taxis-genehmigen/. Last accessed on 14/10/17.

Tech Crunch (2017). BMW's plug-in hybrid 530e iPerformance will get wireless charging. https://techcrunch.com/2017/04/28/bmws-plug-in-hybrid-530e-iperformance-will-get-wireless-charging/. Last accessed on 15/08/17.

Thaler, R. and Sunstein, C. (2009). *Nudge: improving decisions about health, wealth, and happiness*. Yale University Press.

The Guardian (2017). Pant by numbers: the cities with the most dangerous air - listed. https://www.theguardian.com/cities/datablog/2017/feb/13/most-polluted-cities-world-listed-region. Last accessed on 18/07/17.

The New York Times (2017). China's role in climate change, and possibly in fighting it. https://www.nytimes.com/2017/06/02/world/asia/chinas-role-in-climate-change-and-possibly-in-fighting-it.html. Last accessed on 12/01/18.

Tian, Z., Wang, Y., Tian, C., Zhang, F., Tu, L., and Xu, C. (2014). Understanding operational and charging patterns of electric vehicle taxis using GPS records. Proceedings of the 17th IEEE International Conference on Intelligent Transportation Systems (ITSC) on October 8-11 in Qingdao, China.

Tie, S. and Tan, C. (2013). A review of energy sources and energy management system in electric vehicles. *Renewable and Sustainable Energy Reviews*, 20:82–102.

Toregas, C., Swain, R., ReVelle, C., and Bergman, L. (1971). The location of emergency service facilities. *Journal of Operations Research*, 19(6):1363–1373.

Tu, W., Li, Q., Fang, Z., Shaw, S., Zhou, B., and Chang, X. (2016). Optimizing the locations of electric taxi charging stations: A spatial-temporal demand coverage approach. *Transportation Research Part C*, 65:172–189.

Umweltbundesamt (2017). Traffic noise. https://www.umweltbundesamt.de/en/topics/transport-noise/traffic-noise#textpart-2. Last accessed on 18/07/17.

United Nations (2014). World urbanization prospects: the 2014 revision, highlights. https://esa.un.org/unpd/wup/Publications/Files/WUP2014-Highlights.pdf. Last accessed on 13/07/17.

United Nations (2016a). The world's cities in 2016. http://www.un.org/en/development/desa/population/publications/pdf/urbanization/the_worlds_cities_in_2016_data_booklet.pdf. Last accessed on 14/07/17.

United Nations (2016b). Urbanization and development: emerging futures. http://wcr.unhabitat.org/main-report/. Last accessed on 18/07/17.

Upchurch, C. and Kuby, M. (2010). Comparing the p-median and flow-refueling models for locating alternative-fuel stations. *Journal of Transport Geography*, 18:750–758.

Upchurch, C., Kuby, M., and Lim, S. (2009). A capacitated model for location of alternative-fuel stations. *Journal of Geographical Analysis*, 41:85–106.

Urban Foresight (2014). EV city casebook. http://www.cleanenergyministerial.org/Portals/2/pdfs/EVI_2014_EV-City-Casebook.pdf. Last accessed on 20/07/17.

Urban Times (2014). 6 things all cities should be doing to reduce urban air pollution now. https://urbantimes.co/2014/06/6-things-all-cities-should-be-doing-to-reduce-urban-air-pollution-now/. Last accessed on 18/07/17.

US Census Bureau (2015). Who drives to work? Commuting by automobile in the United States: 2013. https://www.census.gov/hhes/commuting/files/2014/acs-32.pdf. Last accessed on 16/07/17.

US Department of Energy (2017). Fuel prices: alternative fuel price report: average retail fuel prices in the U.S. https://www.afdc.energy.gov/fuels/prices.html. Last accessed on 05/09/17.

US Environmental Protection Agency (2006). Life cycle assessment: principles and practice. http://brevard.ifas.ufl.edu/communities/pdf/chapter1_frontmatter_lca101.pdf. Last accessed on 28/07/17.

US Environmental Protection Agency (2017). Particulate matter (PM) basics. https://www.epa.gov/pm-pollution/particulate-matter-pm-basics#PM. Last accessed on 17/07/17.

Van Deventer, P., van der Steen, M., van Schelven, R., Rubin, B., and Kotter, R. (2015). Large-scale deployment of public charging infrastructure: identifying possible next steps forward. In Filho, W. and Kotter, R., editors, *E-Mobility in Europe*, pages 107–124.

Wang, Y.-W. and Lin, C.-C. (2009). Locating road-vehicle refueling stations. *Transportation Research Part E*, 45:821–829.

Wang, Y.-W. and Wang, C.-R. (2010). Locating passenger vehicle refueling stations. *Transportation Research Part E*, 46:791–801.

Wards Auto (2017). Qualcomm gets EV charging off the ground. `http://wardsauto.com/engines/qualcomm-gets-ev-charging-ground`. Last accessed on 15/08/17.

Weber, A. and Friedrich, C. (1929). *Theory of the location of industries*. The University of Chicago Press.

White, J. and Case, K. (1974). On covering problems and the central facilities location problem. *Journal of Geographical Analysis*, 6(3):281–294.

Wolfram, P. and Lutsey, N. (2016). Electric vehicles: literature review of technology costs and carbon emissions. `http://www.theicct.org/lit-review-ev-tech-costs-co2-emissions-2016`. Last accessed on 29/07/17.

Woo, J., Choi, H., and Ahn, J. (2017). Well-to-wheel analysis of greenhouse gas emissions for electric vehicles based on electricity generation mix: a global perspective. *Transportation Research Part D*, 51:340–350.

World Bank (2017). World development indicators. `http://wdi.worldbank.org/table`. Last accessed on 16/07/17.

World Economic Forum (2017). These are the cities with the worst noise pollution. `https://www.weforum.org/agenda/2017/03/these-are-the-cities-with-the-worst-noise-pollution/`. Last accessed on 19/07/17.

World Health Organization (2009). Global health risks - mortality and burden of disease attributable to selected major risks. `http://www.who.int/healthinfo/global_burden_disease/global_health_risks/en/`. Last accessed on 17/07/17.

World Health Organization (2011). Burden of disease from environmental noise. `http://www.euro.who.int/en/health-topics/environment-and-health/noise/publications/2011/burden-of-disease-from-environmental-noise.-quantification-of-healthy-life-years-lost-in-europe`. Last accessed on 18/07/17.

World Health Organization (2016a). Air pollution levels rising in many of the world's poorest cities. `http://www.who.int/mediacentre/news/releases/2016/air-pollution-rising/en/`. Last accessed on 18/07/17.

World Health Organization (2016b). Urban ambient air pollution database - Update 2016. `http://www.who.int/phe/health_topics/outdoorair/databases/cities/en/`. Last accessed on 18/07/17.

World Health Organization (2017). Health topics: environment and health: noise: data and statistics. `http://www.euro.who.int/en/health-topics/environment-and-health/noise/data-and-statistics`. Last accessed on 18/07/17.

World Health Organization (2018). Health and sustainable development: air pollution. `http://www.who.int/sustainable-development/transport/health-risks/air-pollution/en/`. Last accessed on 12/01/18.

Wu, F. and Sioshansi, R. (2017). A stochastic flow-capturing model to optimize the location of fast-charging stations with uncertain electric vehicle flows. *Transportation Research Part D*, 53:354–376.

Yang, J., Dong, J., Lin, Z., and Hu, L. (2016). Predicting market potential and environmental benefits of deploying electric taxis in Nanjing, China. *Transportation Research Part D*, 49:68–81.

Yong, J., Ramachandaramurthy, V., Tan, K., and Mithulananthan, N. (2015). A review on the state-of-the-art technologies of electric vehicle, its impacts and prospects. *Renewable and Sustainable Energy Reviews*, 49:365–385.

You, P.-S. and Hsieh, Y.-C. (2014). A hybrid heuristic approach to the problem of the location of vehicle charging stations. *Computers & Industrial Engineering*, 70:195–204.

Zap Map (2017). Nissan e-NV200 charging guide. `https://www.zap-map.com/charge-points/nissan-e-nv200-charging-guide/`. Last accessed on 09/01/18.