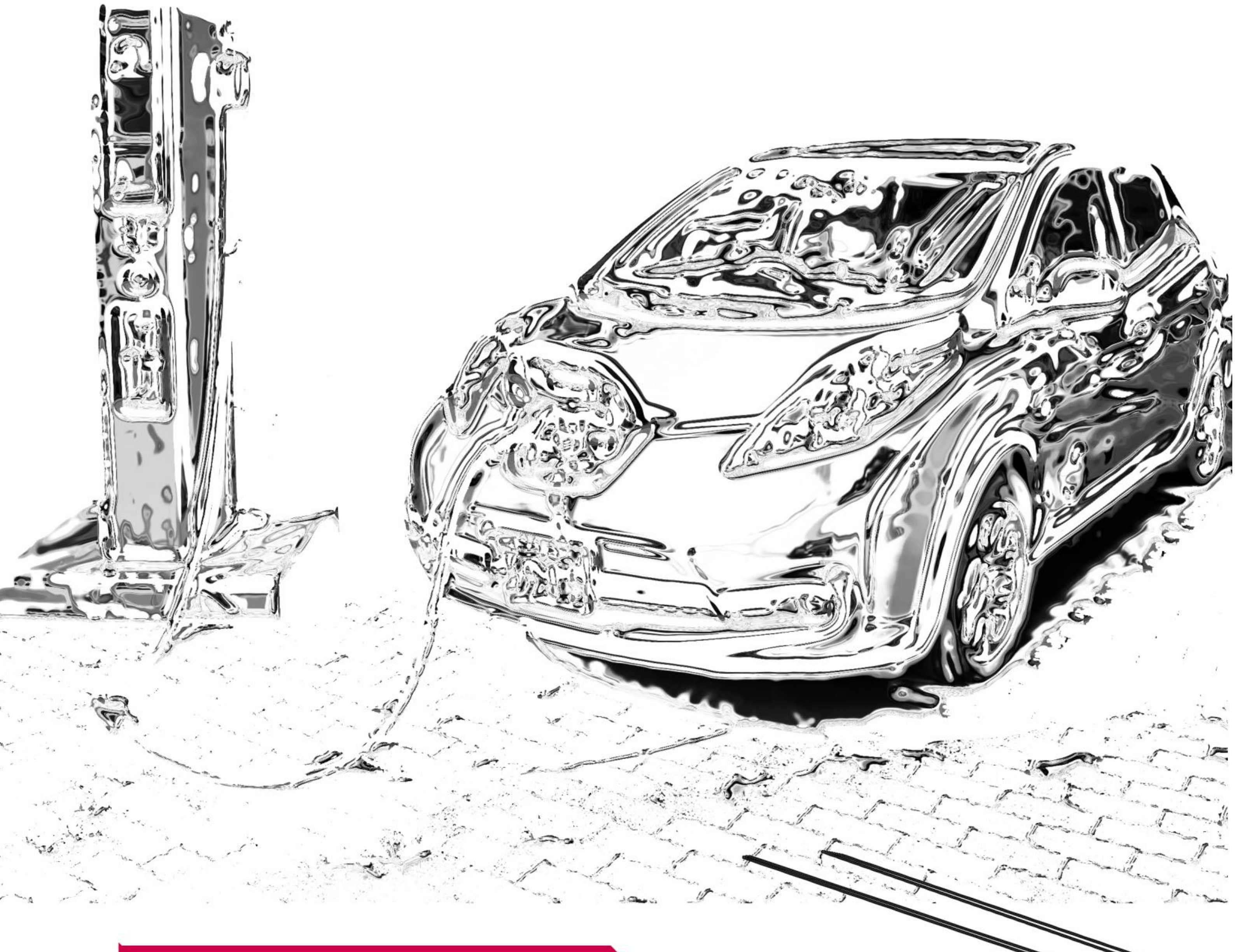
Improving Infrastructure for Electric Vehicles:

A Method to Optimize Locations for Fast chargers



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Master Thesis

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Improving Infrastructure for Electric Vehicles: A Method to Optimize Locations for Fast Chargers

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Preface

This report is the final result of my graduation project I conducted at Goudappel Coffeng and the DIVV Amsterdam. Sustainable mobility is, and is becoming more and more, a hot topic in the world of transport. However, a breakthrough has not been realized yet. To convince car drivers of the benefits of EVs, possible barriers have to be overcome. One of the major drawbacks is the limited driving range, the distance that can be driven with a single battery. This barrier can be partially eliminated by proper infrastructure. This made me decide to choose electric vehicles and the associated infrastructure as the subject of my master thesis. Who doesn't want to contribute to a better environment? In this thesis a method is developed that can be used to find the optimal configuration of fast chargers within a certain area.

There are many people to thank for both support and input in this thesis. First of all, I would like to thank my daily supervisors Robert van den Brink (Goudappel Coffeng), Jeroen Schrijver (DIVV Amsterdam) and Rob van Nes (TUDelft) for their support and advice. Their help, critics and expertise increased the level of my research. I also want to thank the other members in my committee: Chairman Bart van Arem, Cees Maat and Paul Wiggenraad.

Furthermore, I want to thank Sonja Munnix (AgentschapNL), Ronald de Haas (DIVV) and Jantine Boxum (Goudappel Coffeng) for making it possible to execute the survey, my roommates in Deventer and Amsterdam for their humour and enthusiasm and all other colleagues who helped me with my thesis or just for distraction. I highly appreciated the support!

Robbert Verweij

Executive Summary

Introduction

In times of finite oil reserves, rising oil prices and an increasing focus on sustainable mobility, alternative fuels become increasingly attractive. Electric vehicles (EVs) are an alternative to current vehicles. These vehicles are powered by electricity instead of petrol or diesel. Electric vehicles can be charged both home and en route by using a charger. About 80-100 kilometres can be driven on a full battery if negative effects such as weather conditions, extra load and stop-and-go traffic are included. This distance is named the driving range. If a distance larger than this driving range should be driven, an interim charge is required. Here, fast chargers are ideal. Fast chargers can charge the battery to 80% in about thirty minutes. This is much faster compared to slow charging (6-8 hours).

Problem definition

In recent years, some fast chargers have been installed over the Netherlands. The current (and planned) locations of fast chargers are determined without conclusive reasoning: driving patterns are not taken into account. As a result, it is possible that at some locations fast chargers are insufficiently used, and at other locations the demand is too high. In the first case, the fast charger is a poor investment, and in the latter case queues might occur.

An optimal network of fast chargers is designed in such a way that, given a number of chargers, as many trips as possible can be made with an electric car. In other words, it facilitates the maximum use of electric vehicles and stimulates the transition to electric cars. The purpose of this research is to optimize the locations for fast chargers so that the available money will be spent as efficiently as possible.

In this thesis a method is developed that can be used to find the optimal locations and the corresponding number of fast chargers within any area.

User group and relevant patterns

The driving range of an EV is the most important aspect to determine whether a fast charger is required. To determine who might use fast chargers, daily car patterns are analysed. In these patterns, it is shown how a car is used over a day. The EV users that are driving more than the driving range on a day are possible fast charger users. Furthermore, it is assumed that users are not willing to wait twice while their car is charging. In this study it is assumed that the battery is fully charged at the start of the day because the vehicle is fully charged during the preceding night. Using this assumption, it can be determined which daily patterns are relevant:

- The total distance of the daily pattern is larger than the driving range
- The total distance of the daily pattern is shorter than twice the driving range

Analysis showed that 12.1% of the daily patterns are relevant assuming a driving range of 80km. Here, it is assumed that no other chargers are present, for example at activity end (destinations).

The TAGA-method

A method is developed that can be used to obtain an optimal configuration of fast chargers within a certain area. This method, the TAGA-method, consists of three parts:

The input:

- A dataset containing information about daily patterns

Steps required to translate the data from the dataset into an optimal configuration of fast chargers:

- Translation of data into spatial representation of the demand
- Allocation of fast chargers

In order to find the most reliable method, several options are studied per step. The options are illustrated in Figure 1.

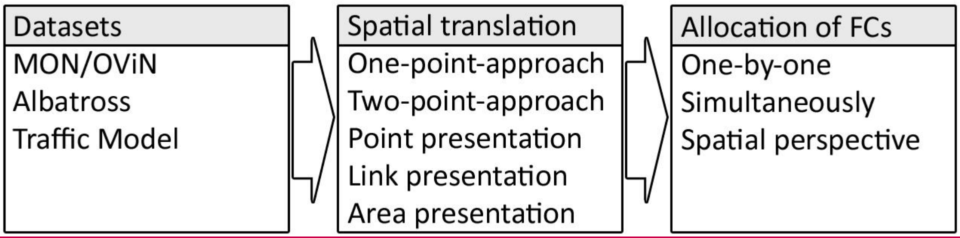


Figure 1, Options studied per step

The dataset

A dataset is required to obtain information about the (spatial) travel behaviour of drivers. The analysis has showed that none of the studied datasets satisfies the set requirements. The following requirements have not been complied:

- Reliability and kind of data: The dataset contains information about daily patterns (quality)
- The size of the dataset (quantity)

Therefore, the decision has been made to use a traffic model combined with data of the MON/OViN to generate daily patterns over an area. Since generating all possible daily patterns will cost (too) much computation time, only three types of daily patterns are created. The created daily patterns consist of 1 tour with two, three or four trips.

Traffic model

An origin/destination morning matrix of a traffic model shows the flows, the number of vehicles, between areas that are made in the morning rush hour (see Figure 2, step 1). However, this is only a single trip. It is unknown how someone will continue his or her daily pattern.

Dutch National Travel Survey

To determine how someone will prosecute his or her daily pattern, data from the Dutch National Travel Survey (MON/OViN) is analysed. Each year, approximately 50,000 people participate in this study. In this survey, people have to fill in how they travel over a single day (daily pattern). Using this data, a probability distribution can be made to decide where someone will go to from a certain departure area. This distribution is based on the following data:

- A gravity model: The areas get a probability based on the distance from the departure area.
- The attractiveness of areas: Probability on the basis of attractiveness of areas. Urban areas, for example, are more likely to be chosen as destination.

By combining both probabilities, it can be determined from any destination where people will travel to and by what probability. In this way, different daily patterns are generated which consist of 1 tour with two, three or four trips (see example in step 2). Because not all daily patterns have an equal probability of occurrence, not all patterns will have the same weight.

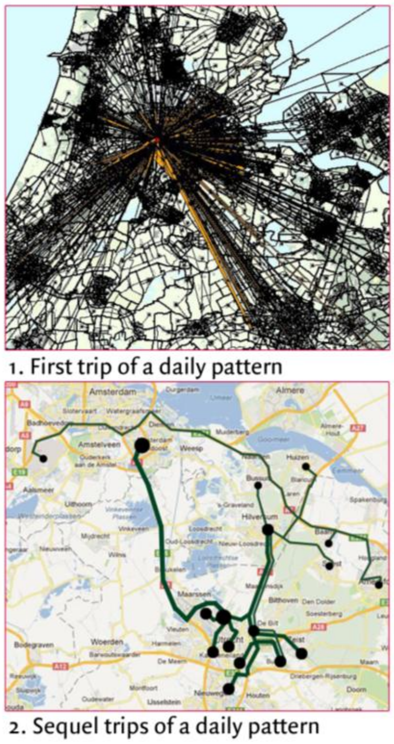


Figure 2, Steps in the TAGA-method (1/2)

Translation into spatial representation of the demand

It can be determined which of the generated daily patterns are relevant. In other words, which daily patterns require a fast charger in order to be able to make the pattern with an EV. The possible locations for a fast charger can be determined for every single relevant daily pattern. Therefore, two extreme points on the route of the daily pattern have to be determined:

- The first possibility is the point on the route where (after a full charge) the battery is empty on arrival at the final destination
- The last possibility is the point where the driver drives until the battery is empty.

A fast charger is required on the road segments between these points; this is the potential interval of the daily pattern. To determine which road sections are situated in this interval, a network is used. Using this network, it can be determined which road sections will be used between all destinations as the fastest route is driven. In this way, the possible locations for a fast charger can be spatially presented. An example of a daily pattern and a potential interval (red part) is depicted in Figure 3 step 3.

The desire to charge is greatest in the centre of the potential interval; the chance to strand with a flat battery somewhere on the daily pattern will be theoretically smallest if the battery will be charged at that location. Therefore, it is chosen to use a triangular distribution to distribute the demand over the interval. This is shown in step 4. Using this distribution, all road sections in the potential interval will get a score. This score is based on the surface under the triangle and is dependent on: the probability that the daily pattern will be made (weight) and the length of the road section.

Next, these scores are assigned to cells. The area in which the daily patterns are generated is divided into cells. In this way, every cell overlapping a road section in the potential interval will get a score. See Step 5.

If this is done for all relevant generated daily patterns and the cell scores of each pattern will be added, a total distribution of the demand will be created. This is depicted in step 6.

To determine the demand in a future year, the following aspects are taken into account:

- The market share of the EV fleet: *The more EVs, the more demand*
- Charge behaviour: *Not everyone with an EV will use fast chargers due to the extra travel time*
- Presence of slow chargers at activity end: *If an EV can also be charged at a destination, less fast chargers are required*.
- Simplification factor*: Only three types of daily patterns are generated. Therefore not all demand is defined.*

These effects have to be applied to the cell scores. This ultimately results in a spatial distribution of demand, the expected number of charges in a certain period of time, within an area.

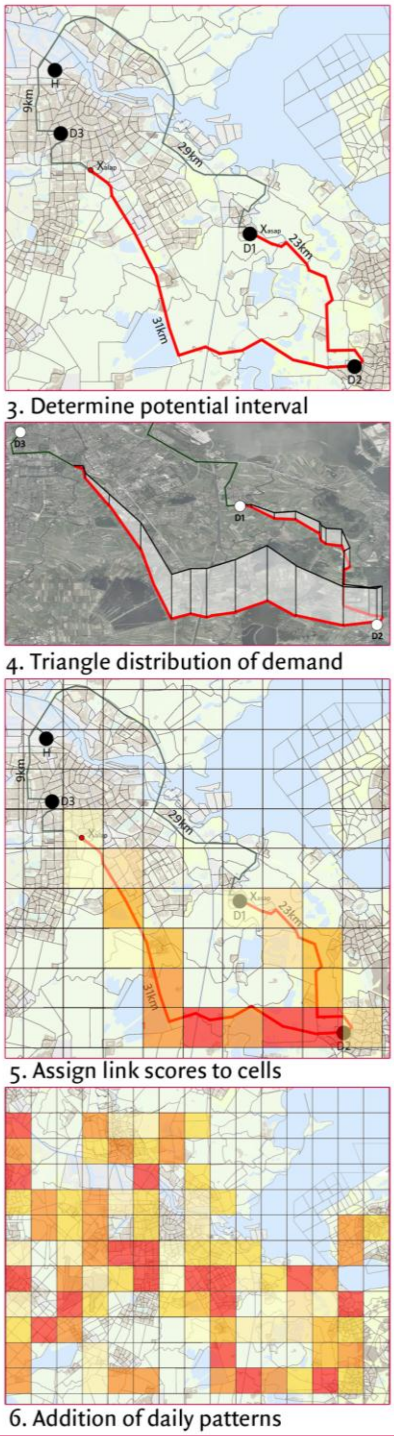


Figure 3, Steps in the TAGA-method (2/2)

Allocation of fast chargers

The spatial distribution of the demand is used to determine the actual locations for fast chargers. The fast chargers are allocated as follows:

1. Find the cell with the highest demand, the cell with the highest score
2. Allocate as many fast chargers to that cell until the remaining demand –which decreases after every allocated fast charger- is too low to place an additional fast charger. This implies that another fast charger will not be profitable at the remaining demand.
3. Repeat step 1

This process is shown in Figure 4. A possible distribution of the demand is shown on the left side. Fast chargers are assigned to the most red cell, the cell with the highest demand. This has effect on the demand on the surrounding cells as shown in the right figure. The following fast chargers will be allocated to the cell that has now the highest score. If there is no profitable spot left, an optimal configuration has been found.

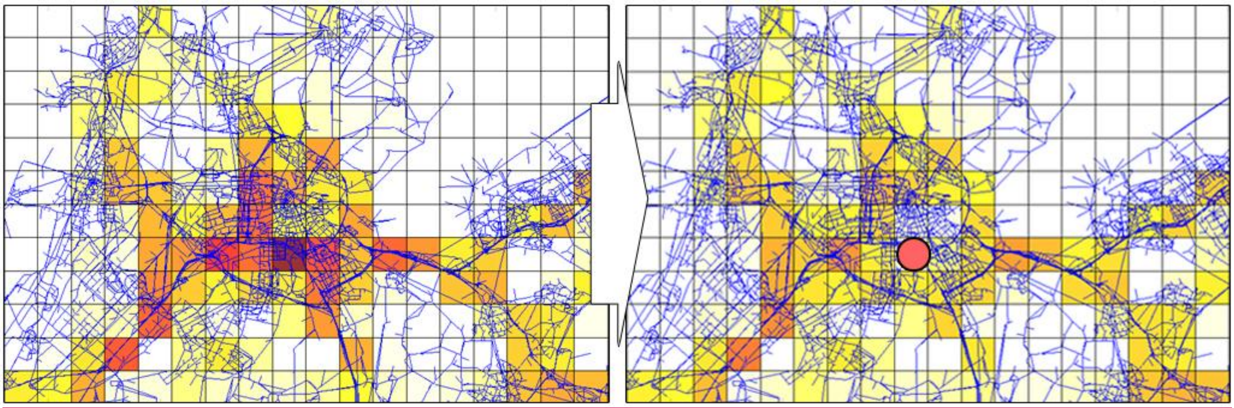


Figure 4, Example of the effects on the demand in an area after allocating fast chargers at a location

The combination of the three steps described results in the TAGA-(Two-Point Approach Greedy Algorithm) method.

Fields of application

The developed TAGA-method can be used for the following purposes:

- Determining the optimal configuration (locations and number of fast chargers per location) for a random area
- Evaluate and rank planned or potential locations on profitability
- Determining which existing locations can best be upgraded to hubs (more chargers at one location)

Application to Amsterdam

The method is applied to find the optimal configuration of fast chargers within the municipal boundary of Amsterdam in 2020 and for the EV owners that live Amsterdam. The daily patterns, the dataset, are created using:

- The O/D morning matrix of VENOM (Verkeerkundig noordvleugel model)
- Stacked data of the Dutch National Travel Survey (MON/OViN)

The first trips are copied from the O/D morning matrix of VENOM and subsequent trips are determined using assumptions derived from the MON/OViN.

The results associated with a driving range of 80 km are depicted in figures 5 and 6. The red dots indicate the optimal locations and the number in the dot is the required number of (profitable) fast chargers.

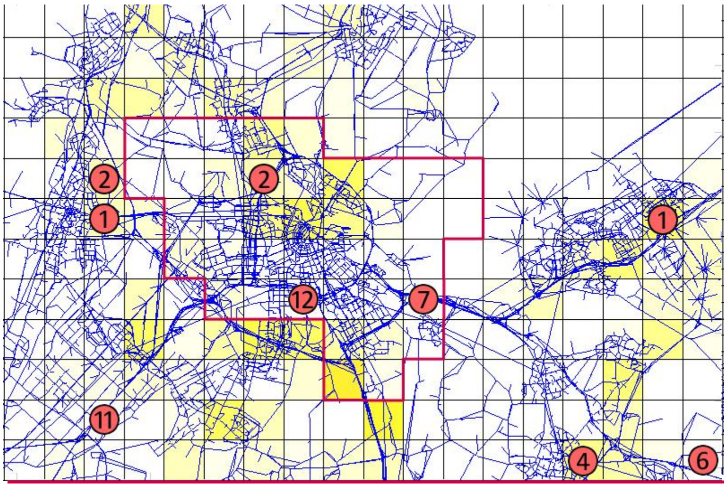


Figure 5, Optimal configuration within the study area assuming a driving range of 80km

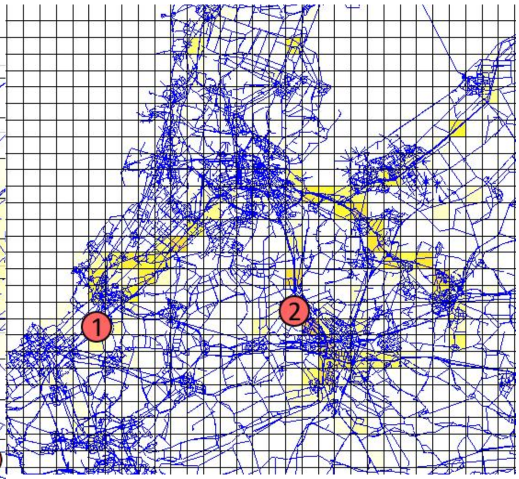


Figure 6, Optimal configuration for residents of Amsterdam assuming a driving range of 80km

Figure 5 shows that the optimal configuration within the borders of the municipality of Amsterdam consists of 21 fast chargers spread over 3 locations.

The EV users that are leaving Amsterdam in the morning require a fast charger about 30-40 kilometers south of Amsterdam. Three fast chargers spread over two locations are required to meet the expected demand. However, these locations and numbers do not fit the ideal configuration for a larger area. Therefore, all daily patterns (departing from all cities) have to be included.

Evaluation of the method

The TAGA-method is evaluated by comparing the created dataset and by means of a sensitivity analysis.

The created dataset containing daily patterns, which is used for the application to Amsterdam, has been validated with daily patterns in the MON/OViN. The average length of the relevant daily patterns, the average length of the potential interval and the percentage of relevant daily patterns is analysed. This analysis shows that the created dataset is in good agreement with the MON/OViN despite the fact that MON/OViN is based on data from the past and the created dataset on the future (2020).

The sensitivity analysis shows that the locations are fairly robust. However, the demand varies greatly in the different scenarios calculated. Related to this is the number of chargers required.

A point of improvement are the daily patterns generated and used as input for the method. The created dataset is supposed to be best available and will provide good results. However, it can be improved by tackling the following (main) weaknesses:

- Illogical daily patterns might be created due to general assumptions with respect to destination choice
- In addition, not all kind of daily patterns are created.

The reliability of the results depends mainly on the quality and quantity of the dataset.

Conclusions

Total distance travelled op a day is indicative for the use of fast chargers
A potential user of a fast charger is an EV user that makes a daily pattern with a total distance between the driving range and twice the driving range if it is assumed that the battery is fully charged at departure.

The TAGA-(Two-point Approach Greedy Algorithm) method is best, dataset point of improvement
The TAGA-method is the best method to determine the optimal configuration of fast chargers within a certain area. However, the method contains some uncertainty. This is mainly because there is no dataset available that meets the set requirements (quality and quantity). The self-created dataset contains the following weaknesses:

- Illogical daily patterns might be created due to general assumptions with respect to destination choice
- In addition, not all kind of daily patterns are created

Despite these improvements, the method and the results are supposed to be reliable.

Fast chargers are required on at least three locations in Amsterdam
At least three locations within the border of Amsterdam are required to serve more than 80% of the expected demand in 2020. The locations are: A10 nearby the RAI, A10 nearby the Coentunnel and on the junction A9-A1. These locations will ensure that everyone passing Amsterdam will encounter a fast charger.

The locations are robust, the demand is uncertain
The optimal configuration of fast chargers will hardly change when a larger driving range is assumed. The number of required fast chargers in a certain year is very uncertain due to: the market share of the EV fleet, charge behaviour (willingness to use fast chargers), presence of slow chargers at activity end and the profitability of a charger. In addition, electric vehicles will mainly be used as a second car.

From a commercial point of view, fast chargers are a risky investment without subsidy. From the perspective of the government, placing (unprofitably) fast chargers might take away the anxiety range. This will ensure EV users have the idea that they can always reach a fast charger, which promotes EV usage. The chargers should be placed in the right order to spend the available money as efficiently as possible. The order can be determined by the TAGA-method.

Recommendations

Application to a large area
The area that is studied in this thesis is too small. The method should be applied to a larger area to obtain a better optimization. In addition, it allows analysing the effect of a larger driving range.

First spatial distribution, then upgrade to hubs
It is not advisable to install the number of predicted fast chargers at a location in one time. It is better to first install one fast charger at each location in the optimal configuration to create a ubiquitous network. Thereafter, more fast chargers can be added. The order of installation can be determined by the TAGA-method.

Monitoring demand and parameters
To make more reliable predictions regarding expected demand, it is recommended to monitor fast charger usage from time to time to calibrate the parameters. In this way, an estimate can be made which scenario is most plausible.

Furthermore, the TAGA-method assumes that the desire to charge is distributed over an interval using a triangular distribution. However, this is not scientifically valid. Additional research might provide insight into charge behaviour of EV users which will eventually lead to better results.

Improving the quality of the generated tours
The dataset, the input of the TAGA-method, is a point of improvement. Improving the created dataset will improve the quality of the results.

Management samenvatting

Inleiding

In tijden van eindige olievoorraden, stijgende olieprijzen en een stijgende aandacht voor duurzame mobiliteit worden alternatieve brandstoffen steeds aantrekkelijker. Elektrische voertuigen (EVs) zijn een alternatief voor de huidige voertuigen. Deze voertuigen rijden op elektriciteit in plaats van benzine of diesel. Elektrische voertuigen kunnen zowel onderweg als thuis worden opgeladen door middel een laadpaal. Met een volle batterij kan in de praktijk ongeveer 80-100 kilometer worden gereden mits negatieve effecten zoals slechte weersomstandigheden, extra gewicht en stop-en-go verkeer worden meegerekend. Deze afstand is de actieradius. Dit betekent dat als er afstanden langer dan deze afstand moet worden afgelegd, een tussentijdse laadbeurt nodig zal zijn. Hiervoor zijn snelladers ideaal, deze kunnen de batterij tot 80% opladen in ongeveer dertig minuten. Dit is veel sneller dan de 8 uur die nodig is als met een gewone (langzaam)lader word geladen.

Probleemstelling

Afgelopen jaren zijn er enkele snelladers geplaatst in Nederland. De locaties van deze snelladers zijn echter niet bepaald aan de hand van rijpatronen of verkeerskundig inzicht. Hierdoor kan het voorkomen dat snelladers op sommige locaties te weinig worden gebruikt en op andere locaties worden overbelast. In het eerste geval is de snellader een slechte investering en in het laatste geval kunnen er wachtrijen ontstaan.

Een optimaal netwerk van snelladers is zodanig ruimtelijk opgebouwd dat, gegeven het aantal laadpunten, zoveel mogelijk autoverplaatsingen met een elektrische auto kunnen worden gemaakt. Met andere woorden, het faciliteert maximaal het gebruik van elektrische auto's en stimuleert daarmee maximaal de transitie naar elektrische auto´s. Het doel van dit onderzoek is om de optimale locaties voor snelladers te bepalen zodat het beschikbare geld zo efficiënt mogelijk wordt besteed.

In deze thesis is een methode ontwikkeld waarmee onder andere voor een willekeurig gebied de optimale configuratie met het daarbij horende benodigde aantal snelladers kan worden bepaald.

Doelgroep en relevante verplaatsingen

De actieradius van een EV is het belangrijkste aspect om te bepalen of iemand een snellader nodig heeft. Om te bepalen wie de potentiële gebruikers zijn, zijn dagpatronen van voertuigen geanalyseerd. In deze patronen is weergegeven hoe een auto wordt gebruikt over een dag. De EV gebruikers die op een dag meer dan de actieradius rijden zijn mogelijke gebruikers. Daarnaast wordt verondersteld dat gebruikers niet twee keer op een dag dertig minuten willen wachten terwijl hun auto wordt geladen. Een uitgangspunt in dit onderzoek is dat de batterij van het EV 's ochtend helemaal opgeladen is omdat gedurende de voorgaande nacht is geladen. Met deze aanname kan worden bepaald welke autoverplaatsingen relevant zijn:

- De totale afstand van het dagpatroon is groter dan de actieradius
- De totale afstand van het dagpatroon is kleiner dan twee keer de actieradius

Uit analyse is gebleken dat 12,1% van de dagpatronen latent (relevant) zijn uitgaande van een actieradius van 80km. Hierbij is verondersteld dat er geen andere laders, bijvoorbeeld op een bestemming, worden gebruikt.

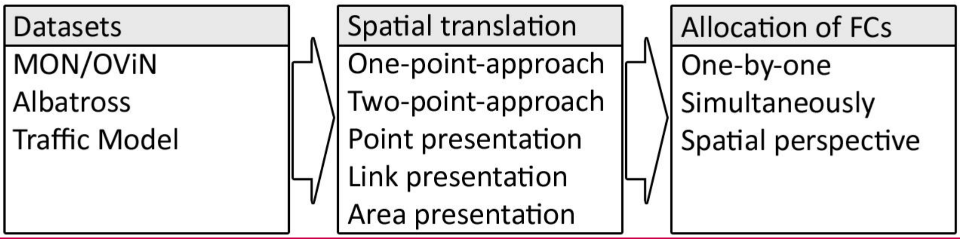
De TAGA-methode

Een methode is ontwikkeld die kan worden gebruikt om de optimale configuratie van snelladers te verkrijgen in een bepaald gebied. Deze methode, de TAGA-methode, bestaat uit drie onderdelen:

De input:
- Een dataset die informatie bevat over hoe mensen zich verplaatsen.

Stappen die nodig zijn om de data uit de dataset om te zetten naar een configuratie van snelladers:
- Vertaling van data naar ruimtelijke vraag
- Toewijzen van snelladers

Om de meest betrouwbare methode te vinden zijn verschillende opties die per stap onderzocht. Deze zijn weergegeven in figuur 1.



Figuur 1, Mogelijke opties per onderzochte stap

De gekozen optie per stap worden hieronder toegelicht:

De dataset

Een dataset is nodig om informatie te krijgen over het ruimtelijke verplaatsingsgedrag van automobilisten. Uit analyse is gebleken dat geen van de onderzochte datasets voldoet aan de eisen die waren gesteld. De twee eisen waar geen van de datasets aan voldeed waren:

- Betrouwbaarheid en soort data: de dataset bevat informatie over dagpatronen (kwaliteit)
- De grootte van de dataset: de hoeveelheid data (kwantiteit)

Er is daarom gekozen om met behulp van een verkeersmodel en data van het MON/OViN dagpatronen te genereren over een bepaald gebied. Omdat genereren van alle soorten dagpatronen (te)veel rekentijd kost is gekozen om slechts drie soorten dagpatronen te creëren. Dit zijn dagpatronen bestaande uit 1 tour met twee, drie of vier trips.

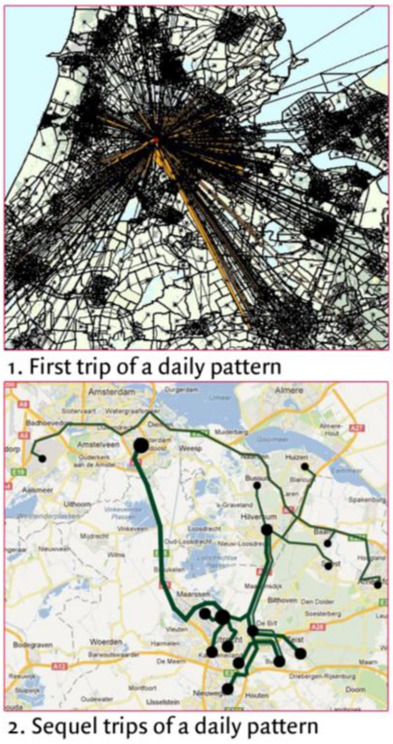
Verkeersmodel

In een herkomst/bestemming ochtend matrix van een verkeersmodel zijn verkeerstromen, het aantal voertuigen, tussen gebieden (zones) weergegeven die worden gemaakt tijdens de ochtendspits (zie figuur 2, stap 1). Dit is echter maar één verplaatsing, het is dus niet bekend hoe iemand zich vervolgens zal gaan verplaatsen.

Mobiliteits Onderzoek Nederland

Om te bepalen hoe iemand zijn reis zal vervolgen is data uit het Mobiliteits Onderzoek Nederland (MON/OViN) geanalyseerd. In het MON/OViN vullen elk jaar ongeveer 50.000 mensen in hoe ze over een dag hebben gereisd. Met deze data is een kansverdeling gemaakt waar iemand naar toe zal rijden vanuit het gebied waar hij is aangekomen. Deze kansverdeling is gebaseerd op de volgende twee gegevens:

- Een gravitatie model: De gebieden krijgen een kans gebaseerd op afstand van het vertrekgebied.
- De attractiviteit van gebieden: Kansen op basis van aantrekkingskracht van gebieden. Stedelijke gebieden hebben bijvoorbeeld meer kans als bestemming gekozen te worden dan gebieden die voornamelijk bestaan uit weiland.



Figuur 2, Stappen in TAGA-methode (1/2)

Door het combineren van beide kansen kan vanaf elke bestemming worden bepaald waar mensen met een bepaalde waarschijnlijkheid heen zullen reizen. Op deze manier worden verschillende dagpatronen gegenereerd die bestaan uit 1 tour met twee, drie of vier trips (zie voorbeeld in stap 2). Omdat niet alle dagpatronen een zelfde waarschijnlijkheid hebben om gemaakt te worden wegen ze niet allemaal even zwaar.

Vertaling van data naar ruimtelijke vraag

Van de gegenereerde dagpatronen kan worden bepaald of ze relevant zijn. Met andere woorden, welke dagpatronen hebben een snellader nodig om gemaakt te kunnen worden met een EV. Voor deze dagpatroon die zijn de mogelijke locaties bepaald waar een snellader kan worden bepaald. Hiervoor worden twee extremen punten op de route van het dagpatroon bepaald:

- De eerste mogelijkheid is het punt op de route waarbij (na volledige lading) de batterij precies leeg is bij aankomst op de eindbestemming
- De laatste mogelijkheid is het punt waarbij er zo lang wordt doorgereden totdat de batterij leeg is.

Op de wegvakken tussen deze punten is een snellader nodig, dit is het “potentiele interval voor een snellader’’. Om te bepalen welke wegvakken zijn gesitueerd in dit interval is een netwerk gebruikt. Hiermee is gekeken welke wegvakken worden gebruikt als er via de snelste route tussen twee gebieden wordt gereden. Op deze manier wordt de mogelijke locaties voor een snellader ruimtelijk weergegeven. In figuur 3 stap 3 is een dagpatroon weergegeven met daarin in rood aangegeven waar een snellader geplaatst kan worden.

De wens om te laden is het grootst in het midden van het potentiële interval, de kans om te stranden met een lege batterij is hier theoretisch het kleinst. Daarom is er gekozen voor een driehoekige verdeling van het vraag over het interval, zoals weergegeven in stap 4. Gebruikmakend van deze verdeling krijgen de wegvakken in het potentiele interval een score toegewezen. Deze score is gebaseerd op het oppervlak onder de driehoek en hangt af van: de waarschijnlijkheid van voorkomen van het dagpatroon en de lengte van het wegvak.

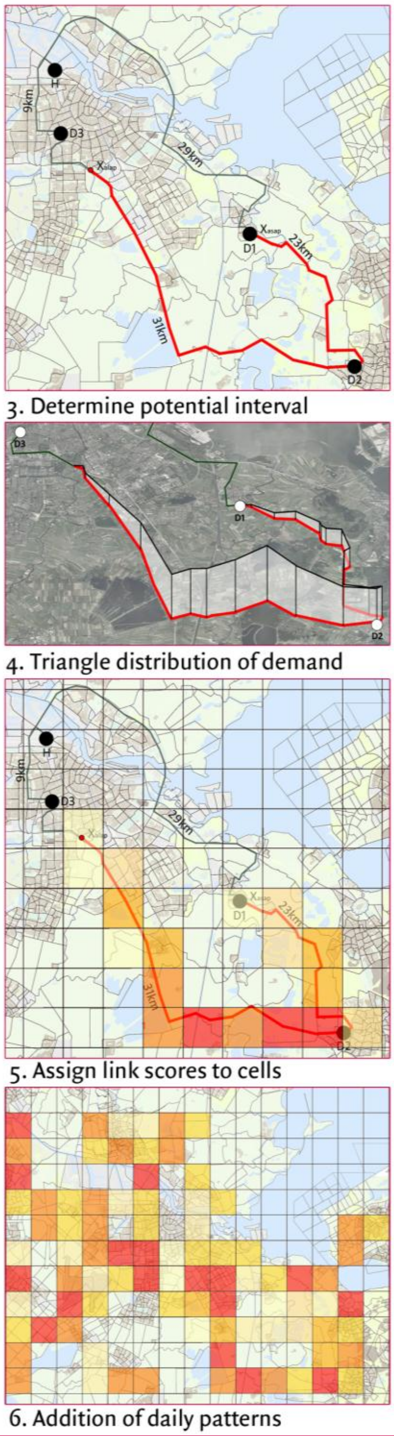
Vervolgens worden deze scores toegewezen aan cellen. Het gebied waarin de dagpatronen zijn gegenereerd is onderverdeeld in cellen. Op deze manier ontstaat er voor elk dagpatroon cel scores, zie stap 5.

Indien dit voor alle gegenereerde relevante dagpatronen wordt gedaan en de cel scores worden opgeteld ontstaat er een totale verdeling van de vraag. Dit is weergegeven in stap 6.

Om de vraag in een toekomstig jaar te bepalen dient er rekening te worden gehouden met de volgende aspecten:

- Marktaandeel van EVs: *Hoe meer EVs er zijn, hoe meer vraag.*
- Laadgedrag: *Niet iedereen met een EV zal gebruik maken van snelladers door de extra reistijd*
- Aanwezigheid van langzaamladers op bestemmingen: *Indien EVs ook op bestemmingen kunnen laden zullen er minder snelladers nodig zijn.*
- Factor dagpatronen: *omdat slechts drie soorten dagpatronen zijn gegenereerd is niet alle vraag weergegeven*

Deze effecten worden toegepast op de cel scores. Uiteindelijk resulteert dit in een ruimtelijke verdeling van de vraag, het aantal verwachte laadbeurten in een bepaald tijdsinterval, in een gebied.

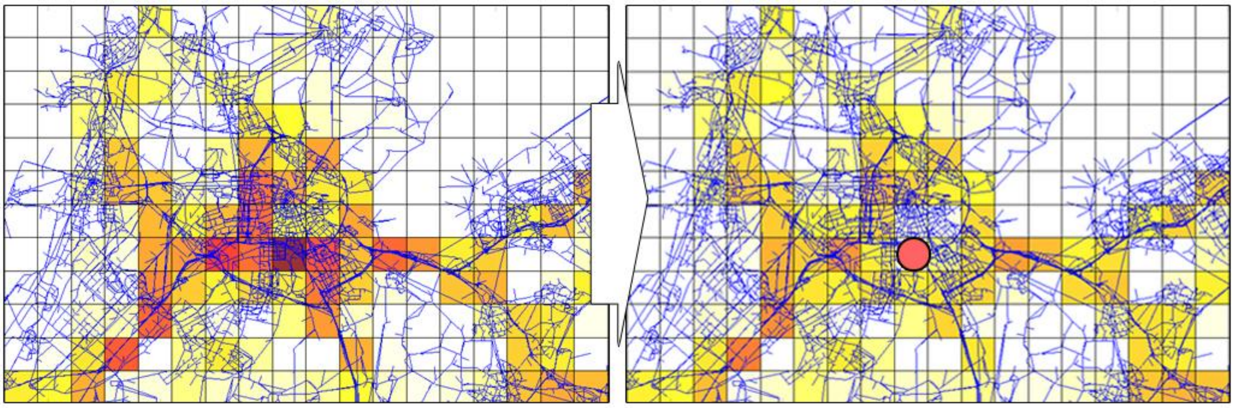


Figuur 3, Stappen in TAGA-methode (2/2)

Toewijzen van snelladers
Met de ruimtelijke verdeling van de vraag naar snelladers wordt vervolgens de stap gemaakt naar daadwerkelijke locaties. De snelladers worden als volgt toegewezen aan het gebied:

1. Zoek de cel met de hoogste vraag, de cel met de hoogste score.
2. Plaats zoveel snelladers in die cel totdat de vraag – die daalt na elke geplaatste snellader- te laag is om nog een rendabele snellader neer te zetten. Dit houdt in dat de snellader niet winstgevend is bij de overgebleven vraag.
3. Herhaal stap 1.

Dit proces is weergegeven in Figuur 4. Aan de linkerkant is een mogelijke verdeling van de vraag te zien. Aan de meest rode cel, de cel met de hoogste vraag, worden snelladers toegewezen. Dit heeft effect op de vraag in de andere cellen, zoals is te zien in het rechter figuur. De volgende snelladers zullen worden toegewezen aan de cel die nu de hoogste score heeft. Indien er nergens meer een rendabele snellader kan worden neergezet is een optimale configuratie bepaald.



Figuur 4, Voorbeeld van de effecten op de vraag in een gebied na plaatsing snelladers op een locatie

De combinatie van de drie beschreven stappen leidt tot de TAGA (Twee-punts Aanpak Greedy Algoritme)-methode.

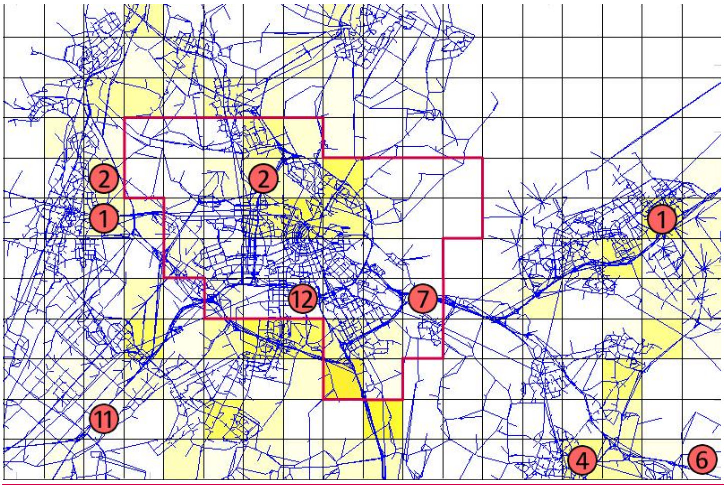
Toepassingsgebieden
De ontwikkelde TAGA-methode kan worden gebruikt voor de volgende doeleinden:
- Het bepalen van de optimale configuratie (locaties en aantal snelladers per locatie) binnen een willekeurig gebied
- Het beoordelen en ranken van geplande of mogelijke locaties op winstgevendheid
- Bepalen welke bestaande locaties het best kunnen worden opgewaardeerd tot hubs (meer laders op een locatie)

Toepassing op Amsterdam
De methode is toepast om de optimale locaties voor enerzijds Amsterdammers en anderzijds mensen die door de regio Amsterdam rijden te bepalen. De dagpatronen, de dataset, zijn gecreëerd door middel van:

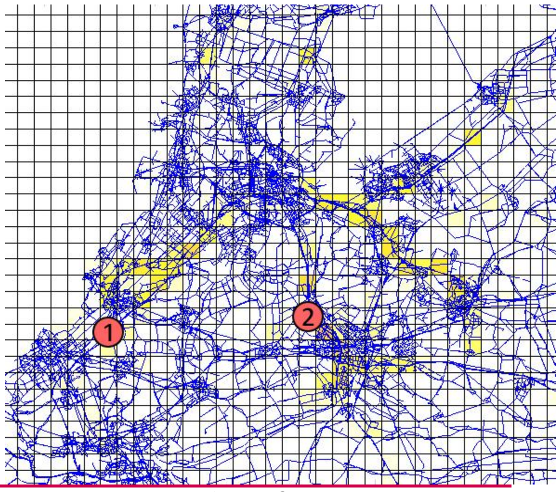
- De H/B ochtend matrix van het verkeersmodel VENOM (Verkeerkundig noordvleugel model)
- Gestapelde data van het Mobiliteits Onderzoek Nederland (MON/OViN 2004-2010)

De eerste verplaatsingen van de dagpatronen zijn overgenomen van VENOM en de vervolgverplaatsingen zijn bepaald met behulp van aannames uit het MON/OViN.

In de figuren 5 en 6 zijn de resultaten weergegeven voor een aangenomen actieradius van 80km. De rode bollen zijn de optimale locaties en het getal wat erin staat het aantal benodigde (rendabele) laders.



Figuur 5, Optimale configuratie van snelladers in en rondom Amsterdam (totaal binnen de gemeentegrens: 21 laders verdeeld over 3 locaties)



Figuur 6, Optimale configuratie van snelladers voor EV gebruikers vertrekkend uit Amsterdam

In figuur 5 is te zien dat voor een optimale configuratie binnen de gemeentegrens van Amsterdam 21 snelladers nodig zijn verdeeld over drie locaties.

De EV gebruikers die 's ochtends vertrekken uit Amsterdam wensen een snellader nodig op ongeveer 30-40 kilometer ten zuiden van Amsterdam. Hiervoor zijn drie snelladers verdeeld over twee locaties nodig. Echter zullen deze locaties en aantallen niet passen in de optimale situatie voor een groter gebied. Daarvoor dienen alle EV verplaatsingen te worden meegenomen.

Evaluatie van de methode

De TAGA-methode is geëvalueerd door het vergelijken van de gecreëerde dataset en door middel van een gevoeligheidsanalyse.

De gecreëerde dataset met dagpatronen, welke is gebruikt voor de toepassing op Amsterdam, is gevalideerd met de dagpatronen uit het MON/OViN. Hierbij is gekeken naar de gemiddelde lengte van de relevante dagpatronen, de gemiddelde lengte van het potentiele interval en het percentage relevante dagpatronen. Uit deze analyse blijkt dat de gecreëerde dataset goed overeenkomt met de MON/OViN ondanks het feit dat MON/OViN is gebaseerd op het verleden en de gecreëerde dataset op de toekomst (2020).

Uit de gevoeligheidsanalyse blijkt dat de locaties vrij robuust zijn. Daarentegen varieert de vraag in verschillende berekende scenario's sterk. Gerelateerd hieraan is het aantal benodigde laders.

Het verbeterpunt zijn de dagpatronen die zijn gegenereerd en zijn gebruikt als input voor de methode. De gecreëerde dataset is verondersteld de best beschikbare te zijn en geeft ook goede resultaten. Echter kan deze worden verbeterd door de volgende (grootste) zwaktes aan te pakken:

- Onlogische tours kunnen worden gecreëerd door de algemene aannames met betrekking tot bestemmingskeuze.
- Daarnaast worden niet alle mogelijke dagpatronen gecreëerd.

De betrouwbaarheid van de uitkomsten hangt daarom vooral af van de kwaliteit en kwaliteit van de dataset.

Conclusies

De totaal gereden afstand met een auto op een dag is maatgevend voor het gebruik van snelladers
Een potentiele gebruiker van een snellader is een EV gebruiker die een dagelijkse verplaatsing maakt met een totale afstand tussen de actieradius en twee keer de actieradius als is aangenomen dat de batterij vol opgeladen is bij vertrek.

De TAGA-(Twee-punten Aanpak Greedy Algoritme) methode is de beste, de dataset is het verbeterpunt
De TAGA-methode is de beste methode om onder andere de optimale configuratie van snelladers te bepalen in een bepaald gebied. Echter bevat deze methode enkele onbetrouwbaarheden. Deze hebben vooral te maken dat er geen dataset beschikbaar is die zowel kwalitatief als kwantitatief voldoende is. De zelf gecreëerde dataset heeft de volgende zwaktes:

- Onlogische tours kunnen worden gecreëerd door de algemene aannames m.b.t. bestemmingskeuze.
- Daarnaast worden niet alle mogelijke dagpatronen gecreëerd.

Ondanks deze verbeterpunten wordt de methode verondersteld betrouwbaar te zijn.

Er zijn minimaal drie locaties snelladers nodig om Amsterdam beter bereikbaar te maken met een EV
Drie locaties zijn minimaal nodig binnen de gemeente grens van Amsterdam om meer dan 80% van de verwachte vraag te bereiken in 2020. Deze locaties zijn: A10 nabij de RAI, A10 nabij de Coentunnel en nabij het knooppunt A9-A1. Deze locaties zorgen ervoor dat iedereen die Amsterdam inrijd een snellader tegenkomt.

De locaties zijn robuust, maar de vraag is onzeker
De optimale configuratie van snelladers verandert in beperkte mate als er een grotere actieradius wordt aangenomen. Het aantal benodigde laders in een toekomstig jaar is zeer onzeker door: de verandering van de actieradius, het marktaandeel van EVs, het laadgedrag (daadwerkelijke gebruik van snelladers), de aanwezigheid van langzaamladers op bestemmingen en de winstgevendheid van snelladers. Daarnaast zullen EV's vooral worden gebruikt als tweede auto.

Vanuit een commercieel oogpunt zijn snelladers zonder subsidie een risicovolle investering. Vanuit het oogpunt van de overheid kunnen (niet winstgevende) snelladers mogelijk de angstradius wegnemen. Dit zal zorgen dat gebruikers altijd het idee hebben dat een lader in de buurt is, wat het gebruik van EV's promoot. De laders dienen in de juiste volgorde geplaatst worden om het beschikbare geld zo efficiënt mogelijk te spenderen. De volgorde kan worden bepaald met de TAGA-methode.

Aanbevelingen

TAGA-methode toepassen op groter gebied
In dit onderzoek is een klein gebied onderzocht. De methode dient te worden toegepast op een groter gebied om een landelijke optimalisatie te krijgen. Daarnaast kan ook de invloed van een grotere actieradius worden bestudeerd.

Eerst ruimtelijke spreiding van snelladers, dan upgraden tot hubs
Het is niet verstandig om het aantal verwachte snelladers op een locatie in één keer neer te zetten. Het is beter om eerst overal één snellader neer te zetten om zo een dekkend netwerk te realiseren. Voor de volgorde van plaatsing kan weer de TAGA-methode worden gebruikt.

Monitoren van gebruik en parameters
Om te voorspellen hoeveel vraag er in de toekomst zal zijn dient de ontwikkeling van de gerelateerde aspecten te worden gemonitord. Op deze manier kan er preciezer worden geschat welk scenario aannemelijk is en hoeveel snelladers daarvoor nodig zijn. Daarnaast De TAGA-methode gaat uit van een driehoek verdeling die weergeeft waar EV gebruikers willen laden binnen een relevant dagpatroon. Echter is dit niet wetenschappelijk gegrond. Extra onderzoek kan inzicht geven in het laadgedrag van gebruikers.

Verbeteren van de dataset
De dataset, de input van de TAGA-methode, is een verbeterpunt. Het verbeteren van de gecreëerde dataset zal de kwaliteit van de uitkomsten verbeteren.

Content

1 INTRODUCTION

1.1 Background

In times of finite oil reserves, rising oil prices and a rising demand for sustainability, alternative fuels are becoming increasingly attractive. Electric vehicles (EVs) are an alternative to the current internal combustion engine (ICE) vehicles. Many pilot projects are currently being implemented to detect possible barriers and convince car drivers of the benefits of electric driving. One of the major problems is the driving range of the car (Direct research, 2011). This is the maximum distance that can be driven on a full battery. The fear of many drivers is to get a flat battery when they want to perform their current daily travel pattern with an EV.

(Fast)charging

The battery can be recharged using a charging station or plug, this can be done at a destination when the vehicle is not in use. This is often during the night; this ensures that the battery is full at departure the next day. Because there is no pressure of time, often regular (slow)chargers are used. The charging time of those chargers is about six to eight hours. It is also possible to charge en route, this is similar to petrol stations for regular cars. In this case, fast chargers (see Figure 7) are preferred. Those chargers can charge the battery up to 80% within 30 minutes.

Figure 7, Fast charger: Epyon Terra (ABB, 2012)

Current situation

There are currently plans developed for a ubiquitous nationwide network of fast chargers that will eliminate the fear of getting a flat battery. Many companies cooperate to exploit fast chargers. Often there is collaboration between energy companies, car manufacturers, petrol station owners and suppliers of (fast) chargers.

At this time, there is no method available that indicates where fast chargers are desirable from the perspective of driving patterns of (potential) EV users. This report provides insight in the methods that can be used to allocate fast chargers as efficiently as possible. This chapter contains the problem definition, the research questions, the relevance of the research and a reader's guide.

1.2 *Problem definition*

Creating a national network in order to boost electric vehicle usage is a good goal. However, it is also a costly development. The current and the planned locations of fast chargers are determined without conclusive reasoning: driving patterns are not taken into account. Because of this, it may occur that fast chargers will be underused or overused (the demand is too high). In the first case, the investment will be a waste of money. The demand will be too low to make a fast charger profitable. In the other case, the fast charger has a shortage of capacity which might result in waiting times. This is a disstatisfier that might diminish consumer's enthusiasm for fast charging and even for electric cars in general.

An optimal designed configuration with corresponding number of chargers will ensure that the money is spent as efficiently as possible.

1.3 *Research questions*

This thesis studies how an optimal configuration of fast chargers within a certain area can be determined. Therefore, several methods are developed that can be used to present the demand for fast chargers spatially and methods that can be used to allocate fast chargers to the studied area with the aim to obtain an optimal configuration. An evaluation of the different methods will lead to a method that will lead to the best solution of the problem. The main question dealt with in this thesis is:

Main research question
What is the optimal configuration of fast chargers to reach the highest potential of electric vehicles usage?

Many aspects have relevance with the topic. Therefore, it is first made clear which aspects are included in this thesis.

Firstly, it should be stated that chargers are not the only way to charge the battery of an EV. Battery swap stations can be used to switch the battery (Better place, 2009). Furthermore, charging is possible using induction. Inductive charging is a type of short-distance wireless energy transfer that can be used to charge the battery of the EV when stationary on a charging plate (John Tarantino, 2011, Nissan, 2011). This thesis will only focus on charging stations.

Many aspects are related to electric vehicles, such as impact on the environment, cost and subsidy, technological developments and infrastructure. This research scopes on the infrastructure for EVs. However, technological developments will affect the way infrastructure has to be designed. This aspect is partly included in this thesis. In addition, the effect of costs and subsidies are included in the scenarios studied and are therefore indirectly included. In this way, many aspects are in some way involved in this study without getting into detail.

Infrastructure
The infrastructure for EVs is different compared to internal combustion engine cars. Regular (ICE) cars only have the ability to increase the driving range at petrol stations along roads. Conversely, EVs can be recharged at home or en route. However, the distance that can be driven on a full battery is way less than on a full tank of petrol/diesel. Because of this, EVs have to be charged more frequently. Despite the fact that it is possible to charge the EV at home and is therefore often full on departure, it might happen that another charge is needed on the same day.

The concept of fast chargers is increasing the driving range, without losing a lot of time due to charging. Therefore, fast chargers are an interesting option to make (incidental) daily patterns (how someone travels over a day) that are larger than the driving range also with an EV.

Methods
The methods studied in this thesis will provide insight into where people prefer a fast charger if they will switch their car to an electric vehicle and would maintain their current travel behaviour. These methods follow from an analysis of how the world of electric vehicles looks like today and in the future. From this analysis, the key aspects and user groups are determined.

Using a dataset containing relevant information about daily vehicle patterns, a spatial distribution of the demand for fast chargers can be presented. The results will be used to allocate fast chargers to the best locations, leading to an optimal configuration. How many chargers have to be placed depends on the requirements which are imposed on the profitability.

To provide an answer on the main question, some sub questions are developed. These questions are arranged and formulated in such a way that the answer of the previous question will be used for the following.

Sub questions

1. *Who are the potential users of fast chargers and which aspects are relevant for determining the optimal locations and corresponding number of fast chargers?*

2. *What methods can be used to determine the expected demand for fast chargers, and what methods can be used to find an optimal configuration that meet the demand?*

3. *Should the municipality of Amsterdam install extra fast chargers to meet the expected demand in the future and where should they be placed?*

4. *What is the influence of the assumptions on the results, are the results reliable and robust?*

The questions are also answered separately in the conclusions (chapter 7).

1.4 Relevance of research

General
Several surveys (Stadspeil, 2009, Research Direct, 2011) show that the major drawback of electric vehicles is the (limited) driving range (mentioned by 74% of the respondents). In addition, the limited presence of chargers is a problem according to 51% of the respondents. This thesis shows how these problems can be (partly) eliminated by installing fast chargers.

The thesis provides insight in the aspects that determine whether or not a location has potention for placing a fast charger and how the optimal locations can be determined. To obtain the best possible configuration of fast chargers, it should be considered where demand is greatest. The method that is developed can be applied for every area. If the proper input data is available, an optimal network of fast charging stations for different scenarios can be calculated. In this way, the available funds can be spent as efficiently as possible.

Amsterdam
The developed method is applied to Amsterdam to provide insight in what (extra) measures have to be taken to keep Amsterdam in a leading position with respect to electric vehicles. Designing the best possible configuration of fast chargers will ensure that the use of EV will increase which eventually lead to improved air quality. In addition, this report shows where the EV owners in Amsterdam want to charge. In this way, Amsterdam can cooperate with other municipalities to ensure that their residents will have a greater range. This will take away the major disadvantage with the possible result that the EV sales might increase.

1.5 Readers guide

The structure of this report is as follows. In the first chapter, a comprehensive analysis is performed to figure out which aspects are relevant to define the potential users of fast chargers and which aspects will influence the location of fast chargers. From this analysis, the potential user groups are outlined and the most important parameters are determined. This is the basis for the developed methods.

In the next chapter various methods are developed and evaluated. Chapter 3 is divided into three parts: In the first part, datasets are studied that can be used as input. In the second step several methods have been examined resulting in a spatial distribution of demand for fast chargers. In the last step, allocation methods are studied that provide the best possible fast charging supply at a given demand. The objective of this optimization is to minimize the number of fast chargers by allocating them to the best positions in such a way that each charger satisfies the predetermined conditions. A combination of the (best) options will lead to a methodology that can be used universally.

In chapter 4, the method that is supposed to be best is described in more detail. Here, a new dataset is created which combines the best characteristics of the datasets studied. In addition, the algorithm that is used to allocate fast chargers is further elaborated.

The method is applied on behalf of the municipality of Amsterdam in chapter 5. First, the optimal configuration of fast chargers within the municipality of Amsterdam is determined. Secondly, it has been studied were residents of Amsterdam with an EV want to charge.

The method is evaluated in Chapter 6. Here, a validation is made between the data of the created dataset and the data of the Dutch National Travel Survey. In the second part a sensitivity analysis is performed to see if the locations and the number of fast chargers will change when the adopted parameters are changed. Furthermore, an overview is given about possible unreliability in the steps taken.

The division of the chapters corresponds with the research questions. This is shown as a flowchart in Figure 8 .

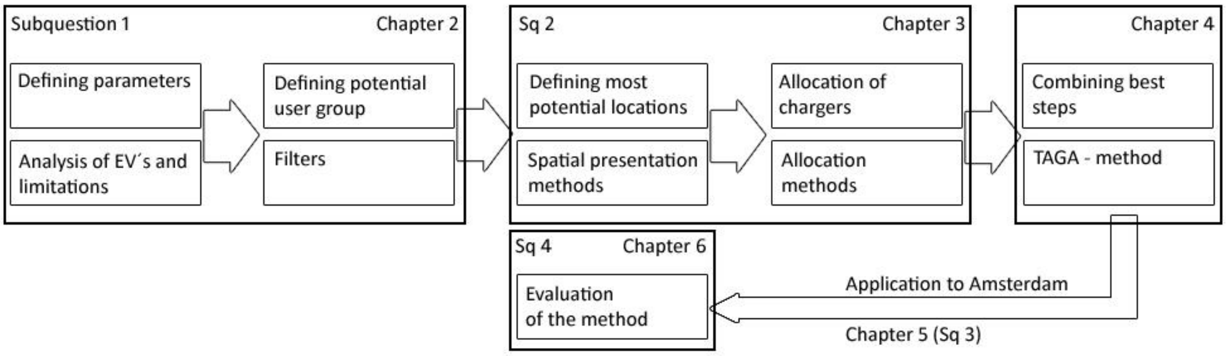


Figure 8, Flowchart of the structure of the report.

2 EV'S, (FAST)CHARGING AND POTENTIAL MARKET

2.1 *Introduction*

This chapter provides general information to become familiar with aspects that are related to electric vehicles. Topics that have been analysed by means of literature study and driver experiences are: types of EVs, market share, driving range, charging times and potential users. For all of these aspects it is briefly explained what it is, why it's relevant and what value it may have for this study. In order to obtain more specific information about charging behaviour, a survey among EV users is held in cooperation with DIVV, AgentschapNL and Goudappel Coffeng. The results are attached in appendix G.

EVs

The introduction briefly describes why EVs are slowly gaining popularity. Surveys that have been done to identify the advantages and disadvantages are analysed. The relevant thresholds are discussed in more detail in order to better understand the problem. In addition, the current market is set out as well as the development and targets that are set by different institutes.

Charging

In the second part, the possibilities how an EV can be charged are further elaborated. The focus will be on fast charging. Fast charging is suitable for charging en route due to the relatively short charge time compared to normal charging. The current locations of (fast)chargers in the Netherlands are presented and it is studied why they have been placed there. To provide more insight in the usage of fast chargers, a survey is held. The results show what EV users want to do while waiting, their attitude towards fast charging and their experiences.

Potential market

Finally, an analysis is done to figure out who might be a potential user. For this, the travel behaviour of car drivers is studied. Firstly, some definitions which are used throughout the thesis are explained. Hereafter, it is examined what characteristics determine which patterns are eligible for a fast charger. For this analysis, the data from the Dutch National Travel Survey is used. Furthermore, an estimate is made about the size of the potential user group under certain conditions.

The chapter concludes with a summary of the aspects that are relevant for determining the relevant daily patterns, a description of a potential user and the size of this group.

2.2 *Electric Vehicles*

2.2.1 History

The idea behind electric driving is invented a long time ago. The first electric vehicle (EV) was a scale model based on calculations of Faraday and was made by the Dutchmen Sibrandus Stratingh. At the end of the 19th century developers were mainly working on improving the battery. In 1906 a method was invented to convert AC to DC leading to a breakthrough. This new technology ensured that the (driving) range of an electric car improved (to 65km) and it was possible to drive faster than 25km/h. At that time approximately 10.000 EVs were in use throughout the world, representing a market share of more than 25% (Encyclopædia Britannica Online, 2012). The batteries could be charged by charging points which were distributed across the country. The market share decreased over the years due to the high costs compared to the emerging internal combustion engine cars and the lack of power (80-300 times smaller than petrol and diesel). Especially during both world wars, the EV lost a lot of ground and became rare. Nevertheless the research to develop better batteries and cars continued.

After World War 2 the electric vehicles regain some ground due to lack of oil. Till the 90's only a few developments with respect to batteries (still the major challenge) were made. During the 90's some car manufacturers decided to experiment with some new technologies which resulted in some test vehicles. These developments have eventually led to the EVs currently on the market.

2.2.2 EVs on market and targets

There are different types of EVs on the market, but not all of them are full electric vehicles. Roughly, three types of vehicles using one or more electric motors for propulsion can be distinguished: BEVs (Battery Electric Vehicles), HEVs (Hybrid Electric Vehicles) and PHEVs (Plug-in Hybrid Electric Vehicles). This report only contains information about BEVs: when the term EV is used, BEVs are considered.

The size of the electric vehicle market has grown in recent years. Currently (Dec 2011) there are about twenty models on the market; these are shown in appendix A. Not all of these models have the ability to use fast chargers due to technical limitations. The most known and best-selling EVs, Nissan Leaf and Mitsubishi iMiev, have this option as well as most of the models that will be released in the future (AgentschapNL, 2012).

At this time there are about 1500 electric cars in the Netherlands[1] (Trouw, 2012). Most of them are used as lease car or have a shared owner (AgentschapNL, 2010). How rapidly the number of electric vehicles in the Netherlands will increase is difficult to estimate. Many factors affect the development, therefore scenarios and targets are often used.

Future

In the beginning of March (2012), only 0.3% of the cars sold is an EV (NU.nl, 2012). The future market share of newly sold EVs is developed by the Ministry of EL&I[2] and is derived from the ambition that has been established. The graph is depicted in Figure 9. This figure clearly shows that from 2015 the market share will grow exponentially and will than flatten to a market share of 75%. In a study of the DHV (DHV, 2010) different phases are linked to the development: from 2010 to 2015 is the test phase, 2015-2020 is the phase in which the 'early adopters' will try out EVs and from 2020 the electric car will be widely accepted by society.

In a study of CEDelft (2011), the market share (of the fleet) of all types of EVs (BEVs, PHEVs and HEVs) is estimated for different scenarios, the result is shown in Figure 10. For all scenario's the same exponentially graph is shown, resulting in a market share of 7%, 18% or 33% in 2030. However, the percentage of BEVs among this group is unknown. The major differences between the scenarios arise because the growth is highly dependent on development costs and performance of both battery technology as well as conventional vehicle technology. Also the fiscal policy plays an important role.

[1] The numbers are also tracked by AgentschapNL, see graph in Appendix A

[2] Ministry of Economic Affears, Agriculture and Innovation

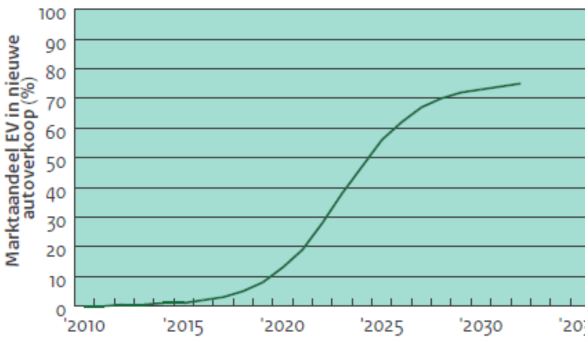


Figure 9, Prognosis of the market share of EVs in new sales (EL&I and I&M, 2009)

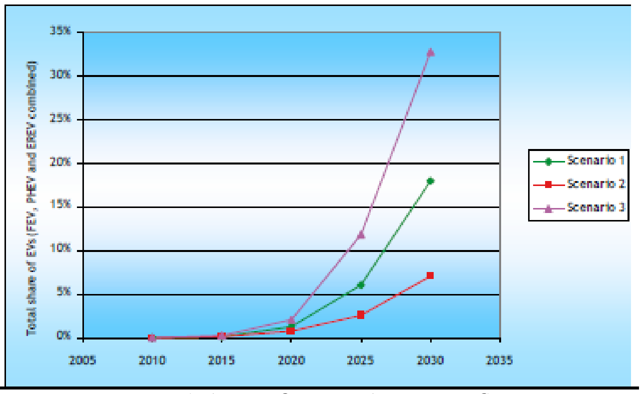


Figure 10, Total share of EVs in the EU car fleet, BEVs, PHEVs and HEVs (CEDelft, 2011)

The number of BEVs the government focuses on in their ambitions is included in the action plan of AgentschapNL (AgentschapNL, 2010). The aim that there will be 20,000 EVs in 2015, 200,000 in 2020 and 1 million in 2025. The Dutch fleet currently consists of 9,451,739 vehicles (CBS, 2011). This means a market share of the fleet of approximately 2% in 2020. Compared with other European countries, these expectations are quite ambitious.

2.2.3 Driving range

The driving range is the distance that an electric vehicle can cover on a full battery. According to the manufacturers, the driving range is around 140-160 kilometres. This value is based on the EPA city driving cycle and Japanese test cycle (Nissan, 2010). However, this is measured under ideal conditions. If you verify some driving conditions and climate controls the range decreases by about 35-45% (Bullis K., 2010, Autozine, 2010). If some more energy consuming conditions, like bad driving style, load, traffic conditions and accessory use, are combined the maximum driving range decreases even more. Some tests even show that driving during busy circumstances, a lot stop and-go-traffic (traffic light / traffic jam) and when the air conditioning is used or the heater is on (to maintain some comfort) the driving range drops below 50% of the promised driving range (Nissan leaf assumed[3], source: Nissan, 2010).

Range anxiety

In addition, there is also a fear of getting a flat battery and get stranded on a roadside. The name for this phenomenon is ‘Range anxiety’, and is one of the most common (71%) perceived disadvantages of EVs (CEA, 2011). Although the remaining range is displayed quite precisely on the display and the locations of chargers have been incorporated in navigation systems it still is a problem. The result is that users want to charge the battery (far) before the battery is flat. In other words, they use only a part of the possible driving range.

A realistic driving range can be estimated if all negative factors are taken into account in a certain degree. For the current EVs (2011), a driving range of 80 kilometres is assumed. In this value both physical and psychological reasons for a driving range decrease are incorporated. More information is attached in annex B.

Future developments

The capacity of the battery is the most important aspect to increase the driving range. Therefore, a lot of research is conducted to improve the driving range. New types of batteries will allow faster charging and/or have more energy storage. To make EVs more acceptable, major steps have to be made (see Figure 11). How rapidly new technologies will be available on the market is unknown, this will depend on the cost of production. In Appendix C, three new kinds of batteries are examined.

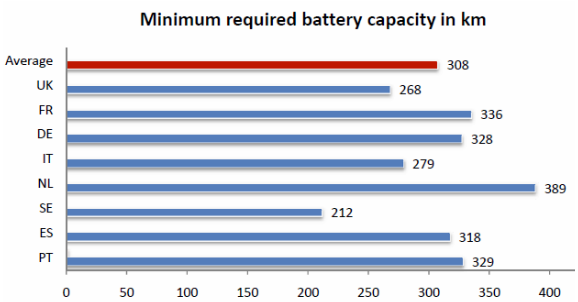


Figure 11, minimum required battery capacity in km (ECN, 2009)

[3] Most sold car (AgentschapNL, 2012)

2.3 Charging

2.3.1 Charging levels & fast charging

To charge the battery of an EV, the alternating current (AC) from the electrical grid has to be transformed to direct current (DC). How long it takes to charge the battery depends on the rectifier, a device that concerts AC to DC. Cost and thermal issues limit how much power the rectifier can handle. Different modes and permissible connections are specified in the standardization of the International Electrotechnical Commission. Here, four modes are distinguished, of which three are used for slow charging and one for fast charging.

Modes of charging

Mode 1, slow charging. The vehicle is connected to a single-phase (250V) or three phase (krachtstroom, 480V) AC network, using the most common voltages and currents (16 A). This charging mode is prohibited in certain countries due to the lack of earthing.

Mode 2, slow charging. The vehicle is also connected to a single phase or three phase AC network. The difference with mode 1 is that the supply network may not exceeded 32A and has an in-cable safety device implemented.

Mode 3, slow/fast charging. The vehicle is connected using dedicated electric vehicle supply equipment (EVSE). This means that a specific EV socket-outlet with control and protection function is installed. With required specialized cables and access to the three phase AC network (eventually smart grid) it is also possible to charge with higher currents up to 250 A

Mode 4, fast charging. This mode charging allows high power levels performed with either a DC of an AC connection. In the DC case, the battery is connected with a rectifier, leading to heavy and expensive infrastructure, whereas for AC fast charging the rectifying is done on-board. Both connections can handle power levels up to 250 kW, decreasing the charge time to less than 10 min. For chargers in this mode a three phase power grid is necessary. In the Netherlands the three phase network provides a power of 50 kW.

The different modes with associated voltages and currents are shown in Table 1.

Table 1, Different modes with respect to charging (INTERNATIONAL STANDARD IEC 62196-1, 2006)

Mode	Charging station	Voltage (V)	Amps (A)	Phases / Volts	Power (kW)
1	*Slow charger*	*230*	*16*	*1* *3*	*3.7*
2	*Slow charger*	*230*	*32*	*1* *3*	*7.4*
3	*Slow charger*	*230*	*16* *32*	*1* *3*	*11.1* *22.2*
	Fast charger	*400*	*250*	*1* *3*	*50*
4	*Fast charger*	*400*	*400*	*-*	*50* *(Netherlands)*

2.3.2 Charging time and capacity

The time that is required to fully charge a battery depends on a number of aspects, such as the type of the battery and the power of the charger. How long it takes to charge a vehicle can be determined by a simple calculation (Bossche, 2010). An example is given:

A Nissan Leaf with a weight of 1500 kg has an energy consumption of 200 Wh/km. This implies that for a trip with a distance equal to the driving range according to the manufacturer (160 kilometres), 32 kWh is required (200 Wh/km x 160 km).

The time that is needed to charge 32 KWh depends on the power available and on the rating (mode) of the charger. For European countries the normal charge rate with the standard outlet (230V, 16A) is 3.7 kW. This means that the battery will be full in 32/3.7 = 8.65 hour. The charging rate can be expressed in km/h for the example, the rate is about 160/8.65 = 18.5 km/h.

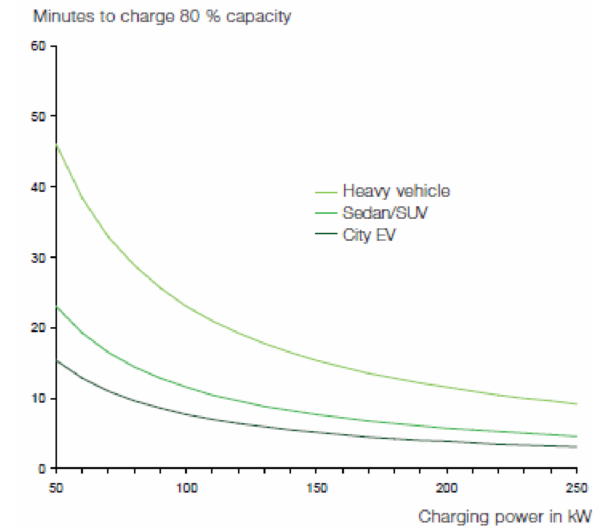


Figure 12, Charging time versus the charging power. Minutes required to charge 80% of the capacity (ABB, 2012)

Fast chargers can cope with much higher power levels, these are currently limited to 50 kW in the Netherlands (three phase). This will greatly shorten the charging time. When charging the same battery as mentioned in the example, the charging time will decrease to 38 minutes (=32 KWh/50 kW). Converted to a capacity of 80%, this means 32 minutes. This is 250km/h. (13.5 times faster than slow charging).

Future developments

The charging time will decrease as higher charging powers will be used. This relationship is illustrated in Figure 12. The figure shows that it is possible to reduce the charging time to less than 10 minutes. In addition, new type of batteries ensures that the charge time will decrease. These are explained in appendix B.

Capacity

As mentioned in the above, a fast charger can charge an electric vehicle to about 80% in less than 30 minutes. However, in many cases it is not necessary to charge up to 80%, for instance when a destination is almost reached. If there is a possibility to charge at the next destination, it would be a waste of time to charge longer than necessary. The capacity of a charger can be estimated by taking this behaviour into account. This value will be determined in chapter 5.

2.3.3 Current and future charge locations

Current

In the Netherlands are currently about 1800 (slow)charging stations (ANWB, 2012) and 14 fast charging stations (AgentschapNL, 2012). A major part of the chargers, approximately 300 (slow)chargers and 7 fast chargers[4], are situated in Amsterdam and more are planned. The current locations are depicted in Figure 13. These locations are determined on the basis of some characteristics (de Haas, 2011); these are discussed in section 2.3.5.

Future

At the end of 2012, ten thousand regular (slow) chargers have to be installed in the Netherlands, according to the ANWB (ANWB, 2012). To achieve this, the current market players should expand their network or new operators should enter the market.

[4] www.oplaadpunten.nl, maps.google.nl, ANWB.nl, leafhebbers.nl

In late January 2012, Rijkswaterstaat announced that they will expand the nationwide network with 459 new fast chargers (NOS, 2012). These will be installed on parking lots along highways, the locations are shown in Figure 14. Another market player is The Green Motion. Their ambition is, in collaboration with Epyon and Essent, to expand their network with 80 fast chargers across the Netherlands (The new Motion[5]). The exact locations are not yet known, but probably few will be placed in and around Amsterdam. The last big market player is Total; this fuel company will realize seven fast chargers in the Netherlands to provide a better market position (Groen7, 2012). In addition, also governments want to contribute to the promotion of EV by placing fast chargers.

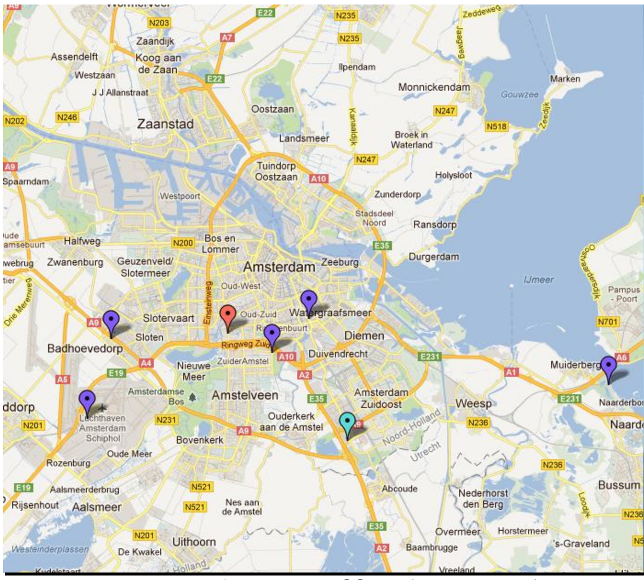
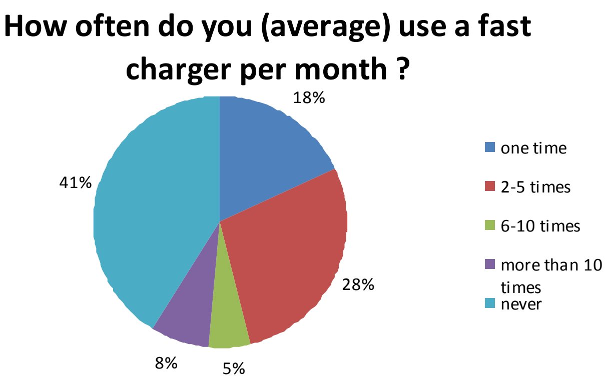


Figure 13, current locations of fast chargers in the Amsterdam region (Leafhebbers, 2012)

Figure 14, current (yellow) and planned (green) locations of fast chargers in the Netherlands (NOS, 2012)

2.3.4 Usage of current fast chargers

How often the current fast chargers are used is unknown. Currently some tests are performed to monitor the usage. In a survey conducted among EV users (GC, AgentschapNL, DIVV, 2012) it is asked how often they use the current fast chargers, the result is presented in Figure 15. This graph shows that a majority of the surveyed EV users has used a fast charger once. However, the use per month is low. In addition, it was asked if the installation of new fast chargers will lead to more usage. A majority (61%) said here that they will do so, presented as a graph in Figure 16.



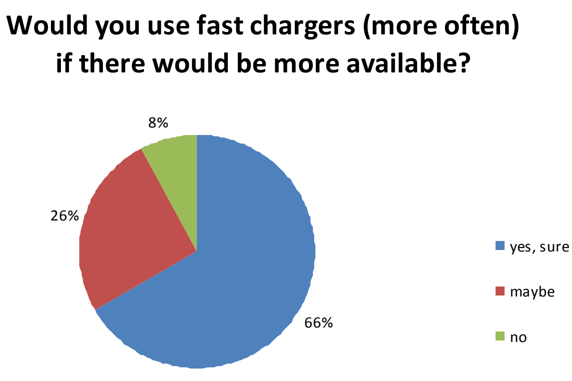


Figure 15, Usage of current fast chargers

Figure 16, usage of fast chargers when more are present

[5] http://www.thenewmotion.com/

2.3.5 Requirements for new locations

The locations of the current fast chargers have been determined on the basis of several criteria (Haas, 2011). From the perspective of a user, these criteria are:

- Near or nearby highway. *It is assumed that most EVs are driving over there;*
- Easy to find. *Fast chargers should be placed at locations where you would expect them;*
- Presence of 'distraction'. *Charging takes about half an hour. To spend this time well, the presence of surrounding facilities (e.g. to drink something) will be fine to "kill time". However, the activity should not take longer than 30 minutes; otherwise queues can occur due to unnecessary occupied chargers. Therefore it should be well considered nearby what activity a fast charger is placed.*

In order to save money, the following aspect may be relevant:

- Accessible from two ways. S*ince fast chargers and connecting a fast charger to the power grid is expensive, it is a waste of money to place chargers on both sides of the road. In addition, two chargers at the same location are not always required.*

Another criterion in the choice of fast charger locations is the presence of an appropriate infrastructure (three phase network). However, this aspect is not taken into account in this thesis.

In the survey of DIVV, AgentschapNL and Goudappel Coffeng is also asked what the EV users would like to do when they have to wait for some time at a charger. The result shows (Figure 17) that a Wi-Fi network will be valuable; in this way drivers can work while waiting. In addition, a cup of coffee or something to eat is desirable.

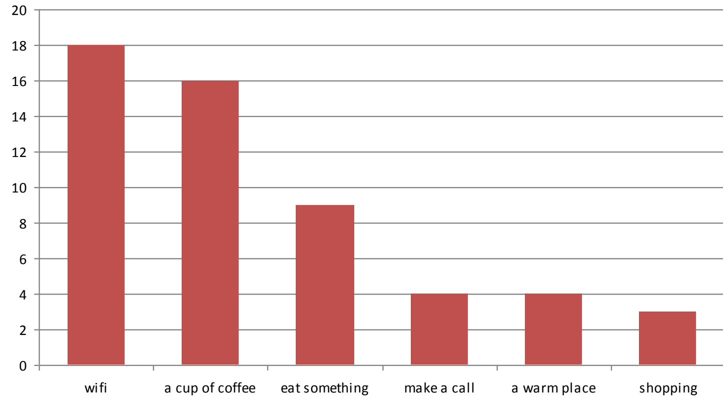


Figure 17, What is preferred to do while waiting? (GC, DIVV, AgentschapNL)

2.4 *Defining the potential market*

In order to determine which users require and might use fast chargers, some aspects have to be considered. As mentioned earlier, the distance to be driven and behaviour play a role. Both of these aspects will be explained.

2.4.1 Definitions

There are several ways to analyse individual or grouped travel behaviour. Three terms related to this are used frequently in this report. To avoid misunderstandings the differences are outlined below.

- **Trip:** A trip is a single movement from one place (origin) to another (destination). See Figure 18.
- **Tour**: A tour consists of multiple trips in a row. A tour is completed when the origin of a first trip and the destination of a trip are the same (see Figure 19).
- **Daily pattern:** A daily pattern shows how someone travels over a day. This can consist out of multiple tours. An example is given in Figure 20.

In this thesis only trips, tours and daily patterns made by a car are considered.

Figure 18, Example of a trip

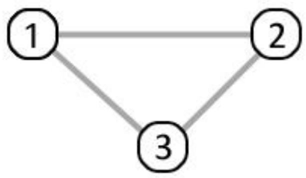


Figure 19, Example of a tour

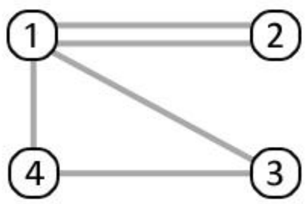


Figure 20, Example of a daily pattern

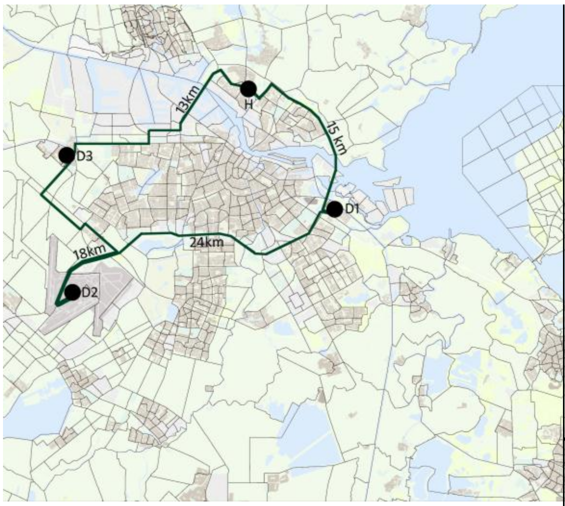
2.4.2 Relevant and non relevant daily patterns

The aspect that determines whether a driver have to use a fast charger is the distance that can be driven on a full battery.

A daily pattern can be made without charging en route when the driving range will not drop to 0 while driving, assuming a full battery at departure. These daily patterns are considered non relevant.

If the total distance of the daily pattern is larger than the driving range, than the remaining driving range will drop at some point on the route below 0 assuming that there is no possibility to charge at a destination. This implies that the EV is not able to complete the daily pattern. In this case, a fast charger is required. These daily patterns are assumed relevant, or in other words: these daily patterns might be 'electrified' if a fast charger is somewhere along the route.

Figure 21 shows a daily pattern that doesn't require a fast charger; the driving range doesn't drop below 0. In other words, the total distance of the daily pattern (68km) is shorter than the assumed maximum driving range (80km). On the other hand, the daily pattern outlined in Figure 22 requires a fast charger. The total length of the daily pattern (92km) is larger than the assumed maximum driving range. If the EV user doesn't charge, than he or she will strand somewhere between destination 2 and 3. This is the point in the graph where the driving range will turn negative.



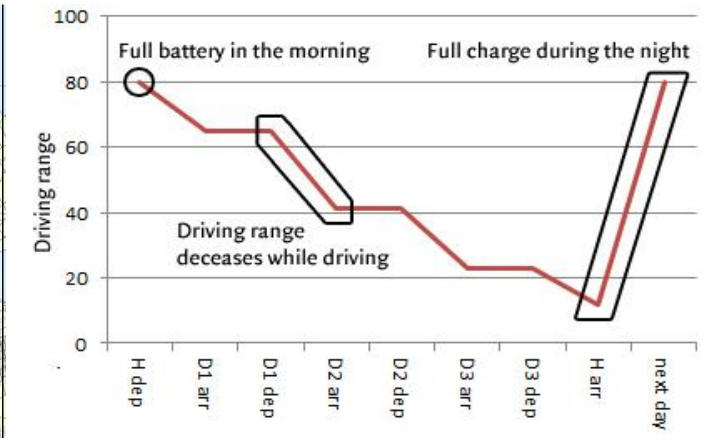
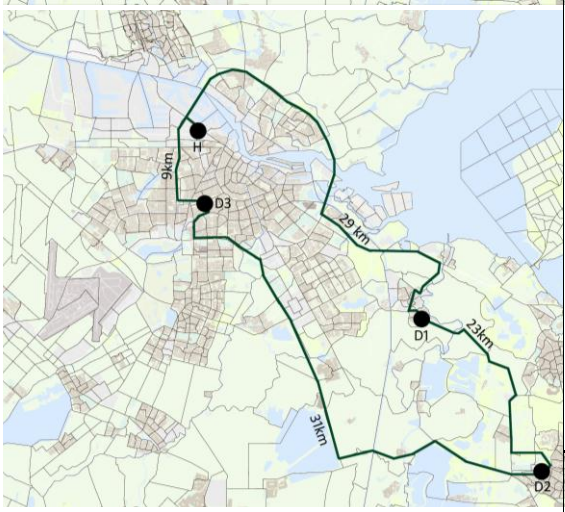


Figure 21. An imaginary daily pattern that doesn't require a charge en route (non-relevant)



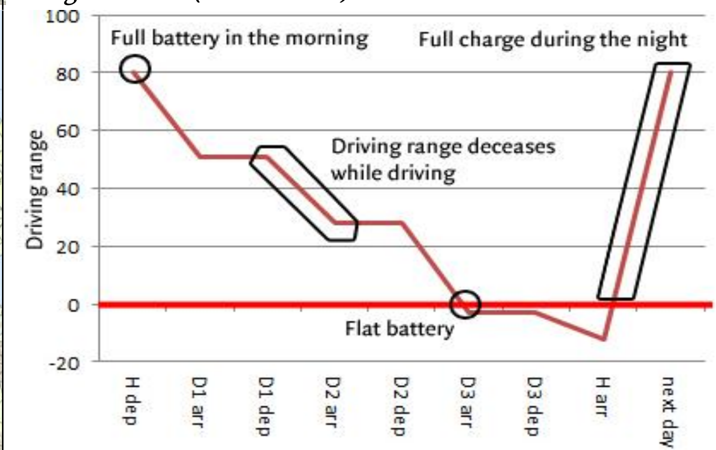


Figure 22. An imaginary daily pattern that does require a charge en route (relevant)

From a behavioural perspective can be assumed that a driver does not want to wait twice a day. This assumption is based on the fact that a single time loss is actually not desired. Daily patterns with a total distance of more than twice the driving range are therefore not relevant. The expectation is that these patterns will always be made with a conventional car or by public transport.

Presence of slow chargers
Finally, there is an aspect that will influence whether a daily pattern is relevant or not. Because a daily pattern can consists of multiple tours on a day, there is a probability that the EV temporary returns home between two tours. In the time that the EV is not in use it can be charged if a (slow)charger is present. In addition, the EV can also charge at activity end (somewhere at a destination). The extent to which the driving range is recharged depends on the time between arrival and departure and the type of charger. In both cases, daily patterns with a total distance which is larger than the driving range can possibly be made without an intermediate charge.

2.4.3 Size of potential market

An analysis is performed to determine how many daily patterns belong to the relevant group in the Netherlands with respect to travel behaviour. For this analysis, the Dutch National Travel Survey (MON/OViN) is used. It is important to notice that the percentage of the relevant daily patterns is not equal to the (extra) number of potential EV users. Therefore, a longer period should be studied[6].

It is assumed that the battery is fully charged at the start of the day and the EV will not be charged at any destination (home and activity end). According to the data from the MON (2008), in almost all daily patterns (99%) there is sufficient time to fully charge the battery at night. This is studied by calculating the time between the last and the first trip of a daily pattern. Using this information, approximately 81% of the daily patterns are shorter than the assumed driving range (80km) and 7% is larger than twice the driving range (160km). Because of those two filters, 12.1% of the daily patterns are relevant on a single day. This number will decrease if a larger driving range is assumed or when chargers are present at home or activity end. These effects are studied in chapter 6.

[6] This is further elobarated in the reflection

2.5 Conclusions

The concept of driving using one or more electric motors for propulsion is actually an old concept. However, it has never been competitive because of internal combustion engine cars being cheaper. Since several years, electric driving is again a hot topic. Rising oil prices and sustainable development ambitions have enhanced the market opportunities for electric cars.

The number of EVs in the Netherlands this year (2012) will probably exceed 2000. How many EVs there will be in the future is uncertain. Many studies show different scenarios with varying assumptions which results in different outcomes. The government has the ambition to have 200.000 EVs on the road in 2020. Electric vehicles use infrastructure to charge, which consists of regular chargers (charging time: 6-8 hours) and fast chargers (30 minutes). Currently (Feb. 2012) there are about 1800 slow charging stations and 14 fast charging stations situated in the Netherlands. The network of charging points will greatly expand upcoming years. According to plans, 10,000 charging stations and dozens of fast chargers have to be installed before the end of this year.

Whether someone (theoretically) requires a fast charger, and thus is a possible potential user, depends on his/her travel behaviour. An extra charge is required, assuming a full battery at departure, when the total distance of a daily pattern is larger than the driving range. A daily pattern presents, in this thesis, how someone travels over a day using a car. To determine how many daily patterns would require a fast charger, some filters have to be applied. The following daily patterns are considered not relevant:

- **The total distance of the daily pattern is shorter than the driving range**
  This implies, because it is assumed that the battery is full on departure, the daily pattern can be made with an EV without charging en route.

- **The total distance of the daily pattern is larger than twice the driving range**
  These daily patterns will not be made with an EV, because it is assumed that EV users do not want to wait twice a day.

A non-relevant daily pattern is depicted in Figure 23 and a relevant daily pattern is shown in Figure 24 assuming a driving range of 80km.

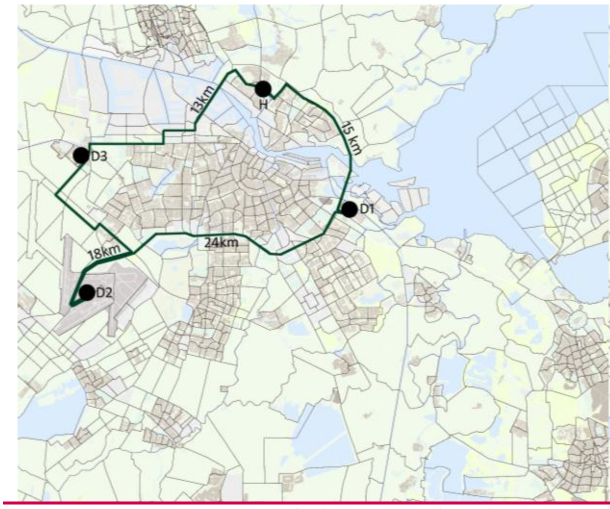


Figure 23. An imaginary daily pattern that doesn't require a charge en route (non-relevant)

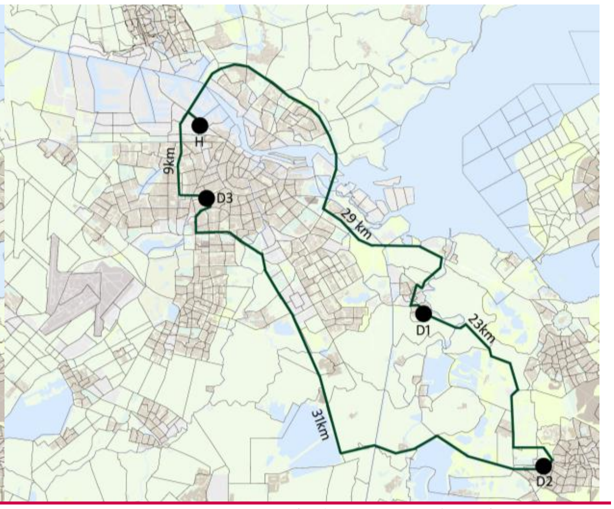


Figure 24. An imaginary daily pattern that does require a charge en route (relevant)

Around 12,1% of the daily patterns on a day is characterized as relevant meaning: can be performed by an electric car if there would be fast chargers on that route. The aspects that influences whether a daily pattern is relevant are: driving range and the presence of slow chargers.

3 THEORETICAL FRAMEWORK

3.1 Introduction

The outlined market of fast chargers and the related user group that is described in chapter 2 is the basis for the methods developed in this chapter.

This chapter consists of three parts which will eventually lead to the best feasible method to determine the optimal locations for fast chargers and the corresponding number of chargers. The chapter starts with an explanation of those steps. Here, some conditions and assumptions are set to simplify the problem.

Datasets

In the first part, datasets are studied which contain data about the aspects that are considered to be relevant in the analysis. This will be the input for the method. The datasets are compared and evaluated on the criteria set.

Translation into spatial representation of the demand

In the next step, methods are studied that can be used to translate (raw) data into a spatial presentation of the demand for fast chargers. The data derived from the datasets can be processed and presented in different ways. Four possible ways are studied. To determine the expected demand in a certain year, some aspects such as market share of the EV fleet, charge behaviour and distribution over time are analysed. This results in a factor which has to be applied. In the end, the options are compared and evaluated.

Allocation methods

In order to determine at what locations fast chargers have to be installed (allocation) to serve the in demand determined in the previous step, different algorithms are studied. Using the capacity of a single fast charger and a stop criterion, the locations and number of chargers can be determined. Again, the options are compared and evaluated.

The best and most feasible option per step combined lead to a method that is supposed to provide the most reliable results. This method is summarized at the end of the chapter. Also possible problems are briefly described at the end.

3.2 *Structure of the method*

Chapter 2 showed which aspects are relevant to determine whether a daily pattern requires a fast. This information is used as a basis for the steps that are developed. These steps provide insight into the methodology followed.

Datasets
The relevant daily patterns are input to find an optimal configuration of fast chargers. Different datasets are studied and compared to find out what data can be used best.

Translation into spatial representation of the demand
Of all patterns that require a fast charger, following from the dataset and applied filters, the desired location(s) for a fast charger have to be determined. These locations have to be plotted on a map in order to find a spatial distribution. The methods that can be used in order to perform this translation are explained in this section. The purpose of this step is to create a map containing the demand within a certain area.

Allocation methods
In the last step, allocation methods are studied that can be used to determine an optimal configuration of fast chargers that will serve the demand as good as possible. A distinction is made between a mathematical approach in the form of algorithms and an approach from the perspective of spatial planning. Finally, an overview of the pros and cons of each method is given.

3.3 *General assumptions & conditions*

To make the problem soluble, some assumptions are set. The following principles and assumptions apply to all options in all steps:

- **Driver behaviour will not change over time**
  It is assumed that the driver behaviour will not change in a way it will affect the locations of the fast chargers. This is about the fact that a driver can make his or her total daily pattern using an EV ('electrify') without changing his driving pattern.

- **A driver will not change car if the driving range is insufficient**
  A daily pattern can consist of multiple tours in one day. It might happen that a driver will return to home between two tours. If the driver wants to make another tour with a distance larger than the remaining driving range, he or she can switch car (if available). However, this is not the aim of this thesis. In other words, it will not contribute to more EV kilometres.

- **Full battery at departure**
  In addition, it is assumed that anyone who owns an electric vehicle can charge it at home. If everyone is at least 8 hours at home during the night, it means that the battery is full at departure the next day.

- **No chargers at activity end**
  It is considered that no chargers are available at activity end or that they will not be used. In other words, the driving range does not increase in a daily pattern.

3.4 Datasets

In the first step three datasets are studied to find out what dataset suits the problem best. Data of the Dutch National Travel Survey, data derived from Albatross and data that is obtained from a traffic model have been compared. Based on the analysis, the following aspects are important:

- The dataset contains daily patterns (and not only trips or tours);
- Destinations in postal code or another division that can be used for spatial presentation;
- Distances between destinations, required to determine whether a pattern is relevant;
- Reliability / accuracy of the data (quality);
  The extent to which the data corresponds with reality.
- Size of the dataset (quantity).

Not necessarily, but interesting to analyse the effect of slow chargers at home and activity end is:

- Time of departure and arrival of each trip in a daily pattern
  The departure and arrival times can be used to make statements about the effect of slow chargers at activity end. The longer the time the EV is not in use, the more the battery can be charged if a charger is present.

3.4.1 Dutch National Travel Survey

The Dutch National Travel Survey (MON (RWS), OViN (CBS)[7]) is an on-going investigation into the mobility of the Dutch population. Each year, approximately 50,000 people participate in this study and the results are published every year. In the survey, people have to fill in how they travel over a single day (daily pattern). The MON/OViN contains the following information that is relevant for this study:

- The location of arrival and departure for each trip (4-digit postal code)
- The distance between destinations, filled in by the respondents (in kilometres)
- The time of arrival of departure for each trip (rounded to 5 minutes)

Using this data, a daily pattern can be presented with departure and arrival times. The postal codes of arrival and departure for each trip are based on four digits. The distance that is filled in on the form usually differs from the distance that is derived from a traffic model by means of a shortest path algorithm[8]. The respondents often make an estimate of the distance or/and do not always choose the fastest route. In order to obtain the most reliable results, the distance derived from the traffic model is preferred. This implies that always the fastest route between origin and destination is chosen. An example of a daily pattern is shown in Table 2.

Table 2, Example of a daily pattern using data of the MON/OViN

Postal code H (home)	Time of departure H (home)	Postal code D1	Distance H-D1 (in km)	Time of arrival D1	Time of departure D1	Postal code D2	Distance D1-D2 (in km)	Time of arrival D2	Time of departure D2	Postal code D3	Distance D2-D3 (in km)	Time of arrival D3	Time of departure D3	Postal code H	Distance D3-H (in km)
1010	8:00	1382	29	8:45	11:15	1242	23	11:35	17:30	1052	31	18:20	20:00	1010	9

To enlarge the dataset, and thus get more information about spatial distribution, the datasets of different years can be merged. The final dataset of the MON/OViN eventually contains around 117,000 daily patterns (years 2004-2010).

[7] New name since 2010
[8] Finds the fastest path between two points on a map

In principle, all daily patterns in the MON/OViN can be plotted. However, not all daily patterns are relevant to use, since not all of them require a fast charger (see the filters in chapter 2). In order to shorten the calculation time, the non relevant daily patterns are removed from the dataset. If the percentage that is calculated in the analysis in section 2.4.3 (12,1%) is applied, 15.000 daily patterns require en-route charging. Whether this is enough to obtain reliable results is unknown. This is further discussed in the comparison and evaluation.

To estimate the travel behaviour of the entire population, the sample should be multiplied with a certain value. A factor is included in the MON/OViN. However, this factor tells something about how many times a kind of pattern occurs. It is therefore not possible to make statements about the spatial travel behaviour of the entire population. Another problem may arise if the data of several years is stacked, the factors should be revised.

3.4.2 Albatross

Albatross is an activity-based model that is calibrated using data of the MON (Arentze, 2005). The model predicts which activities are conducted when, where, for how long, with whom and also which transport mode is used. The dataset has the same structure as the MON/OViN, it only contains fewer properties. The dataset that is available has base year 2004 and contains approximately 700,000 daily patterns. This data is generated data, which means it is a simulation of reality. The O/D matrices of the base year match reasonably well, the predictions are however uncertain (Zwerts, 2004).

3.4.3 Data from a traffic model

A traffic model can also be used as dataset. In a traffic model, the amount of traffic between zones (flow) is determined by different attributes and (trip generation) models. In this way, an O/D (Origin/Destination) matrix is obtained containing the number of trips between each zone within a certain period of time. A zone is an area in a traffic model, for example a postal code area. Time periods that are often used are: the morning rush hour, the evening rush hour and the rest of the day for an average workday. The result of a distribution of the traffic for a particular zone can be displayed in OmniTrans[9], an example for a zone in the area of Amsterdam is depicted in Figure 25. In this example, the model of VENOM[10] is used.

Only the relevant trips in the O/D matrix, the trips that require a fast charger, are used to analyse the optimal locations. This can be done by filtering all non relevant trips. By using the distance matrix, the relevant trips can be indicated. In the distance skim matrix, the distances between the different zones are shown; an example for three zones is given in Table 3 (left). Because the flows between the different zones are also known (right table), it is possible to make an estimation of the demand. The red numbers are relevant flows/intensities.

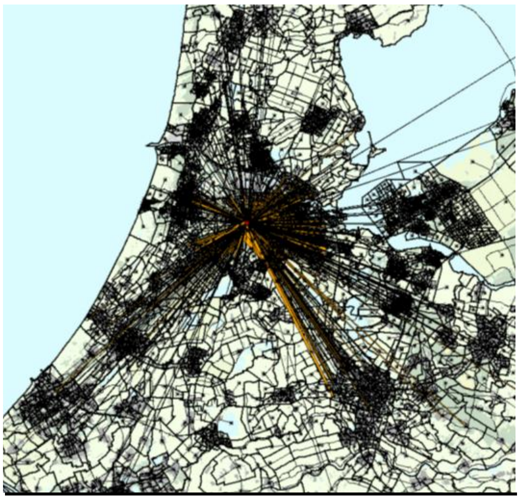


Figure 25, Distribution of traffic departing from a zone in Amsterdam (VENOM, OmniTrans)

Table 3, Example for three zones: the left matrix indicates (red numbers) which trips requires a fast charger if made by an EV. The right matrix shows the corresponding flows.

Distance	1	2	3
1	X	52	70
2	56	X	**95**
3	68	**91**	X

Flow	1	2	3
1	423	41	23
2	65	213	**5**
3	44	**10**	322

The drawback of this dataset is that the traffic model only contains information about single trips. As a result, more trips in a row (tours and daily patterns) cannot be analysed. If single trips are used, only a small part of the demand will be found. Furthermore, the trips indicated relevant in the example require another charge on

9 OmniTrans is a transport planning package (www.omnitrans-international.com)
10 More information about VENOM later in this thesis

the way back. It appears that the red numbers are non relevant trips, because it is assumed that only one charge per day is desirable.

Combining different O/D matrices of a day in order to create daily patterns is impossible, because there is no connection (e.g. car IDs) between the matrices.

3.4.4 Comparison

The datasets are compared and assessed on the set criteria. Besides this, the strengths and weaknesses of each dataset are given. There is no judgment made about which dataset is best/most reliable; this is done in the overall conclusion at the end of this chapter. The comparison of the datasets is shown in Table 4.

Table 4, Comparison of strengths and weaknesses of the datasets

Dataset	Strengths	Weaknesses	Daily patterns	Quality	Quantity
Dutch National Travel Survey	Real data Includes daily patterns Arrival and departure times between trips is known Purposes per trip distinguished	Sample: Only data of one day in a week and only a few years of data available. Quantity of data after filtering Factors required to find demand for entire population Data from the past	Yes	++	-
Albatross	Includes daily patterns More data in comparison with MON/OViN	Simulated data Fewer attributes Reliability of predictions unknown	Yes	O	O
Traffic model	Relevant trips can easily be filtered Entire population (Quantity) Present and future situation	Only contains trips Max. three periods of time Linking cars in different periods of time impossible	No	--	++

None of the studied datasets gets a positive score on all three criteria. The main disadvantage of the MON/OViN is the low number of daily patterns; the main disadvantage of a traffic model is the fact that it provides no information about daily patterns. This problem will be discussed at the end of this chapter.

3.5 Translation into spatial representation of the demand

The data from the dataset can be processed in various ways to translate the (daily) patterns into a spatial presentation of the demand for fast chargers. For this step some criteria are defined to which the methods are assessed. These are:

- Representation of reality and robustness
- Execution time and computation time

First, a distinction can be made in the determination of the desired location for a fast charger in a daily pattern. To find the desired location for a fast charger, two approaches can be used: the one-point approach and the two-point approach. The first approach assumes that in a single relevant daily pattern, there is only one optimal desired point on the route for a fast charger. The two-point approach uses an interval to indicate where a charger can be placed. Within both approaches, variety of ways can be applied to present the demand spatially.

Subsequently, the demand for a fast charger of all daily patterns has to be cumulated to create a total distribution of demand across the study area. Finally, some factors have to be applied to calculate the expected demand, the number of charges within a period of time, in a certain year.

3.5.1 One-point approach

The simplest way to determine the location for a fast charger in a daily pattern is to assume that there is only one point on the route which represents all demand. The probability of getting a flat battery is smallest midway; therefore this is supposed to be the optimal location. This point can be found by determining the total distance of a daily pattern and divide this by two. Subsequently, this distance and the first location of a daily pattern (usually home) can be used to calculate where on the daily pattern this point is situated. This is schematically shown in Figure 26.

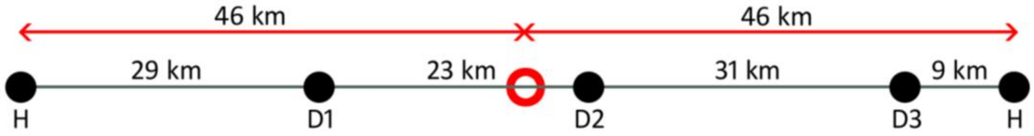


Figure 26, Determining the optimal location for a fast charger in a daily pattern using the one-point approach

To present this point spatially on a map, an area division is required. The desired location can be plotted in a straight line between the two relevant destinations. Advantage of this type of plotting is that it is easily executable. Drawback of this approach is that when no network is used, situations might occur that are inappropriate. For example, it is possible that if someone who wants to drive from Amsterdam to Leeuwarden has an optimal charge location somewhere in the IJsselmeer. Also other issues related to the landscape (rivers, lakes) might occur.

Adding a network will lead to more realistic and specific results, but is more difficult to implement. The optimal location is determined by finding the fastest route between the two relevant destinations using a traffic model. Using this information, the location will be assigned to a road segment.

The options are depicted in Figure 27 and Figure 28 for the daily pattern used earlier in chapter 2. In this case, the desired locations are quite similar.

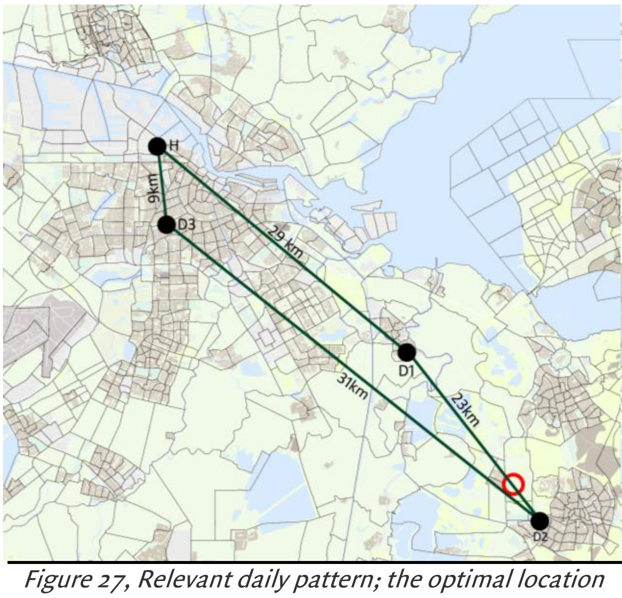


Figure 27, Relevant daily pattern; the optimal location is determined using the one-point approach (without network)

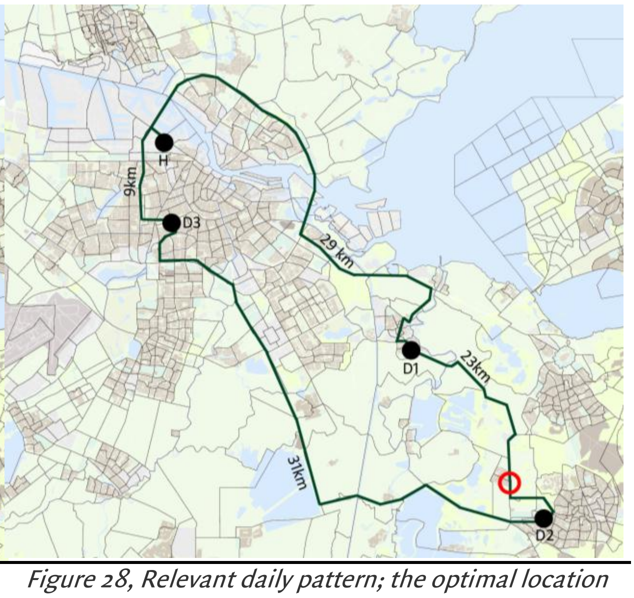


Figure 28, Relevant daily pattern; the optimal location is determined using the one-point approach (with network)

Presentation techniques: addition of relevant daily patterns

All desired locations of the daily patterns determined by the one-point approach can be plotted on a map. This can be done in two ways. First, it is possible to add all daily patterns without extra actions. This creates a map showing all the desired locations together (scatter plot). The higher the density of the points, the more attractive to allocate a fast charger to that area. An example is illustrated in Figure 29.

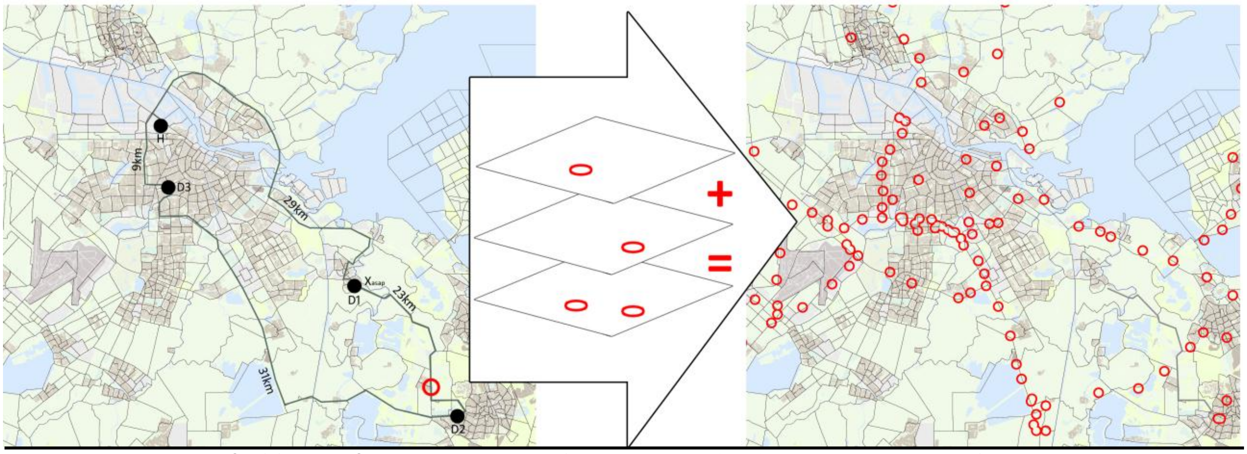


Figure 29, Result of addition of multiple relevant daily patterns that have been processed by using a point presentation

The second option makes use of an area classification. The desired location of a single daily pattern is no longer an independent object, but is assigned to a cell. Cells are created by a grid with a predetermined size. After adding up all the daily patterns, a distinction of potency can be analysed between the cells. The more points in a single cell, the more attractive it is to allocate a fast charger to that cell. An example is shown in Figure 30.

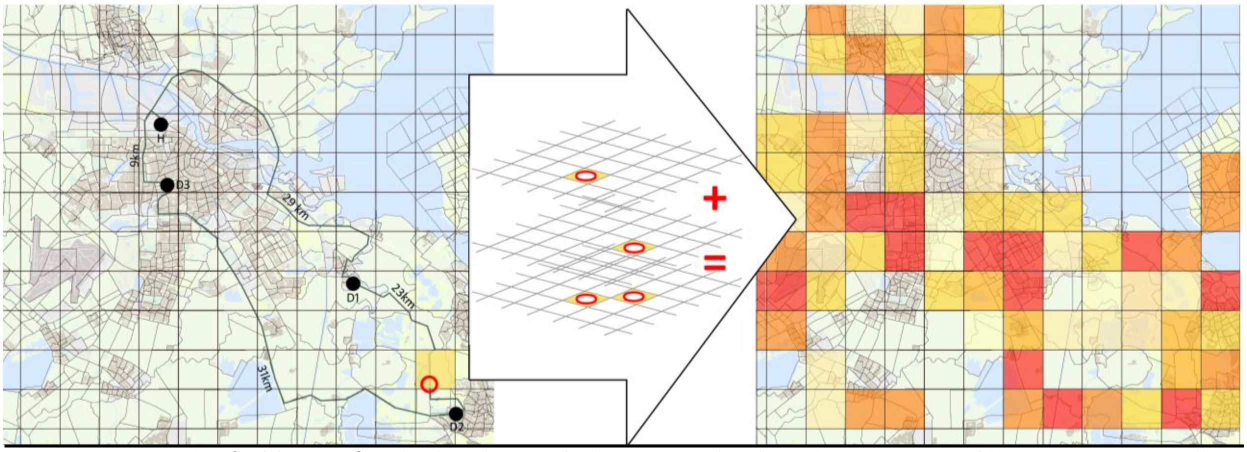


Figure 30, Result of addition of multiple relevant daily patterns that have been processed by using a point-cell presentation

3.5.2 Two-point approach

In order to 'electrify' a certain daily pattern, the fast charger doesn't necessarily have to be located on a single fixed point along the route, but is has to be located between two points. The path between these two points is named the potential interval.

- **The upper boundary of the interval (X_{alap})** is the last opportunity to charge: this will be the location someone gets a flat battery if he or she drives as long as possible without charging. The location of this point is determined by summing up the road segment distances until it exceeds the driving range.

- **The lower boundary of the interval (X_{asap})** is based on the fact that the battery will be empty at the final destination after a full charge (100% of the assumed driving range, this is not equal to the technical range due to range anxiety). If it is assumed that all the EV users can charge at home, this will be the most extreme case. The beginning of the potential interval can be determined by counting back from the final destination.

However, it is not desirable to charge as soon as possible. From the perspective of human behaviour, it is assumed that an EV user does not want to charge if he or she is almost at a destination. It is conceivable that it is boring when someone who is almost at a destination still have to spent time on charging and has also, since it is in the beginning of the potential interval, a (reasonable) chance to get a flat battery before arriving at the final destination. This modification is implemented for all daily patterns that consist of more than two trips.

In order to clarify the two-point approach, the example used before is elaborated (see Figure 31). The last option to charge (X_{alap}) is easy to determine, this is the driving range (80km) from the starting point. The first possible location to charge is located between D1 and H (92-80 = 12km). Because of the set conditions, however, X_{asap} will be located at 63 kilometres before the final destination at D1. The length of the potential interval for this particular daily pattern is thus 51 kilometres.

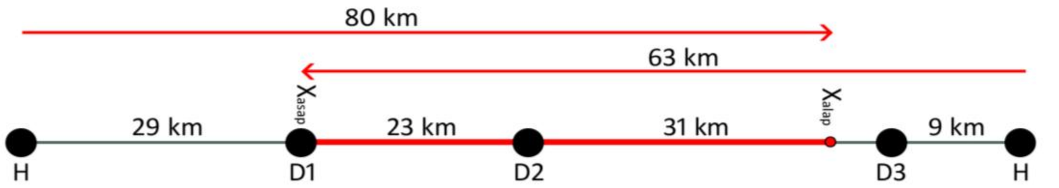


Figure 31, Example of the determination of the potential interval by defining X_{asap} and X_{alap}

Presentation techniques: addition of relevant daily patterns
The two-point approach can only be presented spatially using a network. Again, two possible ways are studied to translate the demand of a single daily pattern into a total spatial configuration. In both ways, the potential interval is converted to potential road sections.

The demand for a fast charger is not evenly distributed over the road sections. From a behavioural perspective, EV users will prefer to charge halfway than at the edges of the potential interval despite the fact that the charging time will everywhere be the same. In addition, the theoretical probability of getting a flat battery is smallest near the centre of the interval. Different distributions can be used to implement this, such as the normal distribution and the Poisson distribution. The distribution that fits the charging behaviour best is further elaborated in chapter 4.

In the first method studied, all road sections in the potential interval will receive a part of the demand. This is named a link score. The link scores of all relevant daily patterns can be added to find a total distribution. This method is shown in Figure 32

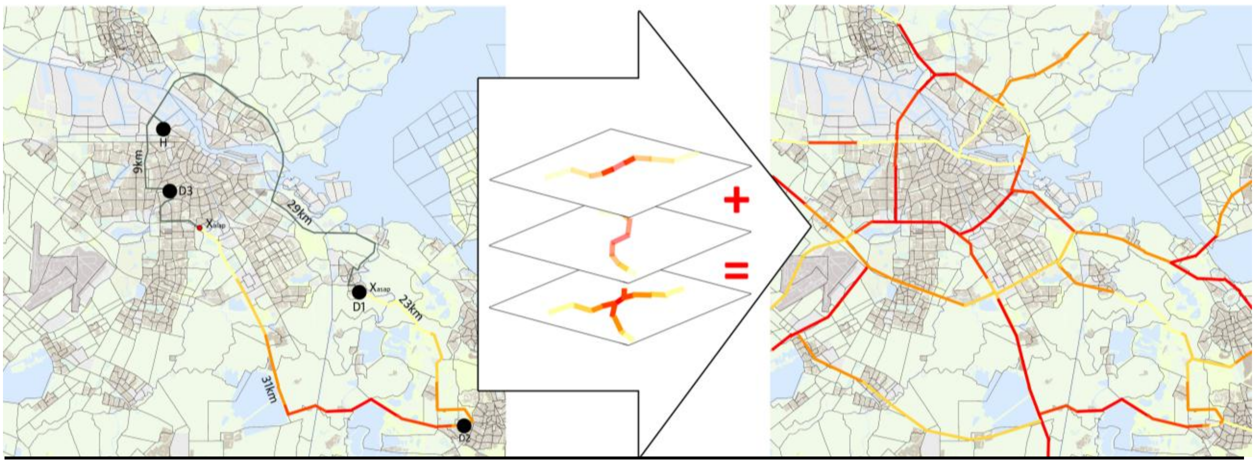


Figure 32, Result of addition of multiple relevant daily patterns that have been processed using a link presentation

The principle of the second option is to assign the road section scores (link scores) to cells. In this way, the cells containing potential road segments will get a (cell)score. This cell score is obtained by adding the link scores situated in that cell. After the addition of the cell scores of all relevant daily patterns, the area is divided in potential and less potential cells. An example is illustrated in Figure 33.

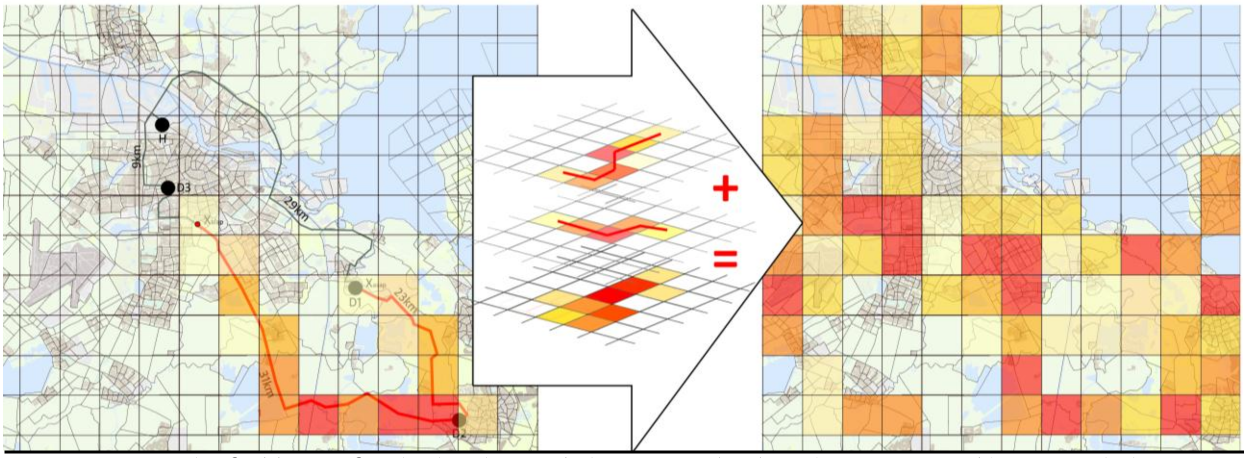


Figure 33, Result of addition of multiple relevant daily patterns that have been processed by using a link-area presentation

The total links and cell scores provide information about the demand for fast chargers in a given cell. Allocating a fast charger to the cell with the highest score (most red), will lead to a maximum number of daily patterns that can be 'electrified'.

3.5.3 Translation to expected demand

The result, both in the one-point-approach as the two-point approach, cannot directly be transformed into the demand, the number of charges in a certain year. Therefore, some aspects have to be considered.

- **Market share of the EV fleet and charge behaviour**
  Firstly, not everyone has an electric vehicle and will therefore not use a fast charger. It is assumed that the market share is evenly distributed over the daily patterns and start zones. Secondly, not all EV users will make use of a fast charger. Extra travel time, costs, negative effects on the battery and other aspects can discourage users to make use of them.

- **Peak hour**
  Another aspect is the distribution of the demand over time: not all demand is evenly distributed over the day. In fact, most EV users have to charge at the end of the afternoon (OViN, 2010, appendix E), assuming they depart every morning with a full battery. Here, the question arises whether there should be designed at peak times or on a uniformly distributed demand.

- **Distribution of potential in the two-point approach**
  In the two-point approach, the demand of a single daily pattern is distributed over the potential interval. As a result, the demand on a particular link or in a particular cell will not be the same as the score presented. To calculate the actual number of relevant daily patterns that can be served by allocating a fast charger to a link or cell, a tool have to be developed.

The magnitude of these parameters are defined in Chapter 4

3.5.4 Comparison

The different approaches that can be used to translate information about daily patterns into a spatial presentation of demand are compared and assessed on the set criteria. Besides this, the strengths and weaknesses of each approach are given. There is no judgment about which method is best/most reliable, this is done in the overall conclusion at the end of this chapter. The comparison of the methods is shown in Table 5.

Adding a network is not difficult to implement and a key aspect to get reliable results. Therefore, all methods will make use of a network.

Table 5, Comparison of the methods that can be used to translate data into a spatial distribution of demand

Options	Strengths	Weaknesses
One-point approach	Easy to implement Computation time	More than one location possible Robustness
• *Point* • *Point-cell*	*Easiest to execute* *(small) detour factors included*	*Robustness* *No exact location*
Two-point approach	More than one location possible	Additional programming Computation time
• *Link*	*Locations along roads (realistic)*	*Longer links will be more potential due to the distribution used*
• *Link-cell*	*Detour factor included* *Effect of link length differences eliminated*	*Additional programming* *Computation time*

3.6 *Allocation methods*

The data from step 1 is translated into a spatial representation in step 2. This result is used to allocate fast chargers to the most potential locations. These locations are the locations that serve most relevant daily patterns. In other words, most patterns will be 'electrified'. The objective is to allocate the fast chargers as good as possible such that the demand is served in a most efficient way. To achieve this, different algorithms have been studied and evaluated. In addition, the problem is also analysed from a non-mathematical perspective containing a comparison with the locations of petrol stations. First, the objective function is given.

3.6.1 Objective function

The addition of a fast charger will ensure that a part of the demand in an area will be served. This implies that car drivers that have a daily pattern with a desired location or potential interval on the location where a charger is placed, now have the possibility to make the daily pattern also with an EV (are electrified). It is likely that the first fast chargers will be used at maximum capacity. After allocating a number of chargers, a new fast charger will no longer be used with a maximum capacity since the demand decreases below a certain value. If the aim is to meet 100% of the potential, most of the fast chargers will barely be used. The objective function that belongs to this problem is globally shown in Figure 34.

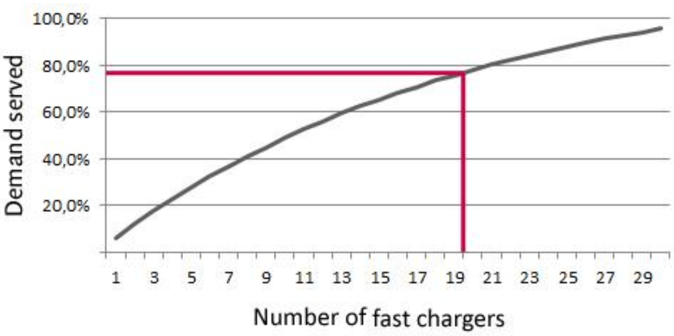


Figure 34, Example of an objective function globally plotted

The derivative of the line in the graph is the expected number of charges, the demand, for each (additional) charger. At a certain number of charges per time unit, a fast charger will no longer be profitable: the costs for the installation of a new charger are higher than the yields (MC>MR[11]). The minimum required number of charges to make a fast charger profitable differs per scenario (production costs, yields per charge etc.). This value can be used to determine how many fast chargers are required, and how much of the demand

[11] marginal cost exceeds marginal revenue

will be served. For example, the red line in the graph indicates a result of an optimization (19 chargers serve 78% of the demand).

3.6.2 Optimization Algorithms

3.6.2.1 Requirements

In order to find out what algorithm can be used best to find a solution, some criteria are set. The algorithms are assessed on the following aspects:

- **Quality of the solution**
  The optimal configuration is found when with minimal number of allocated chargers a maximum number of daily patterns is served, as the objective function describes. To achieve this, a global optimum has to be found (and thus no local optimum)

- **Computation time:**
  The time required to find an optimal solution.

- **Development/programming time.**
  Some algorithms are easily programmable and can be applied without a lot of extra work to this specific problem, while others are much harder to apply. Extra additions to the standard algorithms can for instance be related to the implementation of a maximum distance between points (one-point approach) or effects on surrounding links (two-point approach). This difficulty is estimated to determine the degree of feasibility. If it appears that an algorithm costs too much time, it will not be chosen.

The algorithms that can be used to allocate chargers can be divided into two main categories: one-by-one and simultaneously. Not all algorithms can be applied to both approaches.

3.6.2.2 One-by-one

Greedy algorithm

A greedy algorithm makes the locally optimal choice at each stage with the hope of finding a global optimum (Kuehn, 1963). In the case of allocation fast chargers, the optimal choice is the road section or the cell with the highest score. If a fast charger is placed there, the demand that is served by the fast charger is removed from the total demand. Subsequently, again the road section or the cell with the highest score is determined. This step is repeated until adding a new fast charger is no longer profitable.

Drop algorithm

This algorithm can only be used when predetermined fast charger locations are used as input. The least attractive supply location, the one with the lowest number of expected charges, will be removed from the dataset (Chardaire and Lutton, 1993). An optimum is reached when the removed fast charger has more expected charges than the value (stop criteria) that is assumed. In other words, the removed the fast charger was profitable. (MR> MC).

Allocating fast chargers one-by-one does not take into account the fact that new locations can influence old locations. It is conceivable that adding a fast charger nearby an existing fast charger will lead to a decrease the demand of the existing charger. It is therefore possible that this will result in a local optimum and not the desired global optimum.

3.6.2.3 Simultaneously

The points can also be distributed simultaneously. This will lead to an improvement of the solution, since the same number of chargers will serve more demand (Kaiser, 2000). The optimal configuration of a future situation have to be determined (simultaneously) and can be achieved by placing fast chargers one-by-one since placing all fast chargers simultaneously will result in unprofitable chargers in the first years. Eventually, the configuration will be better than placing chargers one-by-one.

Hierarchical clustering
Determining the locations simultaneously can be performed by means of a clustering algorithm. Clustering is a process of partitioning a set of data (or objects) in a set of meaningful sub-classes, called clusters (Botta, 2002, Tan, Steinbach and Kumar, 2004). The cluster algorithms can be divided into several categories, the main distinction can be made between hierarchical clustering and partitional clustering. Partition clustering is a division of the set of data objects (n) into non-overlapping subsets (clusters (k)) such that each data object is in exactly one subset. If it is allowed to have sub clusters, then hierarchical clustering is obtained. In this way of clustering the set of nested clusters are organized as a tree, also named dendrogram.

Agglomerative (bottom-up): merge clusters iteratively
In this method all objects (points) are placed in its own cluster (k=n). Subsequently, several objects, for example closest to each other, are combined (Johnson, 1967). This is done until all objects are in the same cluster, leading to several sub clusters and levels. This results in a dendrogram. The number of clusters, which is relevant for the number of fast chargers, can be determined to select different levels. This way of hierarchical clustering is most commonly used.

Divisive (top-down): split a cluster iteratively
This method is exactly the opposite of the bottom up approach. Instead of starting with as many clusters as objects (k=n), now all objects are in one cluster (k=1) and subdividing them into smaller sub clusters. Divisive methods are not generally available, and have rarely been applied.

The k-median/k-means problem
The k-median/k-means problem is one of the larger class of problems known as minimum location-allocation problems (MacQueen, 1967). It aims to partition n objects into k clusters in which each object belongs to the cluster with the nearest mean or median (Moore, 2001). The objective is to minimize the total distance from desired locations to cluster centres (fast chargers) (e.g. using a squared error function).

Enumeration (global optimum)
Enumeration calculates all possible combinations to find a global optimum. For a small data set, this method will give the optimal solution within a tolerable calculation time (depending on processor). However, when more data have to be analysed the calculation time will increase exponentially.

Branch and bound
Branch and bound algorithms can be described as systematically enumerating all possibilities, but every possible set of solutions, or branch, is examined first to determine whether the set might contain a better solution than the current selection (Land & Doig, 1960). It starts with considering a root problem and the lower-bounding and upper bounding procedures are applied to the root problem. The two basic stages of a general branch and bound method are:

- Branching: *splitting up the problem into sub problems*
- Bounding: *calculating lower and/or upper bounds for the objective function value of the sub problem*

If the branch might contain a better solution the branch is explored, if not the branch will be skipped. An optimal solution is found if the bounds match. Whether an optimal solution is found depends on the quality of the estimate of the bounds.

Genetic Algorithm
Genetic algorithms (GA's) are based on the evolutionary ideas of natural selection and genetics. This algorithm searches for a faster way to find an optimum configuration than enumeration by using stochastic variables. The basic concept of GA's is to simulate processes in a natural system and is based on the survival of the fittest principle.

Simulated Annealing
A Simulated annealing algorithm (SA) helps to reduce the calculation time by finding the optimum. It was mentioned as early as 1953 by Metropolis et al. A certain amount of random changes and probabilities are introduced to reduce the risk of trapping in a local optimum. An existing heuristic algorithm only accepts a change in the configuration if the objective function increases (more charges). A simulated annealing algorithm

will also accept the change, but also if the modification decreases the objective function; depending on a certain probability. The acceptance of a worse configuration can lead to a better final solution, thus help finding a global optimum. The probability that a change that leads to a worse configuration is accepted depends on the number of iterations.

The algorithms are compared and assessed in section 3.6.4.

3.6.3 Planning perspective

The allocation of fast chargers can also be approached in a total different way. Instead of solving the problem mathematically, it is also possible to approach it from the perspective of a (spatial) planner. This approach compares the allocation of chargers with the locations of petrol stations. Issues such as density per area and distance between stations are relevant.

In areas with a higher potency, a higher density of chargers is desirable. A minimum distance between the charging stations can be determined on the basis of the minimum distance between petrol stations.

In total there are about 4300 stations in the Netherlands (BOVAG, 2008). The density of petrol stations in crowded areas is about 15 stations /25km^2 (Google Maps, 2012). The distance between those stations is less than 1 km.

This information can be used to make a prediction about the density of the fast chargers. However, cars behave total different than EVs. For example, EVs can charge at home or at activity end. Furthermore, the relation density/number of vehicles is difficult to implement. Therefore, this way of optimizing will only be an option if all other options are infeasible.

3.6.4 Comparison

The allocation methods are compared and assessed on the set criteria. Besides this, the strengths and weaknesses of each method are given. There is no judgment about which method is best / most reliable; this is done in the overall conclusion at the end of this chapter. The comparison of the allocation methods is shown in Table 6.

Table 6, Comparison of the studied allocation methods

	Strengths	**Weaknesses**	**Quality**	**Computation time**	**Development time**
One-by-one	Easiest to program Computation time	Global optimum not guaranteed Short term thinking			
Greedy			-	++	++
Drop			-	++	-
Simultaneously	Best solution (highest demand/charger) Long-term thinking	Computation time Programming time Long-term expectations are uncertain			
Hierarchical clustering			+	+	O
K-means			+	++	O
Enumeration			++	--	+
Branch and Bound			O	+	-
Genetic			+	O	--
Simulated Ann.			+	O	--
Spatial planning	Based on existing locations Creates a ubiquitous network	Reliability of solution Differences EV-ICE car	-	++	O

3.7 Conclusions

A combination of one of the options in each step will lead to the best method which can be used to find the optimal configuration of locations and the corresponding number of fast chargers. In order to find the best possible combination, and therefore the preferred method, the options per step are evaluated. Since not all combinations are possible, the best option per particular step does not lead to the best configuration. It is first analysed which method can be used best to translate data into spatial demand. Subsequently, it is examined whether one of the studied datasets meets the requirements.

Two-point approach is most reliable and robust

The two-point-approach with network will provide the most realistic result and is therefore chosen. Primary reason for this approach is that it leads to a robust result, in contrast to the one-point-approach point where a small change of route/detour may lead to a different result. The dataset that should be used must fit the requirements for this approach.

No existing/studied dataset satisfies the requirements

The datasets that have been studied are the Dutch National Travel Survey (MON/OViN), Albatross and data derived from a traffic model. It can be concluded that the Albatross dataset is not an appropriate option. It contains fewer properties per daily pattern compared to MON/OViN, the available matrices have base year 2004 (past) and the reliability is unknown. What remains is data from the MON/OViN and data from a traffic model. The major drawback to a traffic model is that it only contains trips, causing only a part of the demand can be determined. The main disadvantage of the MON/OViN is the amount of data. After filtering, only 15.000 relevant daily patterns for the Netherlands are left. In other words, the traffic model contains data of the entire population, but is qualitatively (1 trip) insufficient and the MON/OViN contains all of the desired elements but the number of relevant daily patterns is limited. To determine whether the number of daily patterns is sufficient to make reliable statements, a small analysis is performed. Here, the O/D morning matrix of a traffic model is compared with the first trip of the daily patterns in the MON/OViN and an outlook is given to the results. This comparison is attached in Appendix C.

As a result of this analysis, it was decided to combine both datasets in order to use both positive qualities. The way this is done is discussed in chapter 4.

Greedy algorithm preferred

The result of the second step is used as input for the allocation problem. The objective is to place the fast chargers in such a way that the demand is served in a most efficient way: none of the fast chargers should be non-profitable. This can be done by using algorithms, which focus on a mathematical approach, or from the perspective of (spatial) planning, which focuses on density and other related parameters derived from petrol stations.

Since the two-point link-cell approach is supposed to be best, it can be determined which allocation method can be applied. The most important aspect is the level of detail which is pursued. Analysis showed that the average length of a potential interval is approximately 40 kilometres. Allocating a fast charger to a cell will therefore affect the cell scores in the surrounding cells. This will allow the outcome of a one-by-one algorithm (probably) to be not much different compared to a global optimum. In addition, a one-by-one algorithm is most easy to program and has a short computation time. It can be concluded that the greedy algorithm fits best to the level of detail and the reliability of the input. This algorithm can be programmed in several ways resulting in different kind of configurations. How this optimization is applied to this specific problem has been explained in the next chapter.

Finally, a flow chart can be made of the method that is supposed to be best. This is illustrated in Figure 35.

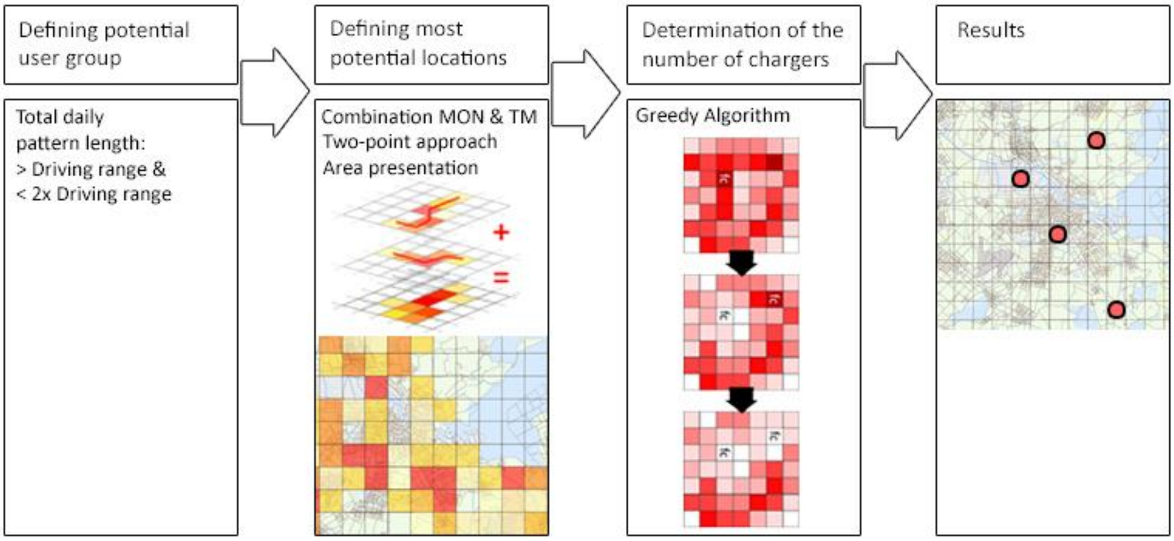


Figure 35, A flowchart of the method that is considered best

The only step missing is the dataset which have to be used as input. The solution to this problem is further elaborated in the chapter 4.

4 THE TAGA-METHOD

4.1 Introduction

General

The method presented in chapter 3 shows that none of the datasets met the criteria set. An alternative should be developed. This chapter explains how a new dataset is composed as well as more technical background information of the other steps. The finally developed method that is considered best is named the TAGA-method (Two-point Approach Greedy Algorithm-method). If you as a reader are not interested in more detailed information, you might skip to the application/results of the method. These can be found in Chapter 5.

Creating a new dataset

The new dataset combines the amount of data in the traffic model with the content of the MON/OViN. A model is created in which simplified daily patterns will be generated on the basis of assumptions. The first trips of the daily pattern are determined by using an O/D matrix from the traffic model, the subsequent trips are determined on the basis of MON/OViN data. Eventually daily patterns will be created from all areas within a certain area.

Translation into spatial representation of the demand

For each relevant daily pattern, the potential interval and the corresponding link- and cell scores can be determined. The distributions that can be used to determine the link scores are analysed. The cell scores are not the same as the expected number of charges in a cell. Aspects that should be taken into account are: market share of the EV fleet, charge behaviour, differences between daily patterns and the created simplified daily patterns and the distribution of weight caused by the distribution. This will lead to potential and less potential cells which are the input for the allocation problem.

Greedy algorithm

The allocation is performed by using a greedy algorithm. How this algorithm works is explained in more detail.

Finally, the final method, the TAGA-method is presented along with technical background. In addition, the possible fields of application are summarized. The method is universal and can be used for all study areas.

4.2 Creating a dataset

The datasets that were studied in Chapter 3 did not satisfy the set requirements. Therefore, a new dataset is developed based on a combination of the studied datasets. The aim of the new dataset is to generate a large number of daily patterns on basis of probability. In this way, sufficient data can be used to determine the optimal configuration of fast chargers. How the dataset is created is described in the following sections.

4.2.1 Simplification of daily patterns

The generation of daily patterns using a computer will take computation time, depending on the size of the chosen study area and the associated number of trips and tours. The more trips and tours of a daily pattern will be generated, the more complex and the more computing time it will take. Therefore it is chosen to simplify the travel behaviour.

Instead of modelling all different kind of daily patterns, only a selection will be generated. To determine which kind of daily patterns represents an appropriate amount of demand, relevant daily patterns are studied. The percentage of relevant daily patterns of all daily patterns is 12.1% as stated in section 2.4.3 (assuming driving range of 80km). Table 7 shows how this percentage is distributed over the possible kind of daily patterns in the MON/OViN dataset.

Table 7, Distribution of the demand over different kind of daily patterns in MON/OViN

	2 trips	3 trips	4 trips	5 trips	6 trips	7 trips	8 trips	Total
1 tour	37,45%	10,27%	6,62%	2,82%	1,45%	1,00%	0,38%	59,99%
2 tours	-	-	16,04%	4,95%	3,03%	1,31%	1,09%	26,42%
3 tours								6.62%
4 tours								1%
Total								94.02%

It can be concluded that most demand can be found in daily patterns consisting of 1 tour with two or three trips or 2 tours with four trips. Those kind of daily patterns are also most often made. If daily patterns consisting of 1 tour with two, three or four trips are created, approximately 54% of the demand will be used. In other words, the locations of fast chargers will be based on the majority of the demand.

Because all relevant daily patterns that will be created are tours, the term tours will be used in the remainder of this chapter. How the tours are designed -how the destinations in the tour are chosen- depends on several aspects.

4.2.2 Required input

A combination of the dataset of the MON/OViN (low quantity, contains daily patterns) and a traffic model (high quantity, only contains individual trips) is used for the generation of tours. What type of data is used as input is explained below. Also other input that is required is appointed.

- **Area of influence and study area**
  The area of influence is the area in which tours will be generated. The study area is the area in which the optimal configuration will be determined.

- **Dataset that contains information about daily patterns**
  The data of the MON/OViN contains information about how someone travels over a day. The data that is relevant for generating tours are: distribution of patterns/purposes for each trip, average distance corresponding to each purpose and the attractiveness of the zones (e.g. postal code areas).

- **Division of the study area**
  To model how people spatially travel over a certain area, a map with destinations is required. It is advisable to use a division that fits the data in the chosen dataset best. For example, the MON/OViN makes use of a postal code division. Here, a 3-digit postal code division can be chosen; this is preferred

over a 4-digit code division from the viewpoint of computing time and the availability of data. If 4-digit postal codes are used, assumptions such as area attractiveness would be based on only some observations.

- **Traffic model: O/D morning matrix of a future situation**
  The O/D morning matrix of a traffic model is required for the first trip of a generated tour. This matrix must be converted to match the chosen division. A future matrix is required to find the optimal locations and corresponding demand in the future

- **Traffic model: Distance skim matrix and corresponding links**
  The distances between the postal code areas (zones) are relevant to determine whether a tour is relevant or not. This distance is defined by using a shortest path algorithm. The road sections, the links in a model, on this fastest route are also relevant for determining the potential interval of each tour. Also here a future situation is assumed, this implies that new infrastructure are included.

It should be noted that the data from MON/OViN is obtained in the past and the O/D matrix of the traffic model tells something about the future. It must therefore be assumed that people's behavior (destinations chosen) will not change over time significantly despite possible changes in the network.

4.2.3 Structure

The departure or start zones in the area of influence will be selected one-by-one and from there, tours are generated. The start zone is the postal code zone from which an EV user starts his or her tour in the morning. In this way, it is always known where the tour started and where it ends. For each trip in a tour, there are some options to choose with regard to travel behaviour. These options are related to the destination a driver will go to. Drivers that have completed their tour (are returned to their start zone) will not make another tour, because only daily patterns consisting of 1 tour are created. The fourth trip is the last trip that is generated. After all tours are generated from the departure zone, the next zone is selected. Then again tours are generated. These steps are repeated until tours are generated from all zones.

4.2.4 First trip of a tour

The first trip of a tour is taken from the O/D morning (rush hour) matrix of a traffic model. It is assumed that this matrix only contains first trips, in other world: the second trip of a tour will take place after the morning rush hour. This implies that the battery of the EV is full at departure in the morning, because the EV was charged in the preceding evening. The assumption will overestimate the intensities. However, this is not taken into account for the calculations.

For the first trip, two options are possible:

- The first option is that departing traffic has a destination in the same zone (intrazonal traffic). The extent to what this occurs can be obtained from the O/D matrix and differs per departure area. This value is assumed to be more reliable than a fixed value determined using the MON/OViN dataset.

- The other option is that people are driving to another zone. The intensities from the start zone (postal code origin) to another zone (postal code destination) are derived from the O/D matrix.

4.2.5 Estimation of sequel trips

Possible options after each trip

After arriving at the first destination, there are three possible options:

- Drive back to home (homebound traffic)
- Make another trip in the same zone (intrazonal traffic)
- Make another trip to another zone (interzonal traffic)

The drivers that do not go home (interzonal and interzonal traffic) will make another trip after arriving at the second destination: the third trip. The same three options as for the second trip are possible. The traffic that is arrived at the third destination has only two options left:

- The driver returns to home (homebound traffic)
- The tour is not completed and is therefore not relevant for this study (rest). This will be a daily pattern that consists of more than four trips

Homebound traffic, intrazonal traffic and interzonal traffic are further elaborated.

Homebound traffic
The percentage of traffic that returns home after the first, second or third trip can be determined using the MON/OViN.

Intrazonal traffic
The percentage of traffic that remains in the same postal zone after the first and second trip can also be determined using the MON/OViN.

Interzonal traffic
The rest of the traffic will change from zone. The probability where a driver wants to go at a particular destination depends especially on two aspects. First, the (average) distance that drivers are willing to drive for each purpose - which is the reason to make a trip - influences the zone that is chosen. And the other aspect is the attractiveness of a zone. Both key factors are described below.

Gravity model distances
Analysis of the MON/OViN has shown that the purposes have different characteristics with respect to distance. For example, a trip with purpose shopping (8 km) is on average shorter than a trip to work (21 km). Those differences between purposes are therefore included in the choice for a destination. In this way, more detail will be added to the tours.

In the MON/OViN, 16 purposes are distinguished. Because some purposes are uncommon and because the computation time that is required to calculate all possibilities for all purposes will be too long, some purposes are merged. This is done by comparing the purposes on average distance. The number of different purposes is decreased to six; these are shown in Table 8.

Table 8, the merging of MON/OViN purposes to new categories

New purpose number	Contains the following MON/OViN purposes
1	Home (1)
2	Commuting traffic (2), driver as job (4)
3	Travelling for business(3)
4	Pick up and bring people (5) and shopping (8)
5	Visit (9), touring, walking (10) and other leisure activities (12)
6	Going to services (13), personal care (14), go along with supervisor and other (15)

For all the new purposes, except home, the average distance and the frequency can be determined. This information is required to create a gravity model. To find this function the following has to be considered.

Intrazonal and interzonal traffic are separate options, therefore intrazonal traffic is not used for the determination of average distances for interzonal traffic. The average distance for an intrazonal trip within a zone can roughly be estimated, for example by dividing the surface by the perimeter of an average zone. All values equal and smaller than this distance are removed.

The trip length distribution of the remaining data can be plotted in a histogram; an example is depicted in Figure 36. The formula that fits best is an exponential-formula with the shape $P_{ij}(d) = \alpha*\exp(\beta*d)$[12] (Bovy, 2006). Here, i is the departure zone, j is the arrival zone, d is the distance and α and β are shape parameters that differ per purpose. This formula is plotted for some purposes in Figure 37. Using this formula, the probability that a trip will be made from an origin to any destination for each purpose can be determined. Zones closer to the departure zone will have a higher probability to be chosen than zones further away.

[12] The parameters (α,β) in this formula are determined using Excel

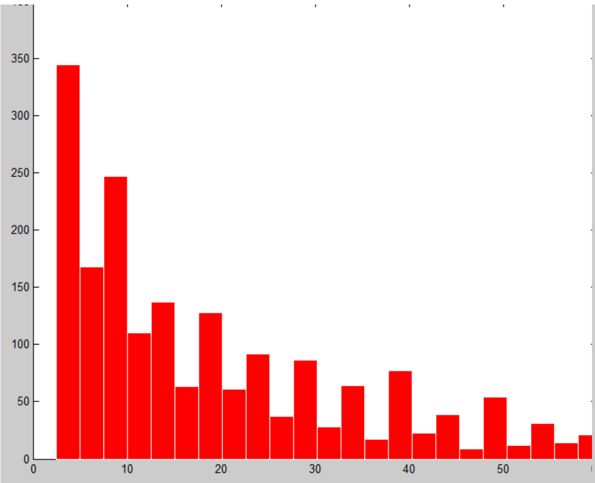


Figure 36, Example of a trip length distribution for a random purpose (MON/OViN)

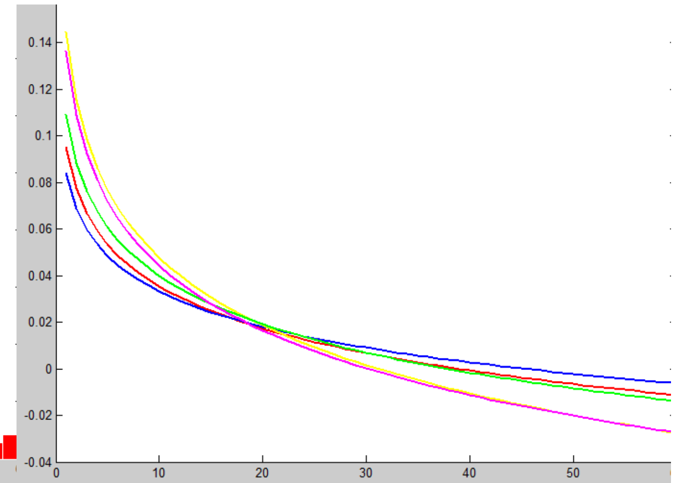


Figure 37, Formula ($P_{ij}(d) = \alpha * exp(\beta * d)$) plotted for different values of α and β

Attractiveness zones

In addition to the distance, attractiveness of a zone is relevant for the choice a driver will make. Not all zones are equal with respect to attractiveness; some zones consist of urban area and are supposed to be more attractive compared to zones that primarily consist of nature, water and/or roads. To cope with these differences, data of the MON/OViN is used again.

If all locations are assumed to be equally attractive to all motives, some illogical choices with respect to destination choice might be made. For example, shopping areas will be more attractive for purpose shopping than for work. Therefore, the attractiveness of the areas is considered separately for purpose work. Eventually, the probability from each origin to each destination for the two categories can be determined. The more attractive a zone, the higher the probability that this zone is chosen as destination.

Combine and distribute

The combination of both aspects is used to predict where a driver will go to when he or she is at a particular zone. This is done by multiplying the probabilities that are derived from the gravity model and the attractiveness of a zone. In this way, a list is created containing the probability that a zone is chosen as next destination. After sorting this list, the 'x' most attractive zones can be obtained. This step should be repeated for all purposes.

Eventually a matrix is generated containing for each purpose, from every zone, the 'x' zones (destinations) that are most likely to be chosen. The 'x' is the number of possible destinations that can be chosen for each purpose. The more options, the more possible tours and the more computation time. For example, if 'x' is assumed five, than a maximum of 25 (5 purposes x 5 zones/purpose) zones for each departure zone are possible. However, some purposes can have the same zones that are likely to be chosen. Therefore, the number of options will be lower. A schematic representation of the process is shown in Figure 38.

Destination	Distance	Attractiveness	Probability
102	0.062	0.0001	6.200e-06
103	0.043	0.0022	9.460e-05
104	0.002	0.0031	6.200e-06
105	0.101	0.0041	4.141e-04
106	0.055	0.0018	9.900e-05
...	...	...	...

sort by probability

Destination	Probability
111	5.318e-03
109	5.266e-03
106	4.847e-03
118	4.111e-03
107	4.063e-03
...	...

for each departure zone

Departure zone	Most potential	2nd	3rd	4th	5th	Distribution over destinations (converted to 100%)				
101	111	109	106	118	107	0.306	0.201	0.173	0.161	0.159
102	101	111	110	107	118	0.413	0.290	0.115	0.094	0.089
103	101	111	109	107	110	0.475	0.205	0.134	0.105	0.081
104	101	106	111	118	150	0.441	0.161	0.160	0.132	0.107
105	101	106	111	107	104	0.467	0.140	0.134	0.133	0.125
...	...	...	...	...	...	...	...	...	...	...

Figure 38, Example of the distribution of the intensities to other zones (interzonal traffic) (x = 5)

4.2.6 Weight of the generated tours

The possibilities after each trip and the associated probability per option are known. Using this information, tours can be generated over an area. To convert the probability of a generated tour to the amount of people who will actually make that tour, the intensities in the O/D morning matrix are used. The intensity of the first trip of the tour is divided over the sequel trips. In this way, all tours will get certain 'intensity'. This value is also named the weight of a tour. This is the value that will be used for the distribution over the links in the potential interval. The more likely the tour occurs, the higher the weight of a tour and the higher the sum of the link scores.

4.2.7 Example

To get an idea how a tour is generated using the steps above, an example is elaborated. In Figure 39, different tours are generated from a departure zone in Amsterdam. The first trip has a destination in the northern part of Utrecht. From here, nine other destinations for interzonal traffic are selected. The other options (homebound and intrazonal) are not shown. The destinations for the second trip are mainly situated in Utrecht itself. Also a zone in Hilversum is chosen; from here it is again determined what possible zones are most likely to be chosen. These are the smallest black dots. From these destinations is the only relevant option to return to the starting zone (this is the fourth trip). Most of the generated tours in the figure require a fast charger if they have to be made an EV.

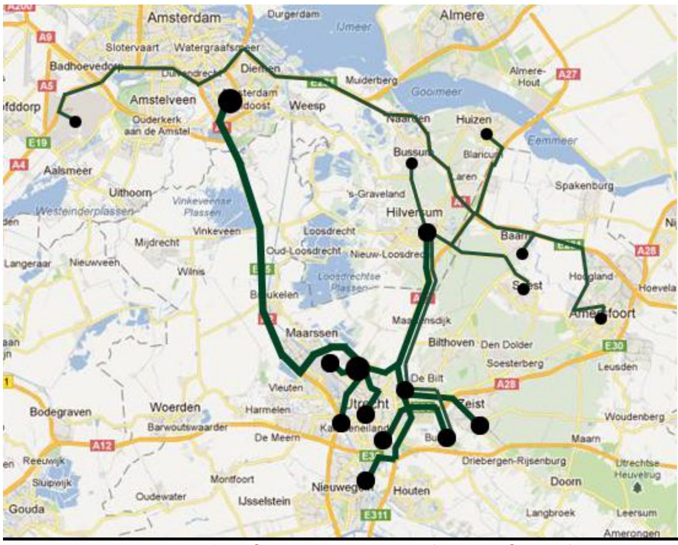


Figure 39, Example of some generated tours for a departure zone of Amsterdam

4.3 *Spatial presentation of the demand*

The tours generated are not all relevant. Tours with a total distance shorter than the driving range and larger than twice the driving range are not relevant due to the filters assumed in this thesis. Of the relevant tours, the weight of each tour will be distributed over the links in the potential interval. In the end, the link scores will be assigned to cells. This section describes two relevant aspects that will influence the result: the distribution used and the size of the cells.

4.3.1 Distribution of the weight over the potential interval

In section 3.5.2 it was mentioned that the desire of a fast charger is not equally distributed over the potential interval. The distribution used is very decisive for the outcome. The time required to charge if roughly the same over the interval, the same 'distance' have to be charged. A fast charger is theoretically preferred somewhere in the middle of the area, the probability of getting a flat battery is here smallest. With this point of view, some distributions are examined.

It is unknown how the demand is distributed over the rest of the potential interval. However, one aspect have to be considered. Most of the distributions (Normal, Poisson) have a bell-shaped probability density function (see Figure 40). The limits of these distributions are infinite: this will cause that links outside the potential interval will also get a (low) score. This can be remedied, but is not desired.

Since there is too little knowledge about charging behaviour, a basic distribution is considered. The distribution has the shape of a triangle: the desire is greatest in the middle (=weight/0.5*length of potential interval) and takes off straight to the edges. This is shown in Figure 41.

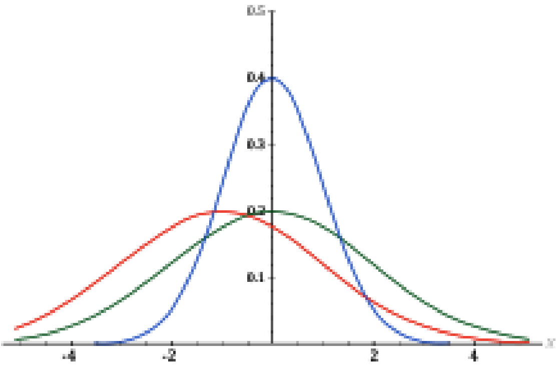


Figure 40, Various normal distributions

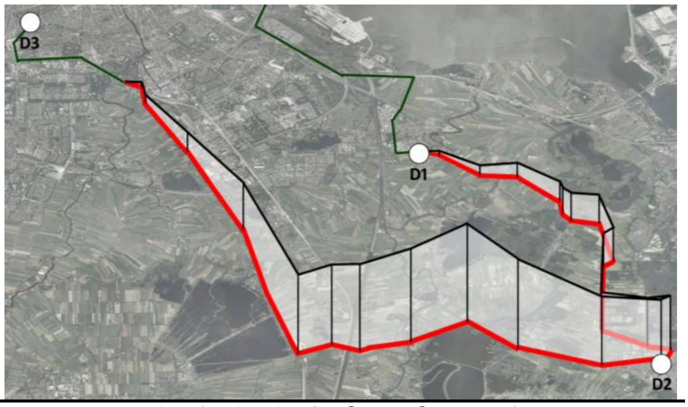


Figure 41, Distribution in the form of a triangle

4.3.2 Converting weight of a tour to cell scores

The links in the network situated in the potential interval will get a score that represent the weight by using the surface under the triangle. The link score is determined by three aspects.

- First, the weight of a tour is relevant. This value is derived from the intensity and probabilities in the generation of the tours. This is the total score that is assigned to the links.
- The second aspect is the location of the link. The links that are situated in the middle of the potential interval will get a higher score than the links at the edges due to the used triangle distribution. The surface of the triangle is larger in the centre.
- Furthermore, longer links get higher scores because they represent more surface.

The links are assigned to cells. This is done by determining the middle of each link and allocates it to the cell in which this point is situated. In this way, the cell scores are determined. These values have to be multiplied with factors such as market share and charge behaviour, distribution over time and a factor that compensates the differences in demand between the generated tours, three kind of daily patterns, and all kind of daily patterns.

4.3.3 Size of the cells

The size of the cells is a factor which can influence the robustness of the results. Some aspects have to be considered for determining an appropriate size:

Detour factor

If a fast charger is allocated to a cell, it will affect traffic driving through surrounding cells. Electric proposed traffic in need for a fast charger and driving in neighbouring cells will probably make a detour to use the charger; the consequence of this is that a fast charger will also serve tours that are not running via the cell where a fast charger is present. As a consequence, the demand in surrounding cells will drop too. The extent to which this happens depends on how far people are willing to make a detour. If this is a few kilometre, for example five, then a cell size of 10x10 km will provide a fairly robust network. If the fast charger is allocated in the middle of a cell, this won't affect the demand of the surrounding. If a smaller cell size of 2x2 km is assumed, a certain percentage of the traffic in the surrounding cells will probably change their route. However, this percentage will be based on assumptions and will differ over the study area. How a reliable size can be obtained with respect to detour factors is shown in chapter 5.

Network limits: Size of the links

The links in the network will be assigned to cells by using the middle of a link. Larger links will get a higher score (the surface -see 4.3.2- is larger) and are therefore reasonably decisive for the difference between cells. If the cell size is too small, a link can overlap more than one cell and only one cell will get the score.

Level of detail

The general assumptions tell something about the quality of the data that is used as input. If coarse assumptions are made (e.g. the input and processing is relatively poor), it doesn't make sense to adopt a small cell size. This will cause false precision.

Computation time

The last aspect is the computation time required to find a solution. The smaller the size of the cell is chosen, the more cells there will be in an area. The computation time will increase exponentially when more cells are in the study area.

4.4 *Greedy algorithm*

In chapter 3 it was found that a Greedy algorithm provides an acceptable solution to the problem. In this section a detailed (technical) explanation of the functioning and expected outcomes are presented.

Structure of the Greedy algorithm

A greedy algorithm aims to determine the following two aspects:

- The locations of the fast charge stations
- The number of fast chargers at each location

There are two types of greedy algorithms that involve both aspects. These have the following structures:

- Greedy algorithm A: Determine location first and allocate as many profitable fast chargers as possible to that location. *Results in few locations with multiple fast chargers.*

- Greedy algorithm B: Determine the location of each additional fast charger separately. *Resulting in multiple locations with one or few fast chargers.*

Both types of algorithms have advantages and disadvantages. The advantages of both algorithms are shown in Table 9.

Table 9, Pros and cons of clustering locations

Greedy algorithm A	Greedy algorithm B
Probability of finding a free fast charger is greater Less expensive: only one connection to the three-phase network per location is required[13] Opportunities for economic activities related to EVs / meeting point	More locations will further reduce range anxiety

It is chosen to apply algorithm A in this thesis. This algorithm provides the most cost effective solution (commercial point of view) and fewer locations will also ensure that EV users have a chance to meet each other. In addition, the algorithm will find the most potential locations among the existing locations to place more fast chargers (upgrade to hub). To demonstrate the differences between the algorithms, algorithm B is also executed. This is further discussed in Chapter 5.

In order to explain the steps of the chosen algorithm, a flow chart is used which is illustrated in Figure 42. The cell scores in the study area, the spatial distribution of demand, which have been obtained by previous steps, are used as input for the allocation method. In addition, some initial conditions can be set (e.g. adding the existing locations of fast chargers).

Location of the fast charge station

The first step is to search for the cell with the highest score in the study area; this is the most potential location. A fast charger will be allocated to this cell.

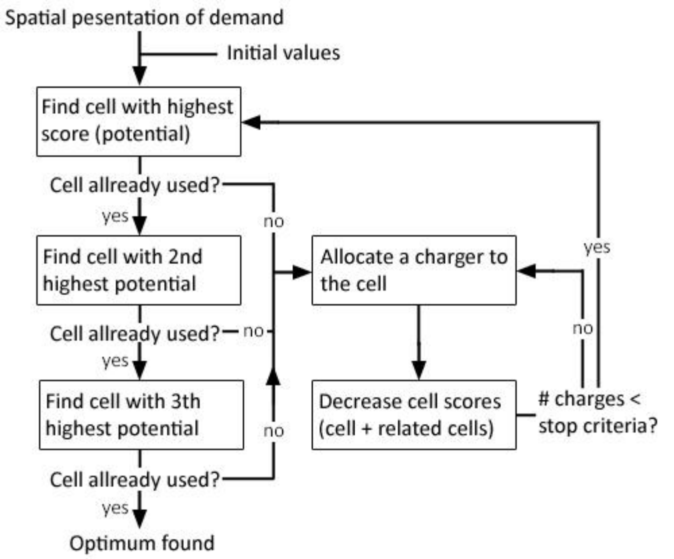


Figure 42. Flow chart of the used greedy algorithm

[13] A major cost

Number of chargers at each location

The number of chargers required at each location depends on the capacity and the minimum required charges per charger. If a fast charger is allocated to a cell, some demand will be served. In other words, the cell scores will reduce. This reduction relates to the cell score of the cell in which a fast charger is placed and the cell scores on the surrounding cells due to the triangle distribution.

The triangle distribution used will distribute the weight of a relevant tour over the links in the potential interval. Thereafter, the link scores are assigned to multiple cells. If a charger is allocated to one of those cells in the potential interval, a portion of the weight on the other cells is served as well. This will reduce the cell scores of the surrounding cells. To what extent this will happen and which cells are involved, depends on the structure of the generated tours. To determine this, a selected cell tool is developed.

It is possible to store (a part of) the potential intervals of the generated tours. This makes it possible to determine which cells are connected to a selected cell and with what ratio. In other words, where could the same EV user also charge?

In chapter 2 it is showed how the capacity of a fast charger, the number of EVs that can charge at a single fast charger within a certain period of time, can be calculated. This value should be distributed among all cells that have relevance. Therefore the cell score of the cell to which the fast charger is allocated is not reduced by the value assumed as capacity, but with a certain percentage of this value. The same applies to the surrounding cells. To clarify this, an example of this process is depicted in Figure 43.

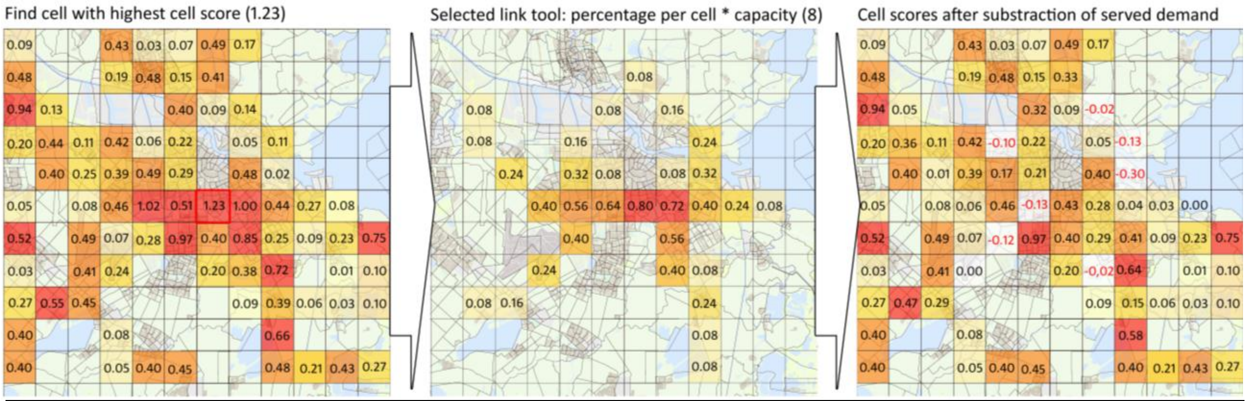


Figure 43, Example of the effect of allocating a fast charger on the surrounding cells

The left picture shows the cell scores within a certain area. The sum of all cell scores, the demand, is 26.52. The highest cell score is 1.23. A fast charger is allocated to this cell.

The middle figure shows the effect of allocating a fast charger to this cell: it will affect the scores of the cell and surrounding cells. This is the selected cell tool. The sum of the scores is equal to the capacity of a fast charger. In this example, the capacity is set to 8 charges per period of time.

The scores in the middle figure will be subtracted from the cell scores in the area (left figure). The result is shown in the right figure. The sum of the demand in this figure is calculated (18.52) and compared with the initial demand in the study area (26.52). If the fast charger is used optimally the difference will be equal to the capacity of the charger. However, it is possible that due to the subtraction some cell scores will be negative. These are the red scores in the right figure. Since negative demand does not exist, these values are set to 0. As a result, it may occur that the difference in total demand between for and after allocating a fast charger is not equal to the capacity of a charger, but lower. This difference is the actual use of a charger. In the example the actual use is 7.18 charges per period of time.

Stop criteria per location

As has been indicated in section 3.6.1, a fast charger is no longer profitable if the expected demand drops below a certain value. If the demand is higher than this value, a new fast charger will be allocated to the same cell (# charger < stop criteria). If the demand is lower than this value, than the loop starts again by finding the new highest cell score (location with most expected demand).

Second and third highest cell

It is possible that this new selected cell is the same as the previously studied cell. This will result in a re-calculation of the effects and the subsequent same conclusion. The cell with the second highest can, however, still be a profitable spot. The same applies to the cell with the third highest score. Therefore, these cells are also studied before the algorithm ends. If none of the three cells with the highest scores are a profitable spot for a fast charger, the algorithm stops and an optimum is found. The result is the optimal configuration of fast chargers.

Outcomes

Per additional charger, a part of the total demand served. The percentage of the demand in a certain area that is eventually served depends on the established minimum demand which is necessary for a cost-effective fast charger. If this value is set to 0 charges per period of time, 100% of the demand will be served. This is depicted as a graph in Figure 44. The vertical axis is the percentage of demand that is served and on the horizontal axis the number of allocated fast chargers.

The red line indicates the percentage that is served by the number of fast chargers. This is not a straight line, because some fast chargers are not used optimal (max capacity).

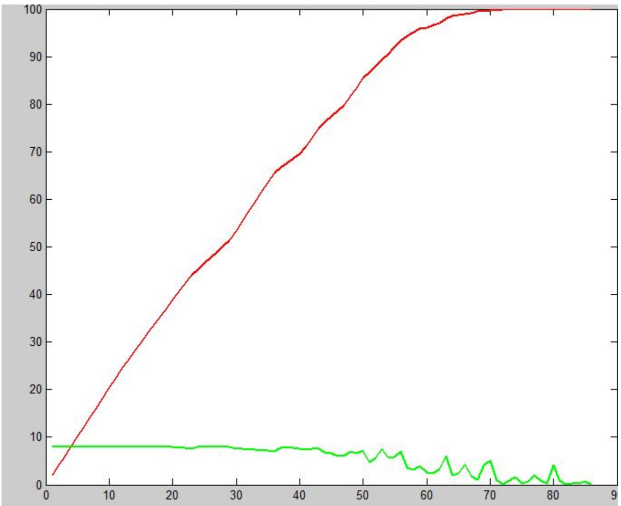


Figure 44, Possible result of the greedy algorithm

The green line (the derivative) indicates the use of the (new) fast charger, the capacity per time period in this example is assumed to eight. After allocating fifty fast chargers, the use of new fast chargers drops. The peaks indicate that a fast charger is assigned to a new cell.

4.5 Conclusions

The method that can be used to the find the optimal locations and the corresponding number of required fast chargers, the TAGA (Two-point Approach Greedy Algorithm)-method, is further elaborated.

Creating a new dataset

A new dataset is developed. This dataset generates daily patterns using an O/D morning matrix of a traffic model and data that contains information about daily patterns. Due to computational limits, the world is simplified: only daily patterns consisting of 1 tour with two, three or four trips are generated instead of all possible kind of daily patterns. Only a part (54%) of the relevant daily patterns in the MON/OViN consists of one tour with two, three or four trips. This implies that the datasets represents a majority of the actual demand.

From each start zone, the first trip to other zones is copied from the O/D matrix of the traffic model. The following trips are determined on the basis of probability. For both the second and third trip there are three options drivers can choose: go back home (homebound, to the start zone), drive to a destination in the same zone (intrazonal) or drive to a destination in another zone (interzonal). The probabilities corresponding with each option are derived from the MON/OViN. Only one option is left for the fourth trip, returning home because daily patterns with more than four trips are not generated.

The probability of that a tour will be made can be converted to intensities by using the O/D matrix. The intensity of the first trip in a tour can be copied and will be divided among the 2nd, 3th and 4th trip using probability. The 'intensity' of every tour represents the weight of the tour. This value will be used to determine the most potential locations. The more weight, the more likely the tour occurs, the more influence it has on the results.

Translation to expected number of charges in a certain year

The generated tours with a total distance larger than the driving range and shorter than twice the driving range are relevant. Based on the relevant tours, the potential interval is determined. The weight of each tour is distributed over the links in the potential interval using a triangle distribution. A triangle indicates the effect that EV users have a preference to charge in the centre of the potential interval. Subsequently, the links situated in the potential interval will get scores. Those links are assigned to cells, resulting in cell scores which represent the preference for a fast charger within an area. This is done for all relevant tours. Eventually the cell scores of all tours can be added. The cell scores have to be multiplied with some factors, such as market share of the EV fleet, charge behaviour and distribution over time, to find the actually demand during a period of time in a certain year.

The greedy Algorithm

The final cell scores within an area are used as input for the allocation method. Broadly there are two types of greedy algorithms possible. First, an algorithm that will search for the most potential location (highest cell score) and allocate as many as profitable chargers to that cell. The second algorithm will search for the most potential location every time a fast charger is allocated. In the first case, few locations with many fast chargers will be created (clustering). This has the following advantages:

- Probability of finding a free fast charger is greater
- Less expensive: only one connection to the three-phase network per location is required
- Opportunities for economic activities related to EVs / meeting point

Therefore this algorithm is preferred. The greedy algorithm will search for the cell with the highest score (most potential area). A fast charger will be allocated to that cell and the demand on the cell and surrounding cells will decrease. This step is repeated until the demand on the cell is lower than the demand that is required to install a profitable fast charger. If this is the case, the algorithm will search again for the cell with the highest score. These steps are repeated until there is no cell left where a profitable fast charger can be placed. Whether a fast charger is profitable will depend on the minimal required number of charges per period of time, the profitability.

The steps in the TAGA-method

In summary, the following steps are executed in the TAGA-method:

1. Generate tours using an O/D matrix and a dataset that contains information about daily patterns
2. Calculate the weight of each tour
3. Define the potential interval of each relevant tour
4. Distribute the weight over the links in the potential interval
5. Assign the link scores to cells
6. Add up the cell scores of all relevant tours
7. Convert the scores to expected demand
8. Find the cell with the highest score
9. Allocate as many profitable fast chargers as possible
10. Repeat step 8 until no profitable locations (cells) are left

Fields of application

The TAGA-method can be used for the following purposes:

- Determining the optimal configuration (locations and number of fast chargers per location) for a random area
- Evaluate and rank planned or potential locations on profitability
- Determine which existing locations can best be upgraded to hubs (more chargers at one location)

The TAGA-method is applied to Amsterdam in the next chapter.

5 APPLICATION TO AMSTERDAM

5.1 Introduction

The municipality of Amsterdam currently has the leading position with regard to electric vehicles and infrastructure. The municipality promotes electric vehicles in order to improve the air quality. The installation of fast chargers can contribute to this. To make Amsterdam more accessible for electric vehicles and to promote EVs among the people of Amsterdam by eliminating driving range restrictions, fast chargers have to be placed on the right locations. In this way, the available funds will be spent as efficiently as possible. The following two questions are answered in this chapter:

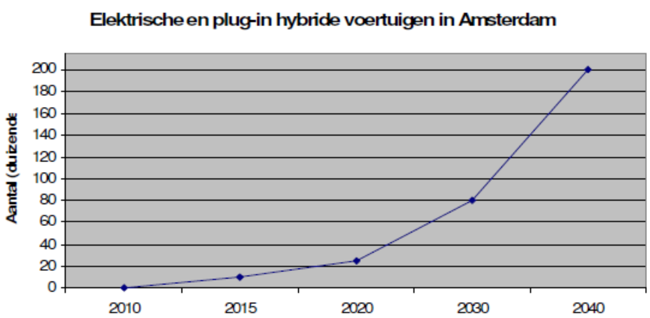
- *What is the optimal configuration of fast chargers in and around Amsterdam in 2020?*
- *What is the optimal configuration of fast chargers for EV users who live in Amsterdam in 2020?*

The year 2020 is chosen because a future situation is required to obtain an optimal configuration and most data is available for this year.

Scenario	Percentage of cars	Total number of EV's (inc plug-in hybrid)
High	8%	20000
Target	4%	10000
Low	2%	6000

Table 10, Possible distribution and number of EV's in Amsterdam in 2015 according three scenario's (source: TNO, 2009)

Figure 45, forecasts for the market share of EV's and plug-in hybrid vehicles in Amsterdam (source: TNO, 2009)



The municipality of Amsterdam has the ambition to have 10,000 electric vehicles in 2015 (or 5% zero-emission kilometres) according the average (most likely) scenario (TNO, 2009). Of this number, 3000 vehicles are BEV's (Full Battery Electric Vehicles). All scenarios are shown in Table 10. In 2008 there were approximately 215,000 vehicles in Amsterdam, this number will increase to about 225.000 in 2020[14]. According to forecasts, the number of electric vehicles between 2015 and 2020 will be doubled (see Figure 45). The same will count for BEV's; The number of BEVs is therefore estimated at 6000 in 2020. This will be a market share of 3%, which means that the ambition is greater than the average of the Netherlands. In this chapter, the TAGA-method that has been developed in the previous chapters is applied to Amsterdam. First of all, the required input is explained. It includes some specific assumptions and conditions, the composition of the study area and area of influence and the traffic model that is used. The distribution of the demand for fast chargers presented and the best configuration is determined.

[14] Estimate based on trends (DIVV)

5.2 Study setup

In this section the input and assumptions are explained that are required to find an optimal configuration of fast chargers in 2020. This year is chosen because most information, e.g. an O/D morning matrix and a network including new infratructure, is available and a future situation will be most realistic. In addition, this year possible changes for different aspects can be simulated. In subsequent years, the development of those aspects is uncertain or unknown.

5.2.1 Area of Influence & Study area

The area of influence is the area in which the tours will be generated. The larger this area, the more tours have to be created and the more computation time. The area of influence is chosen on such a way that the optimal locations for the people that live in Amsterdam can be determined. Therefore, an area around Amsterdam should be taken with a radius of at least 50 kilometres. This will ensure that the residents of the municipality of Amsterdam will have their potential interval, the locations where a fast charger is required to 'electrify' a tour, are situated in the area of influence. The height of the area is 90 km, the width 120km. Because most of the traffic has a destination south of Amsterdam, the entire Randstad is included. This is at the expense of the smaller zones (less attraction/production) north of Amsterdam. Zones outside the area are not relevant because they won't influence the demand in Amsterdam or with a significant quantity (flows are very low). The area of influence is shown in Figure 46.

In the study area, the optimal configuration of fast chargers will be determined for all drivers who drive through this area. In this case, the study area includes not only the municipality of Amsterdam but also a part of the region. Fast chargers allocated just outside the border can influence the locations within the border. The study area chosen is based on the Noordvleugel area and the Stads Regio Amsterdam (SRA). The area has a size of 60x30 km and is shown in Figure 47.

Figure 46, The area of influence

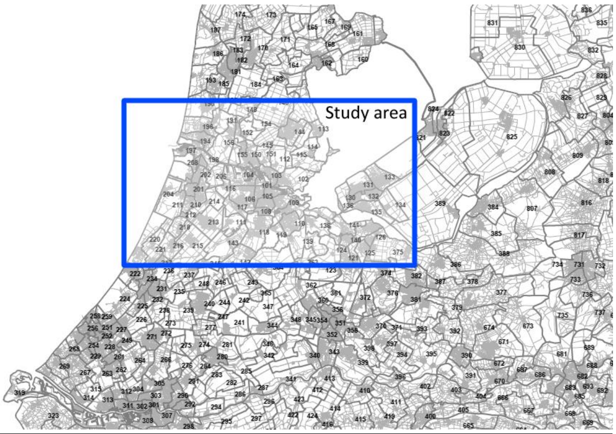


Figure 47, The study area

5.2.2 Datasets used for generation of tours

Traffic model

The model that fits best to the area of influence and study area is the Verkeerskundig Noordvleugelmodel (VENOM). This model is developed by Goudappel Coffeng on behalf of the metropolitan region of Amsterdam and is intended to make forecasts to maintain a smooth functioning traffic and transport system.

This model is preferred over other models, because the level of detail is greater in this region: the links (road sections) are designed detailed and the zones (area classification for attraction and production of traffic) are specific (smaller than 4-digit postal code). In order to reduce the calculation time, a 3-digit postal code division is used. Therefore, the area of influence is divided into 260 zones.

The O/D morning matrix is also derived from VENOM. VENOM consists of 3722 centroids[15], but many of them are located outside the area of influence or are situated in the same zone. The traffic generated by the centroids in the same zone is added and the centroid closest to the centre of the zone is chosen to be relevant. Because a future situation is studied, the O/D matrix and network of 2020 is used. This network includes future

[15] Indicates where in a zone the traffic is generated and absorbed

developments such as the Westrandweg. The fastest routes between all relevant centroids are determined using OmniTrans, leading to a matrix containing 67.600 shortest routes (260x260) with associated links.

Making assumptions with respect to sequel tours
The dataset that is used to make assumptions about travel behaviour is a combination of the MON/OViN and Household surveys Amsterdam. To maximize the size of the dataset, with the aim of increasing the reliability, several years (2004-2010) are stacked. This stacked dataset contains a total of 117,000 daily patterns.

There is a difference in travel behaviour between urban areas, such as the Randstad, and non-urban areas, such as the province. Because the facilities in non-urban areas are often further away, the distances associated with those trips will give a distorted picture relative to the area of influence (urban area). Therefore, the parameters are only based on trips that have an arrival and destination postal code within the area of influence. After this filter, approximately 60,000 second trips and 27,000 third trips are left for determining the parameters.

5.2.3 Assumed parameters

The input values used are outlined for the steps taken (dataset, filters, spatial presentation and allocation of fast chargers):

Creating a dataset

- **Number of zones**
  As mentioned before: 260 (3-digit postal code)

- **Distribution over options for each trip**
  In Table 11, the probabilities per option for each trip are presented. From this table it can be concluded that the major part of the drivers returns to home after the first trip (73%) and only a small part of the drivers (3.7%) makes a daily pattern that consist of 1 tour with more than four trips.

Table 11, Probabilities associated with the possible options for each trip (MON/OViN)

Trip number	Returns home	Intrazonal	Interzonal	Leaving the model
First trip	--	Varies by zone	Varies by zone	0
Second trip	0.733	0.051	0.216	0
Third trip	0.567	0.093	0.330	0
Fourth trip	0.676	--	--	0.324

- **Distribution over purposes**
  The probabilities that are required to create tours are derived from the MON/OViN. The distributions of the purposes for the second and third trip are shown in Table 12. In addition, the average distances (in km) for the purposes are given. Purpose home (homebound traffic) is not included, since this is a fixed destination by creating the tours and therefore not used for interzonal traffic.

Table 12, Probabilities associated by the purposes for the second and third trip (MON/OViN)

Cat.	Include purposes used in MON/OViN	Trip 2		Trip 3	
		Distribution	Avg.dist.	Distribution	Avg.dist.
2	Commuting traffic (2), driver as job (4)	0.049	27.52	0.106	26.44
3	Travelling for business (3)	0.056	35.35	0.095	28.75
4	Pick up and bring people (5) and shopping (8)	0.083	14.38	0.122	17.99
5	Visit (9), touring, walking (10) and other leisure activities (12)	0.065	25.56	0.094	22.90
6	Going to services (13), personal care (14), go along with supervisor and other (15)	0.015	17.05	0.017	16.25

- **Number of possible destinations for interzonal traffic**
  The number of possible destinations is fixed at 5. Using this value, the computation time is tolerable[16].

Filters

- **Driving range**
  The driving range is set at 80 km. This value is derived from the current driving range, because it is unknown how this value will change for 2020[17].

Spatial presentation of demand

- **Cell size**
  The cell size used is 3x3 km. This assumption is based on a maximum detour factor of 10% of the trip length. The value is substantiated in Annex E. The area of influence is thereby divided in 1200 cells and the study area consists of 273 cells.

- **Factor daily patterns – tours generated**
  The created dataset contains only three possible kind of daily patterns. These are, as defined in 4.2.1, daily patterns consisting of 1 tour with two, three or four trips. In order to achieve a realistic demand, two factors have to be determined:

  According to the MON/OViN, 64% of all daily patterns consist of 1 tour with two, three or four trips. Since the O/D matrix contains the intensity of all kind of daily patterns, the cell scores have to be multiplied with 0.64.

  The second aspect that must be taken into consideration is the percentage of relevant daily patterns. As calculated before, the percentage of daily patterns that is relevant is 12.1%. A majority (54%) of the relevant daily patterns consist of 1 tour with two, three or four trips. To calculate the total demand, the cell scores have to be multiplied 1.84 (=1/0.54).

  Both factors combined result in a factor 1.1912 (0.64*1.84)

- **Market share of the fleet and charge behaviour**
  The market share of the fleet that is used is taken from the targets of the government. Their ambition is a market share of 2% in 2020. It is assumed that this value is uniformly distributed over the Netherlands. How many EV owners will actually use a fast charger is unknown. This is provisionally set at 50%.

- **Peak hour**
  The number of fast chargers depends on whether there is dimensioned at peak times or on demand over a day. Because queues are not desirable, peak times are considered. The demand for fast charging over a day is provided in Appendix E. From this analysis, a peak value of 0.5 is assumed. This implies that 50% of the demand over a day is expected during two hours.

- **Presence of slow chargers**
  Currently, there are hundreds of (slow)chargers situated in Amsterdam (see 2.3.3). Nevertheless, it is assumed that no slow chargers are present at activity end.

Allocation of fast chargers:

- **Capacity of a charger**
  The capacity of a fast charger is set at eight charges per two hours. This value is determined by taking into account the charging time studied in 2.3.2. It is assumed that a charge cost about 20 minutes in 2020. However, not all users will need a full charge. The charging time is therefore set at 15 minutes and the capacity for two hours at eight (=2/0.25).

---

[16] 90 hours (Intel core i5 @2.63GHz, 4 GB RAM)
[17] A underestimation provides a more robust results than an overestimation

- **Profitability of a charger**
  The minimum demand required to ensure a fast charger is profitable is fixed at seven charges / two hours. How this value has been established is explained in Appendix E.

Some of the aspects are included in the sensitivity analyses in chapter 6.

5.3 Results

5.3.1 Tours generated

Per 3-digit postal code area, approximately 20.000 different tours are generated. This implies that for all 260 zones situated in the area of influence, approximately 5M tours are created. Of these, 49% tours are relevant (require a fast charger to be 'electrified'). Because the tours are determined by probability and intensity of the O/D matrix, not all of tours have the same weight. Tours with a 'heavy' weight belong mainly to the non-relevant group. Therefore, the relevant intensity, the expected demand, will be lower.

5.3.2 Spatial presentation of the demand

The relevant tours are processed using the steps in the TAGA-method to make a distinction between the potential and less potential cells (areas). The results for the study area and for the residents of Amsterdam are presented in this section. The results are based on 2020.

The study area

The distribution of demand over the study area is depicted in Figure 48. The red cells represents the greatest demand, the yellow cells have less potential.

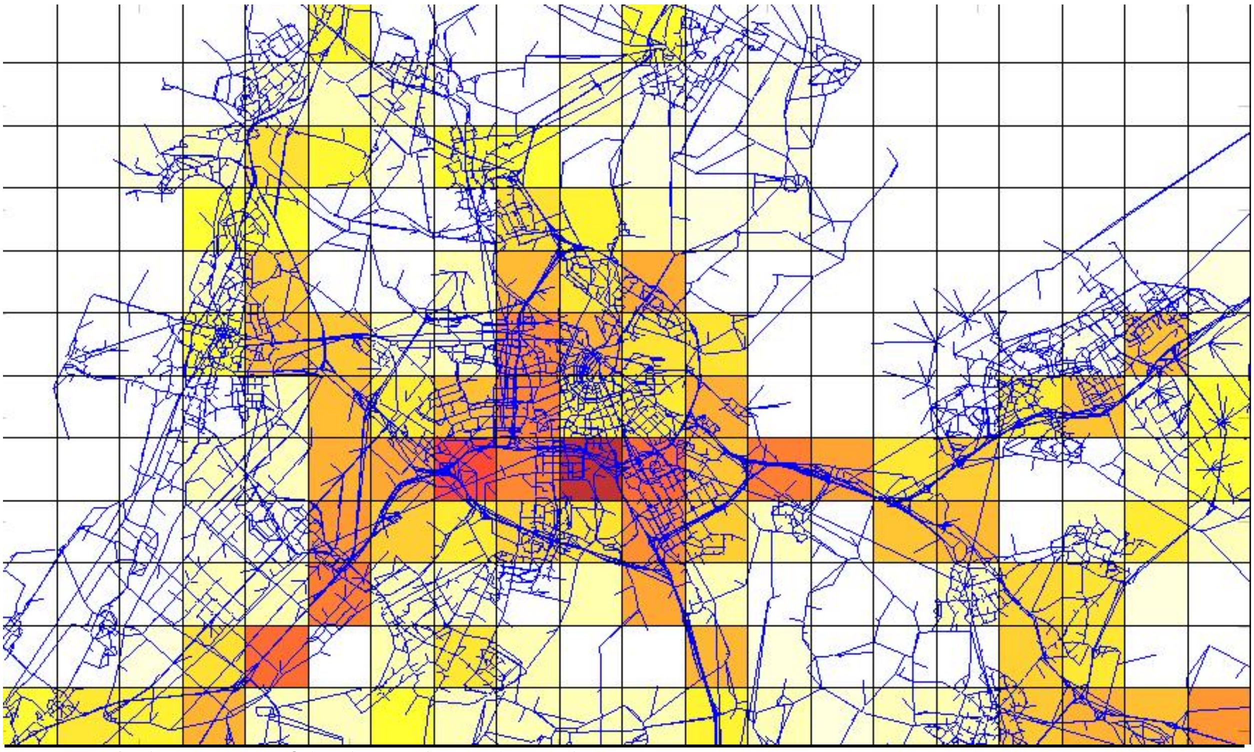


Figure 48, distribution of the demand over the study area

This figure shows that the most potential locations are situated on the south side of Amsterdam. The A10 near the RAI is the most desired location for a fast charger. The next potential cell is cell that contains the junction of the A4 and A9. The total demand in the study area, the number of expected charges during peak times, is 345.

Residents of Amsterdam
The distribution of the demand for the drivers that depart from Amsterdam in the morning is illustrated in Figure 49. Here, only tours are generated from the zones situated in Amsterdam. The red cells represents the greatest demand, the yellow cells have less potential.

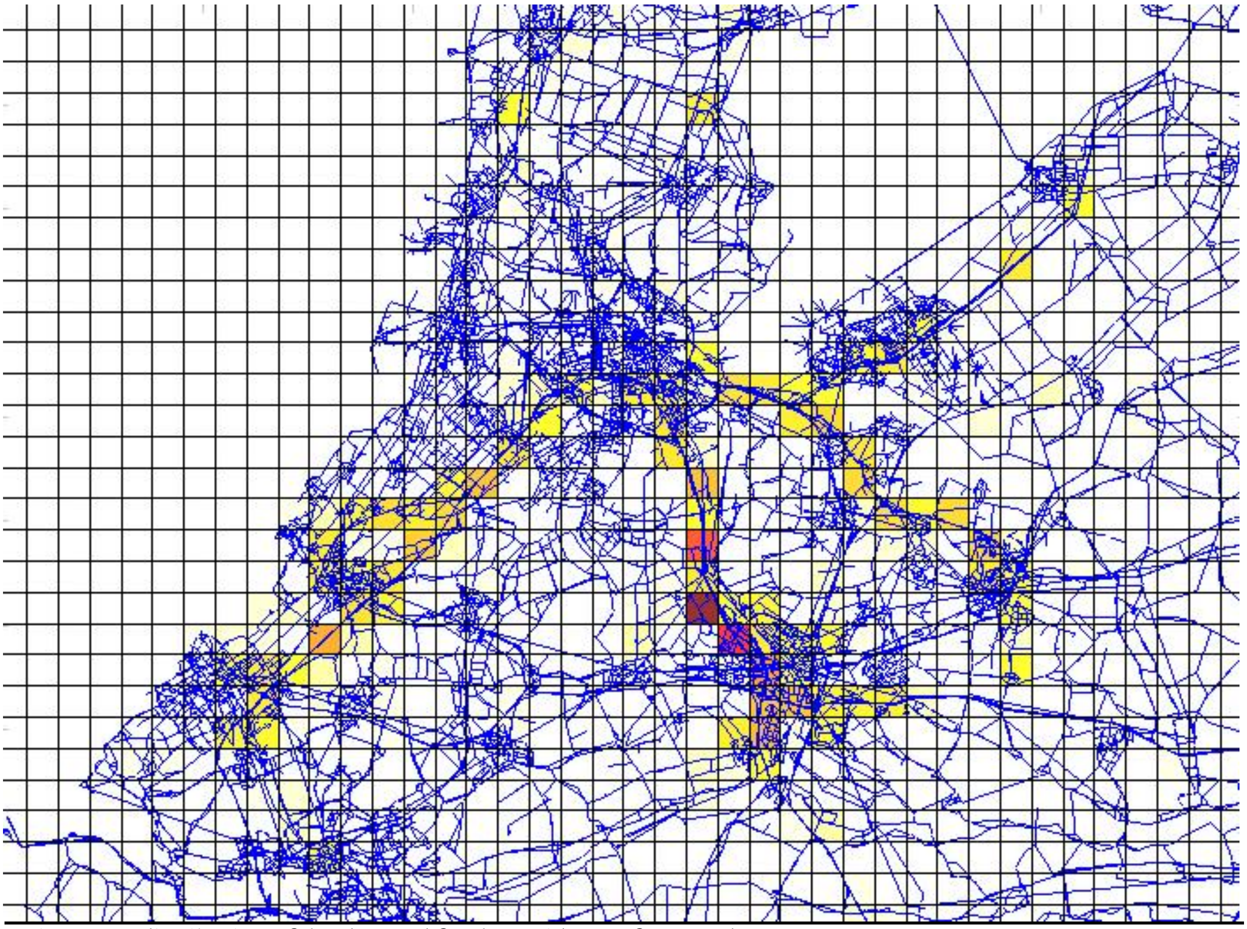


Figure 49, distribution of the demand for the residents of Amsterdam

The result shows that the cells that indicate the A2, the highway between Amsterdam and Utrecht, contain a lot of demand. Especially just north of Utrecht, near the junction between the N230 and the A2. This implies that Utrecht is (better) accessible by EVs when a fast charger is allocated to the appropriate location. Furthermore, it is clear that fast chargers are desired along the A1 and A4. The demand here is however lower. The total score in the area, the number of expected charges during the during peak times is 66.

5.3.3 Optimal configuration of fast chargers

The greedy algorithm, developed in section 4.4, is applied to the results presented in the previous section. In this section, the possible fields of application of the TAGA-method are elaborated:

- Determining the optimal configuration (locations and number of fast chargers per location) for a random area. (*Applied to: The study area and for the residents of Amsterdam).*
- Evaluate and rank planned or potential locations on profitability (*Applied to: study area*)
- Determine which existing locations can best be upgraded to hubs (more chargers at one location) *(Applied to: MC Donald's within the border of Amsterdam)*

Optimal configuration: The study area
The result for the study area is depicted in figures 50 to 51.

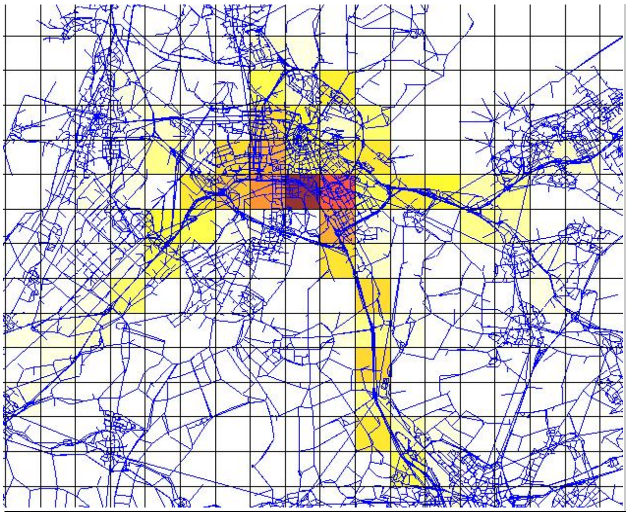


Figure 50, Selected cell tool shows the cells that are related to a selected cell

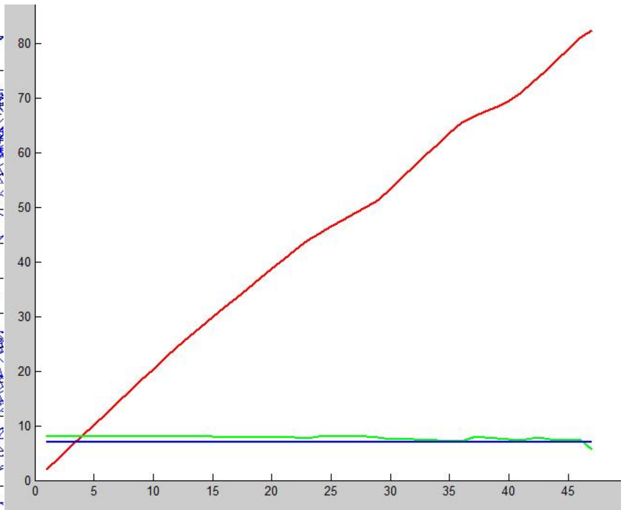


Figure 51, Graph that shows the relationship (red line) between the number of chargers (x-as) and the total demand served in the study area (y-as)

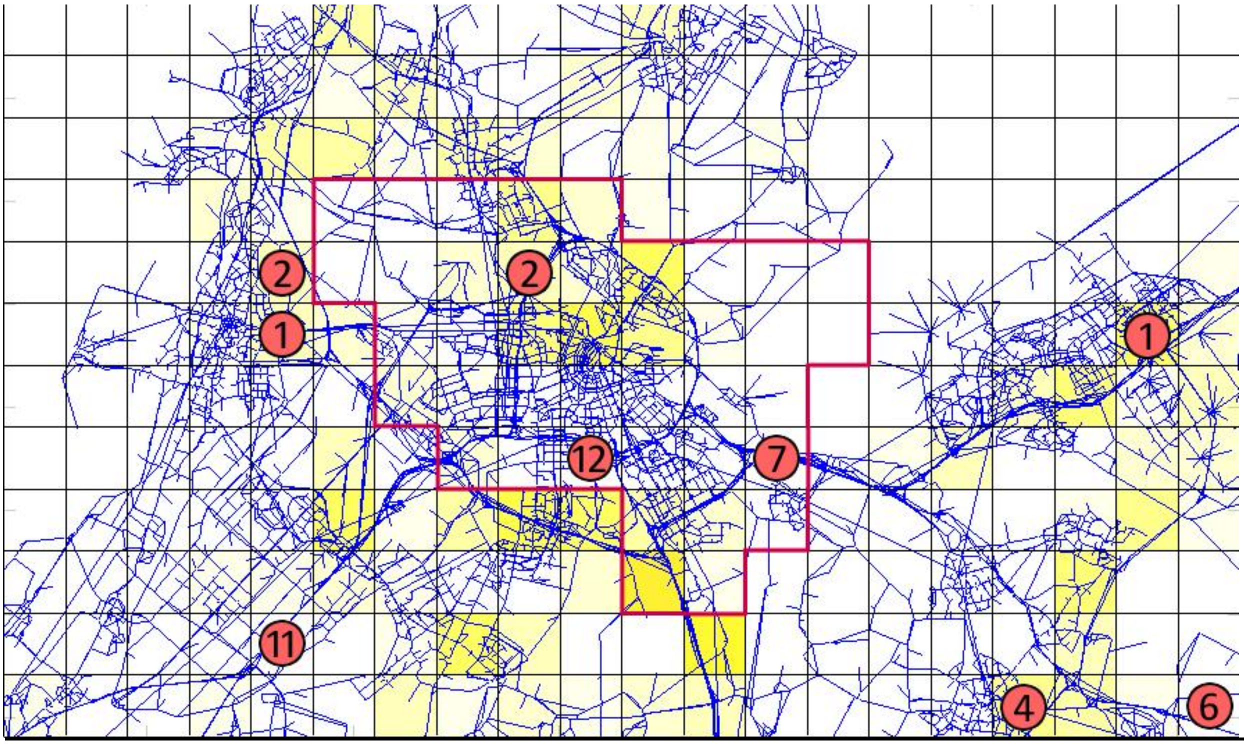


Figure 52, The optimal configuration of fast chargers in the study area (number of locations within the municipality of Amsterdam (within the purple line): 3, number of chargers: 21)

In the first figure, the most potential cell is selected to analyse which surrounding cells are related (the selected cell tool). Because the first fast charger will be allocated to this cell, the scores of those cells will reduce.

Figure 51 shows the relationship between the number of chargers and the demand that is served in the study area (red line). The blue line indicates the minimum number of charges that is required (7) to make a charger profitable. If the green line, that shows the number of charges for every additional charger, drops below this line an optimum is found. The optimum will be 46 chargers. In total 82% of the demand in the study area is served in this configuration.

The optimal locations and corresponding number of fast chargers is shown in Figure 52. The locations are displayed as the red dots and the number of fast chargers at a location is indicated by the number in the dot. As a result of the chosen algorithm, only three locations within the border of Amsterdam -the purple line in the figure- will be sufficient to serve most of the demand. The location where most of the fast chargers are preferred is along the A10 south nearby the RAI. Here, 12 chargers are required. Another location for a large charging hub is nearby the junction A1-A9. Here, seven chargers are desired. Finally, there are two chargers required on the west side of the A10 near the Coentunnel. In total this means that 21 fast chargers are required within the border of the municipality of Amsterdam. These three locations ensure that EV users passing Amsterdam do not need to make a (intolerable) detour.

In the rest of the study area more fast chargers are required. However, the number of chargers at each location is less reliable, because problems will occur relating the size of the area of influence.

Optimal configuration: Residents of Amsterdam

The optimization is also performed in order to find an optimal configuration for the residents of Amsterdam. This configuration will ensure that EV users in Amsterdam can reach destinations that they could not reach with a single full battery. The result of the optimization is illustrated in Figure 53.

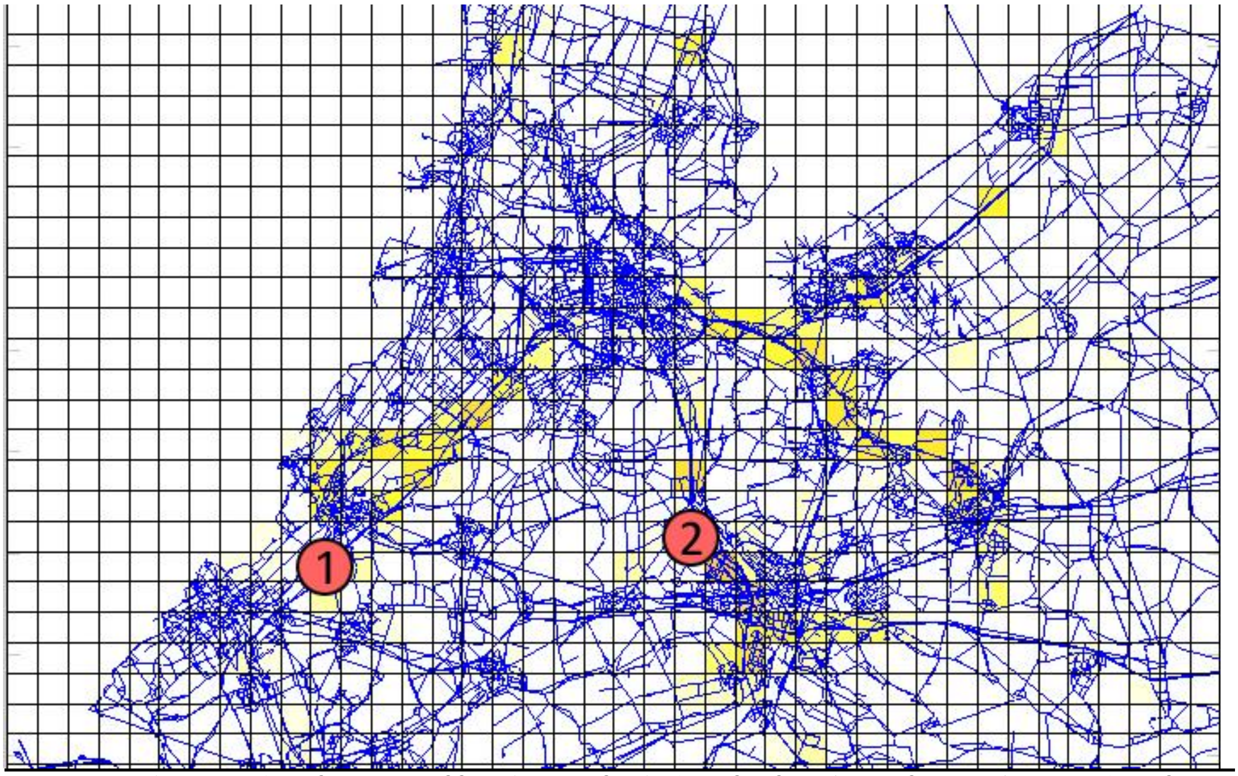


Figure 53, The optimal configuration of fast chargers for the benefit of residents of Amsterdam (number of locations: 2, number of chargers: 3)

The demand for the EV owners living in Amsterdam is only 66 charges per period of time and is scattered over the cells containing highways. Therefore, only three fast chargers are profitable from the perspective of traffic that is leaving Amsterdam in the morning. Two of these are located along the A2 north of Utrecht. The other is situated on the A4 between Leiden and The Hague. These three fast chargers cover 33% of total demand. However, also traffic from leaving from other cities can use those chargers. The number of required chargers at both locations is therefore not relevant. In addition, those locations will not be part of an optimal configuration within the area.

Upgrade to hubs: Implementing existing locations

The initial conditions in the algorithm were set at 0. This implies that there are no existing fast chargers in the area. However, some fast chargers are already installed in and around Amsterdam as mentioned in chapter 2. These locations (illustrated in Figure 54) are used as input. The optimal configuration is shown in Figure 55.

It can be concluded that the existing fast charger location on the A10 south is an appropriate location for a meeting point. This corresponds to the earlier determined optimal configuration. In this configuration, however, no fast chargers are required on the north side of Amsterdam.

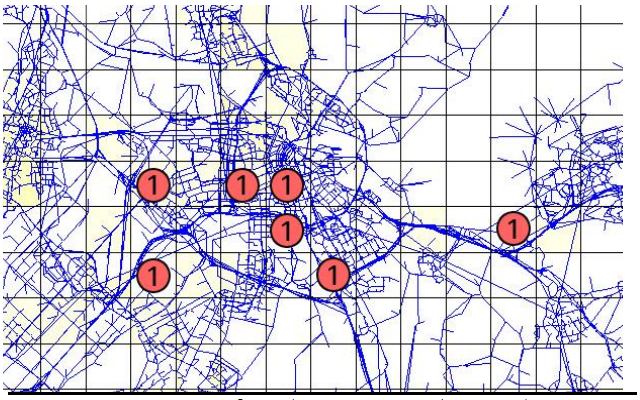


Figure 54, Existing fast chargers in and around Amsterdam

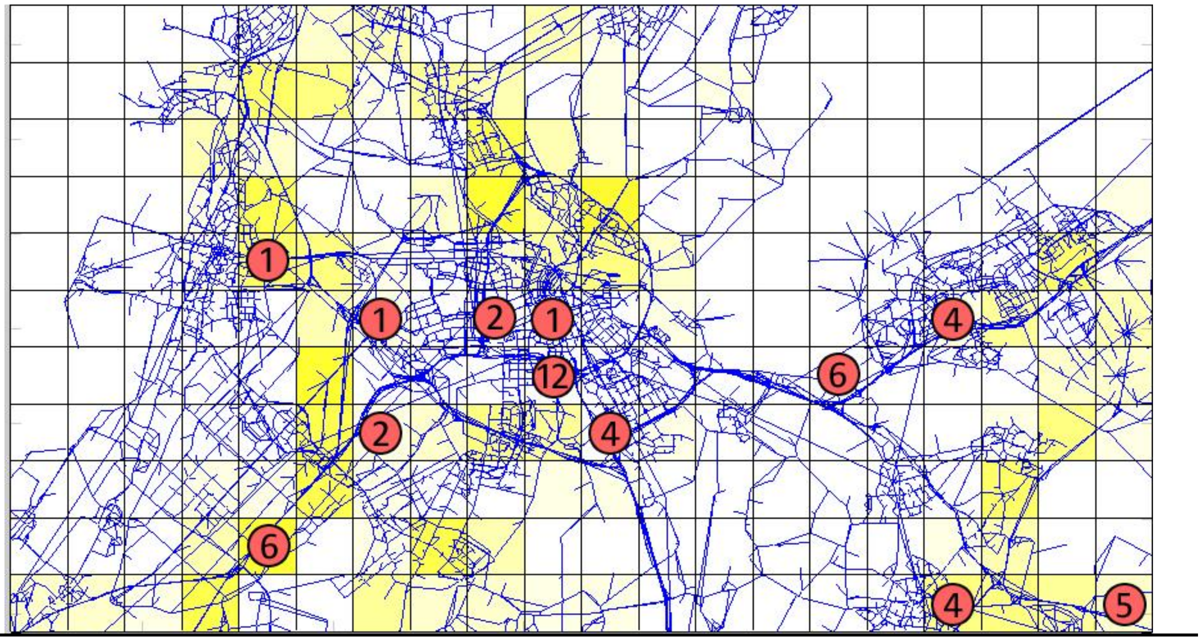


Figure 55, Optimal configuration within the study area using initial locations

Evaluate and rank: MC Donald's in Amsterdam

The TAGA-method can rank predetermined locations on profitability. To demonstrate this, the locations of the MC Donald's in Amsterdam are ranked. The cells in which MC Donald restaurants are situated are illustrated in Figure 56. The numbers in Figure 57 indicate the order of profitability. Number 1 indicates the most profitable location, allocating a fast charger to this cell will be the best investment. In contrast, number 8 will be a poor investment.

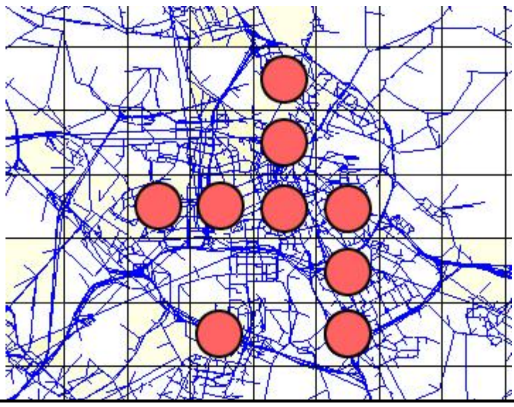


Figure 56, MC Donald locations in Amsterdam

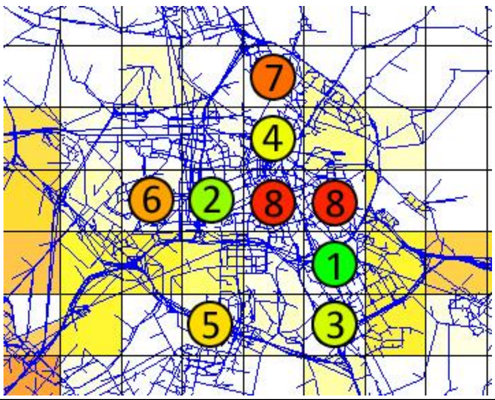


Figure 57, MC Donald locations in Amsterdam ranked by profitability

5.4 *Conclusions*

In this chapter, the TAGA-method is successfully applied to Amsterdam. The future network and the O/D morning matrix (2020) of VENOM are used in combination with stacked MON/OViN data (117.000 daily patterns). In addition, many assumptions are made. These are summarized in the table below.

Area of influence	Cell size	Factor tours-daily patterns	Market share of fleet & charging behaviour	Peak factor	Presence of slow chargers	Capacity	Profitability
260 3-digit postal code areas	3x3 km	1.19	0.02 & 0.5	0.5	0	8	7

In total, 5M different daily patterns consisting of 1 tour with two, three or four trips are generated in the area of influence. The data is processed and presented using the steps described in chapter 4 which results in the following optimal configurations.

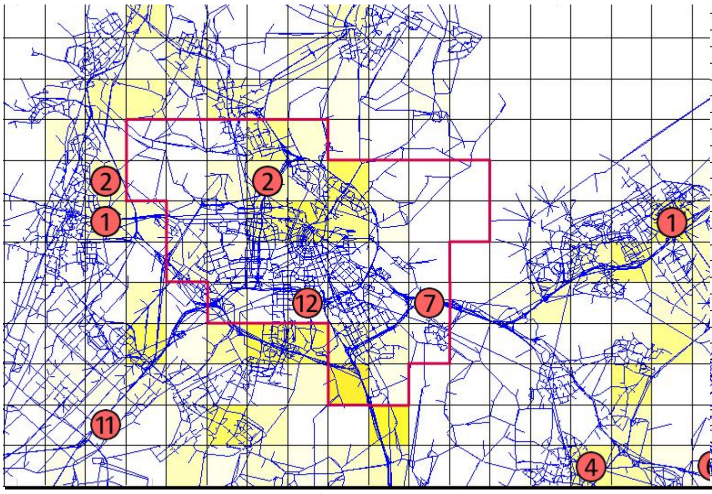


Figure 58, The optimal configuration of fast chargers in the study area (number of locations within the border of Amsterdam: 3, number of chargers: 21)

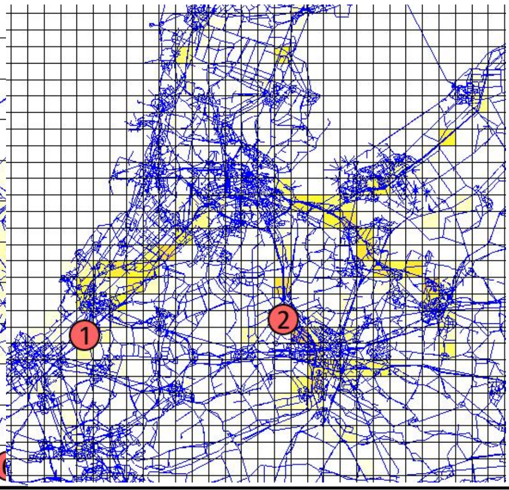


Figure 59, The optimal configuration for the benefit of residents of Amsterdam (number of locations: 2, number of chargers: 3)

The results indicate that the most potential locations are situated along the busiest roads. There are three locations within the borders of the municipality of Amsterdam where fast chargers are desired (Figure 58). These are situated along the A10, close to a junction with another highway. In this way, the fast chargers are easily accessible from several directions making detours not necessary. Because only a few locations are sufficient, opportunities will arise to develop (desired) economic activities nearby the charge locations.

From the perspective of EV users departing from Amsterdam in the morning, fast chargers are desired at locations with a distance of about 45-60 km from the city centre. This seems logical because these locations ensure that the driving range of an EV is increased to about 130 kilometres. Instead of the limited range of 40 kilometres, now cities situated within a range of 65 kilometres can be visited using an EV. Especially Utrecht, a city located at 40 kilometres from the city centre of Amsterdam, is better accessible due to the presence of fast chargers. The possibility to charge will cope with the uncertainty to get a flat battery. The same effect occurs on the A4 in the direction of The Hague. Here, a fast charger is required to reach the city of Den Hague with an EV. The expected demand on those locations is however low, therefore only one and two fast chargers are required. However, also traffic departing from other cities can use these chargers. The number of required fast chargers at both locations are therefore not relevant.

6 EVALUATION OF THE METHOD

6.1 Introduction

In this chapter, the TAGA-Method is evaluated by means of a validation and a sensitivity analysis.

Validation of the dataset

In the first part, the created dataset is compared with data from the MON/OViN. Here, different aspects are compared to make a statement about the quality of the input. This comparison will emerge if the created dataset contains more or less relevant daily patterns and whether the total demand in the dataset is over or underestimated.

Sensitivity analysis

Furthermore, a sensitivity analysis is performed to study the influence of the adopted parameters and conditions set. Topics that are studied include: driving range, market share, charge behaviour, the presence of slow chargers and the profitability of a charger.

At the end, the different configurations are compared and the robustness of the locations is analysed. The locations that are the same in most of the results are supposed to be most reliable.

6.2 Validation of the dataset

The tours that are generated to create a dataset are compared in different ways to find out to what extent they match to reality. First, it has been studied whether the model generates the same kind of tours as in the MON/OViN. Here, the average length of the created tours and the related length of the potential interval are compared. The length of the potential interval is the distance between the first and the last possible option to charge.

In addition, it is compared to what extent the percentage of relevant daily patterns consisting of 1 tour with two, three or four trips in the MON/OViN match with the total weight of the relevant generated tours. This is done by comparing the three created kind of daily patterns. An overview is given in Table 13.

Table 13, Comparison MON/OViN – TAGA-method (driving range: 80km)

Compared variable	**MON/ OViN**	**TAGA-Method**	**Difference**
Average length of a relevant tour with two, three or four trips	113.3 km	123.3 km[18]	+8.8%
Average length of the potential interval	46.7 km	50.2 km[18]	+7.5%
Demand (weight) in relevant daily patterns consisting of 1 tour with 2 trips of all daily patterns consisting of 1 tour with two, three or four trips	8.95%	9.37%	+4.7%
Demand (weight) in relevant daily patterns consisting of 1 tour with 3 trips of all daily patterns consisting of 1 tour with two, three or four trips	2.49%	2.36%	-5.2%
Demand (weight) in relevant daily patterns consisting of 1 tour with 4 trips of all daily patterns consisting of 1 tour with two, three or four trips	1.54%	1.45%	-5.8%
Demand (weight) in relevant daily patterns consisting of 1 tour with two, three or four trips of all daily patterns consisting of 1 tour with two, three or four trips	12.98%	13.18%	+1.5%

This validation shows that the average length of the generated relevant tours is overestimated in comparison with the MON/OViN. The same effect can be seen for the average length of the potential interval.

In addition, the total demand of the relevant daily patterns generated slightly overestimates the 'real' demand (12.98% vs. 13.18%). This can be explained by the fact that the generated dataset prevents from future data and MON/OVIN is based on the past. The difference is supposed to be acceptable.

[18] Weight of the tour is taken into account: potential intervals are weighted (intensity*probability)

6.3 *Sensitivity analysis*

The conditions set, the assumptions made and the techniques chosen as input for the TAGA-method are analysed to make a statement about the robustness and reliability of the locations and the corresponding number as chargers. The aspects that can influence the final result are depicted in Figure 60.

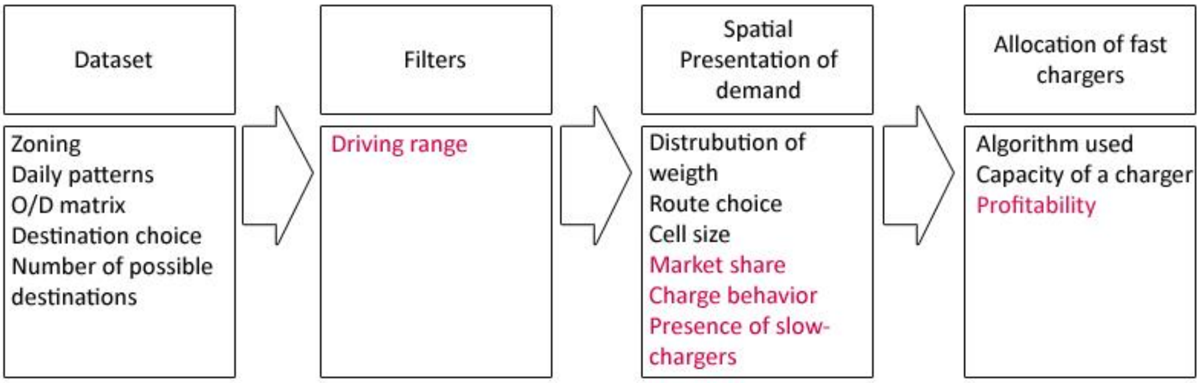


Figure 60, Conditions, assumptions and techniques used per step that can influence the final result.

First, the aspects in black are discussed in general terms. These effects are not passed (calculated). The aspects in purple, however, are calculated and the effects on the locations and number of required fast chargers are analysed and compared.

6.3.1 General aspects

The influence of some assumptions and principles is briefly reviewed on possible effects. Some of them are combined.

Zoning, number of possible destinations and destination choice
The more zones in the area of influence and the more destinations that can be chosen after each trip will increase the computation time. It is assumed that this effect is relatively large because of the wide distribution of the demand: the five destinations with the highest probability to be chosen represent less than 10% of the total probability. Increasing the number of possible destinations will greater the level of detail.

The destinations that are chosen from each (departure) zone for each purpose are determined using a gravity model and the attractiveness of the zones. A combination of both will often lead to a location close to the departure zone. Long trips in a tour are therefore underrepresented. In addition, selecting the destination with the highest probability does not take into account the direction a vehicle came from (the destinations are always the same). As a result, it might occur that tours with illogical detours are generated.

Data used: Traffic Model and daily patterns
The morning O/D matrix of a traffic model is generated using socioeconomic data[19], such as car ownership, population and jobs, trip generation formulas and a trip distribution. This includes an (unknown) unreliability, especially for a future year. In addition, the municipality of Amsterdam doubts about the correctness of the traffic forecasts of VENOM. The data from MON/OViN tells something about the travel behaviour in the past, while future forecasts are studied. In addition, travel behaviour can change over time as well as travel behaviour when a different type of car is used, such as an EV. The effects, however, are unknown.

The distribution of the weight of a tour over the potential interval and route choice
The potential interval is determined on the basis of the road sections which are situated on the fastest route between two destinations. It is therefore assumed that the fastest route is always chosen. However, due to congestion or other preferred routes other choices can be made. The effect will be limited, because EV users will (probably) only make a detour if they know that they don't need to charge on that part of the trip. In

[19] Sociaal Economische Gegevens

addition, the distribution used to distribute the weight of a tour over the potential interval is an important assumption. Because nothing is known about the shape of the distribution, it is difficult to make a statement about the correctness of this choice. If a distribution is chosen which assigns more demand to the middle of the interval and less to the sides, it is plausible that the results will be less robust. This will be more similar to the one-point approach that is supposed to be less robust.

Algorithm and capacity

The capacity of a charger will change when the time required for charging will reduce. It is unknown how this will change over time.

6.3.2 Influence of driving range

An important assumption is the driving range. In section 2.2.3, it is described how the adopted driving range has been established. In the future, the batteries will improve, allowing a longer driving range. The extent to which this occurs is still uncertain. To study the influence of a greater driving range, the TAGA-method is applied again on the area of influence set in chapter 5. In this analysis a driving range of 100km is used. The area of influence is, however, is not large enough to study the effects of a larger driving range. This is a recommendation for further research.

Spatial distribution of the demand

The distribution of the demand in the study area derived with a driving range of 100 kilometres is depicted in Figure 61. The result for the residents of Amsterdam is shown in Figure 62.

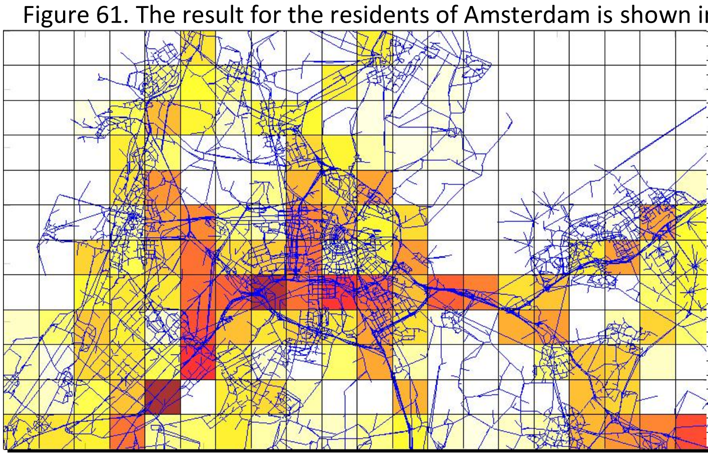


Figure 61, Distribution of demand in the study area assuming a driving range of 100km

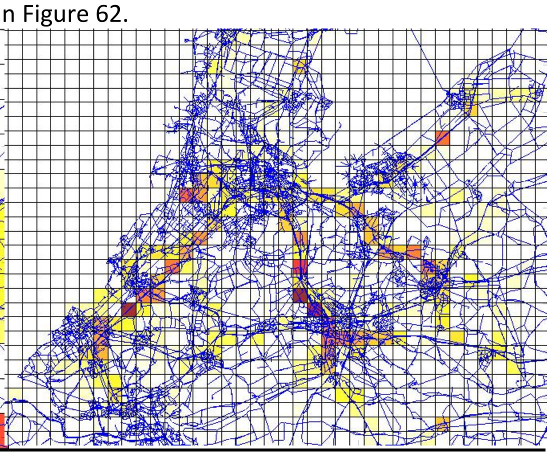


Figure 62, Distribution of demand for residents of Amsterdam assuming a driving range of 100km

Optimal configuration

Using the results, an optimal configuration can be determined. The configuration for the study area is illustrated in Figure 63 and for the residents of Amsterdam it is shown in Figure 64.

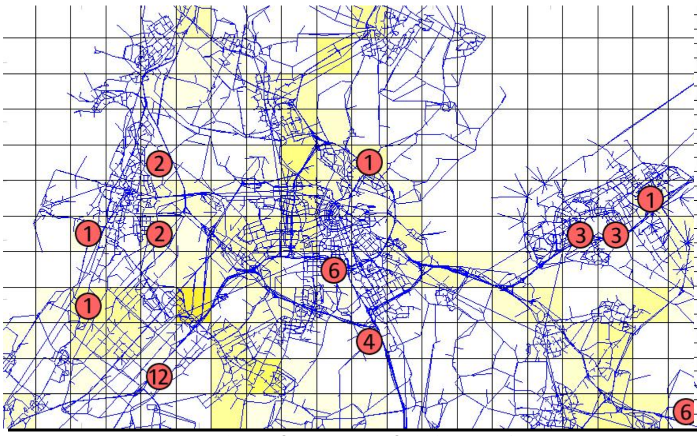


Figure 63, Optimal configuration for the study area assuming a driving range of 100km

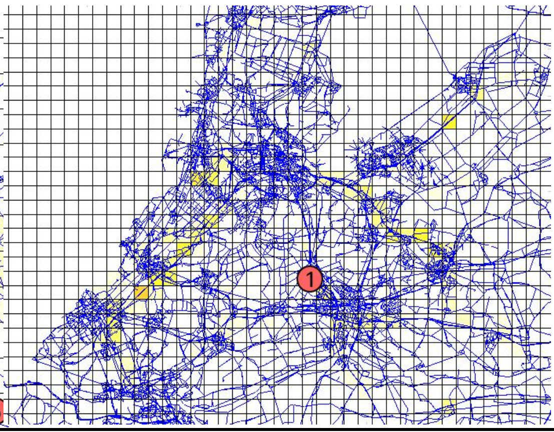


Figure 64, Optimal configuration for residents of Amsterdam assuming a driving range of 100km

In summary, the following table is made to compare both outcomes.

Table 14, Influence of the driving on the locations and number of fast chargers

Driving range	**80 km**	**100 km**	**Difference**
# of expected charges in study area	345	274	-26%
% potential served	81.1	81.2	+1%
Study area			
# Locations	3	3	0
# Number of required fast chargers within the Municipality of Amsterdam	21	11	-47%
Residents of Amsterdam			
% potential served	33	20.2	-39%
# Number of required fast chargers	3	1	-67%

The robustness of the locations can be explained by analysing the way the weight is distributed over the potential interval of a relevant tour. The extreme points (X_{alap} and X_{asap}) will change, but the shape remains the same, as shown in Figure 65.

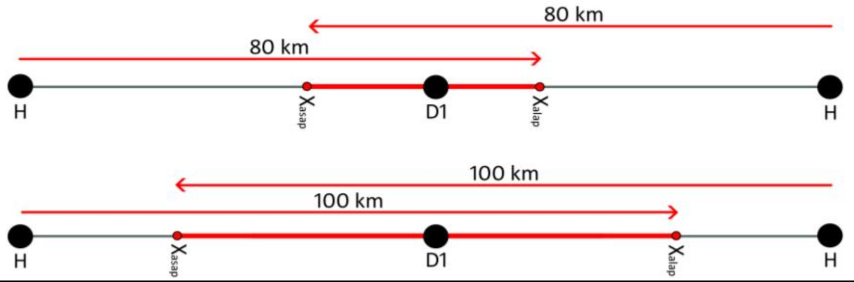


Figure 65, Explanation of the robustness of the locations as the driving range increases

Therefore, most locations will be the same. An aspect that could influence the results is the tours in the dataset that become relevant at a longer driving range and vice versa. In addition, the locations of fast chargers don't need to change due to the large potential interval of an average tour. This implies that a driver can charge over a large distance, a small change in the configuration will not affect seriously the amount of demand served.

6.3.3 Influence of market share & charge behaviour

The expected size of the market share of the EV fleet depends on the scenario chosen. In section 2.2.2, several scenarios are described that estimate the number of electric vehicles in a certain year. Considering the year 2020, the percentage of EVs on the road will be between 1% and 2%. The market share has a linear relationship with the demand: if the market share increases by 1% then the demand will also increase by 1%. The same applies to the charging behaviour of the users. Therefore, these two components are merged. The amount of EV users who will actually use fast chargers is unknown. It was decided to examine 25% and 75%. In this way, six categories are created. The results for the study area are presented in Table 15.

Table 15, Influence of the market share and charge behaviour on the locations and number of fast chargers within the border of Amsterdam

Market share	**1%**	1.5%	2%	1%	1.5%	**2%**
Users that wants to use	**25%**	25%	25%	75%	75%	**75%**
Factor	**0.0025**	0.00375	0.005	0.0075	0.01125	**0.015**
# of expected charges in study area during peak hours	**86**	130	173	259	389	**518**
% potential served	**75.6**	87.2	86.4	83.1	83.6	**83.2**
# Locations within the Municipality of Amsterdam	**3**	4	4	3	4	**3**
# Number of required fast chargers	**5**	8	11	16	24	**31**

It follows logically that more fast chargers are required if the market share increases and when more people will really use fast chargers. The number of fast chargers in the study area varies from 5 to 31, while the number of locations substantially remains constant. The two most extreme combinations are shown in Figure 66 (MS = 1%, USE = 25%) and Figure 67 (MS = 2%, USE 75%).

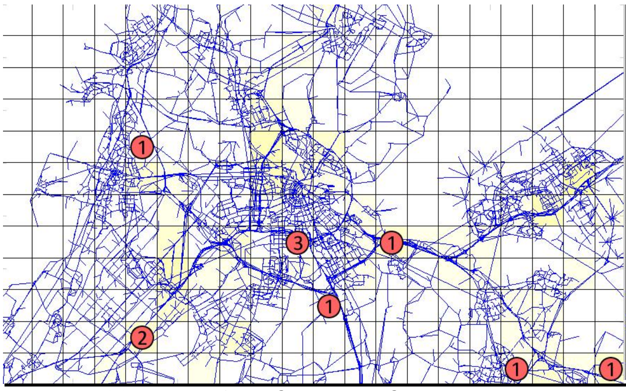


Figure 66, Optimal configuration for MS = 1%/USE = 25%

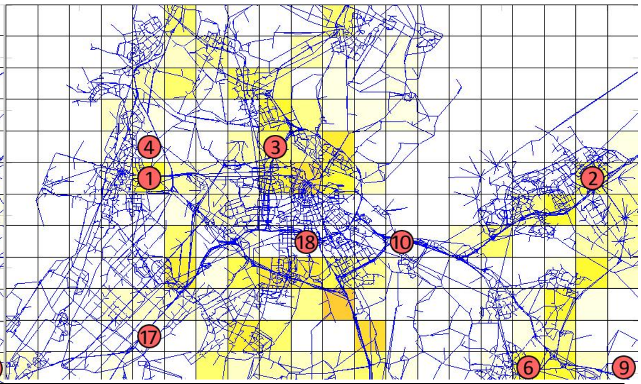


Figure 67, Optimal configuration for MS = 2%/USE = 75%

These figures show that two locations within the municipal boundary are matching. This is the location in the cell near the RAI and the cell east of Amsterdam (junction A1-A9). The number of fast chargers required differs. Because the likelihood of the scenarios is unknown, it is difficult to assess whether extra fast chargers have to be placed.

It should be noted that the market share is evenly distributed over all starting zones (home). However, there are areas with (probably) more potential users. The high purchase cost, for example, will only be affordable for higher incomes.

6.3.4 Presence of slow chargers at activity end

In the Netherlands more and more slow chargers become available (see 2.3.3), particularly at locations where people work (commercial areas). These slow chargers make it possible to make tours that are longer than de driving range without using a fast charger. The time between arrival and departure is indicative to what extent the battery will be charged. Because time is not taken into account when creating the dataset, the MON 2008 is used for this analysis. The values which are determined are based on an average of iterations. The presence of a slow charger changes per iteration: if the percentage is set at 60%, it means that in 6 out of 10 destinations (4-digit postal code area) a slow charger is present. To get reliable results, twenty iterations for each scenario are performed. The effect of slow chargers at activity end is shown in Table 16. In all cases, the EV will depart with a full battery.

Table 16, Influence of the presence of slow chargers at activity end (home = 100% slow charger) (MON, 2008)

Percentage of slow chargers at activity end	**0%**	**20%**	**40%**	**60%**	**80%**	**100%**
Percentage of daily patterns that requires a fast charger	12.05%	11.39%	10.71%	7.92%	5.35%	2.96%
Difference		-7.28%	-12.79%	-35.51%	-56.41%	-75.91%

It is likely that when more slow chargers are installed, less fast chargers are required. Of course, it is also possible to place fast chargers at activity end. Because of this, the demand for fast chargers will reduce even more. However, fast chargers are more expensive compared to slow chargers (ABB, 2012) and therefore not preferred to be installed at activity end.

6.3.5 Profitability of a charger

The stop criterion of the greedy algorithm is the profitability of a fast charger. If fewer charges per unit of time are required to make a charger profitable, more fast chargers can be allocated and more demand will be served.

The value determined in Appendix E is established from a commercial viewpoint. This value is based on the fact that no loss-making chargers are allowed in the optimal configuration. In this way, the profit is maximized. The value may be lower by the following aspects:

1. Fast chargers will be less expensive in the future, so fewer chargers are required to break even
2. The government is committed to reducing emissions. Therefore, loss-making chargers contribute to better air quality. This can be converted into money and are added to the revenues.

For this reason, a sensitivity analysis is performed in which the value has been reduced from seven to five charges per two hours. The results are shown in Figure 68 and Figure 69.

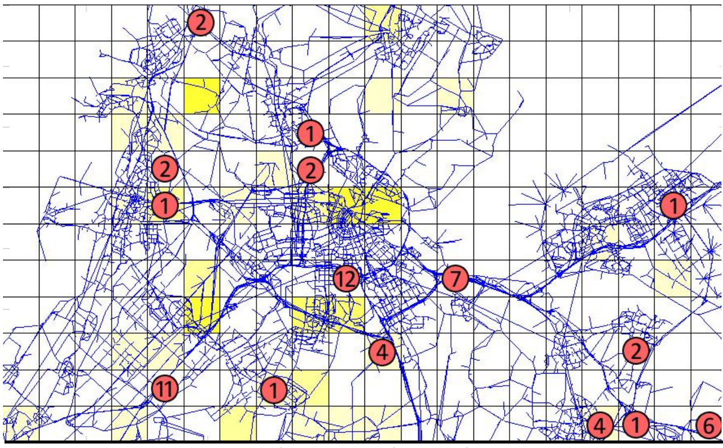


Figure 68, Optimal configuration for profitability = 5 charges/2 peak hours

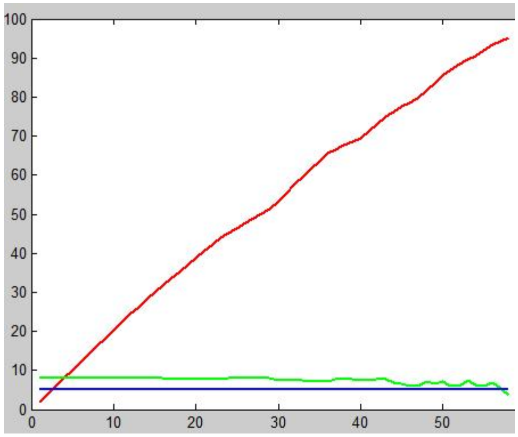


Figure 69, Graph corresponding to the result. 94.2% of the demand will be served (x-as: # chargers, y-as: percentage served)

The optimal configuration gives approximately the same locations as seven charges per two hours. At some locations outside the borders of Amsterdam, new chargers are allocated. This ensures that more demand in the study area is reached (94% vs. 80%).

6.4 Conclusions

This chapter discussed the validation of the dataset and a sensitivity analysis that is performed to study the effects of changing conditions. In this way, a statement can be made about the reliability and robustness of the results. From this analysis, the following conclusions can be drawn:

VALIDATION

The created dataset is in reasonable agreement with reality with respect to the size of the potential market

The created dataset is compared with data from the MON/OViN. In this way, it is determined to which extent the created daily patterns corresponds to daily patterns in the MON/OViN. This shows that the percentage of relevant generated daily patterns slightly overestimate the real potential market (13.18% vs. 12.98%). The small difference can be explained by the fact that the dataset is created with an O/D matrix from a future situation (2020) and MON/OViN data is obtained in the past (2004-2010). Furthermore, it is studied to which extent the average size of the potential interval per tour match. This comparison shows good agreement, with a deviation of only a few kilometres.

SENSITIVITY ANALYSIS

To determine whether the TAGA-method provides reliable and robust results, the conditions, assumptions and the choices made are analysed. These aspects are illustrated in Figure 70. For some aspects (purple), the effects are passed (calculated) for the Amsterdam case. For the aspects in black, an estimate is made of the effects on the results.

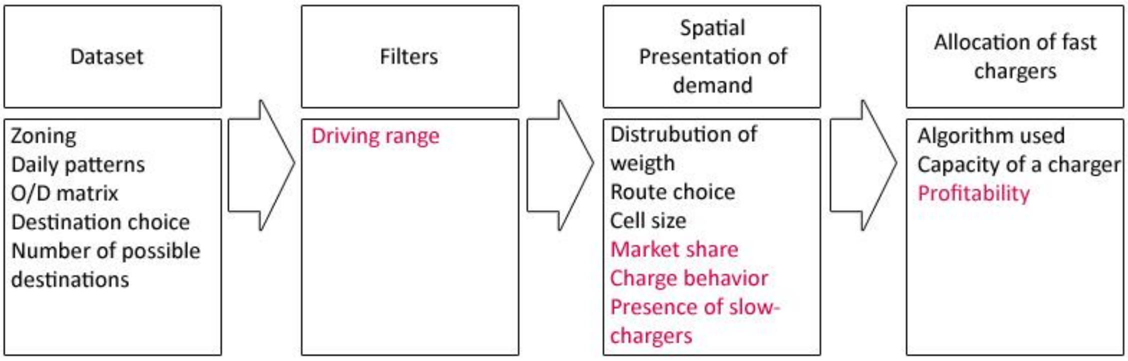


Figure 70, Possible uncertainties in the TAGA-method

Aspects in black:

The way the tours are generated contains uncertainty. Firstly, the number of possible destinations for interzonal traffic for trip two and three is limited to five. In reality, however, all destinations have a certain probability to be chosen. If all destinations are included by creating tours, the computation time will be intolerable. It is assumed that this effect is relatively large[20], because of the wide distribution of the demand: the five destinations with the highest probability to be chosen represent less than 10% of the total probability. Secondly, the destinations that are chosen from each zone for each purpose are determined by a gravity model and the attractiveness of zones. A combination of both will often lead to a destination close to the departure zone. Long trips in a tour are therefore underrepresented. In addition, selecting the five destinations with highest probability does not taken into account the direction a vehicle came from (the destinations are always the same). As a result, it might occur that tours with illogical detours are generated. Those three aspects will (probably) cause the greatest unreliability. Effects related to the chosen O/D matrix, travel behaviour and the distribution of the weight of a tour over the links are unknown.

Aspects in purple:

The size of the driving range has minimal influence on the potential locations

The locations of fast chargers within the border of Amsterdam will slightly change if the driving range is chosen larger. The fast chargers on the north side of Amsterdam will slightly displace and one location will switch from the A2 to the A1.

[20] 23% is interzonal or intrazonal traffic after first trip and are thus involved

The larger the driving range, the fewer fast chargers will be required
The driving range is one of the most important variables to determine the demand. The further can be driven on a full battery, the fewer relevant tours. Assuming a driving range of 80km, 12.1% of the daily patterns are relevant and for a driving range of 100km this percentage is decreased to 9.72%. A driving range greater than 100km is also conducted with the method, but contains limitations due to the chosen size of the area of influence (see recommendations). Using the MON/OViN, it can be analysed to what extent the demand will decrease for greater driving ranges. For the Netherlands, the percentage of relevant daily patterns drops to 8.2% for a driving range of 120 km and to 6.8% assuming a driving range of 140 km.

Market share and charging behaviour has a linear relation with the expected demand
The demand in a study area is determined on the basis of several factors. Because the weight of the relevant tours are determined using all vehicles in the O/D matrix, some factors are applied to convert the cell score to expected number of charges. These factors include market share, charge behaviour and distribution over time. All aspects have a 1 to 1 relationship to the demand: if there are 1% more EVs, the demand will also increase by 1%. The same applies to the percentage of EV owners that will actually use a fast charger.

Furthermore, it is assumed that the market share is evenly distributed over the areas. However, there are (probably) areas with more potential users. The high purchase cost, for example, will only be affordable for higher incomes. In addition, it is assumed that the market share is evenly distributed over the daily patterns. But it is likely that most EVs are used and purchased by drivers who make only incidental daily patterns larger than the driving range. If only incidental daily patterns are studied, the locations might be different.

The more (slow) chargers are present, the less fast chargers are required
The presence of slow chargers will affect the demand. If the battery can be recharged at a destination, some relevant tours will become non relevant. If at all locations slow chargers are installed, the demand will decrease with more than 70%.

The more charges are required to make a fast charger profitable, the less demand is served
Every time a fast charger is allocated to a cell, the scores on that cell and surrounding cells will decrease. A fast charger requires a certain demand, number of charges per unit of time, to be profitable. If there is no cell that can provide that demand, an extra charger will not be profitable. The minimal number of charges that is required might change by, for example technological developments. The lower the value, the more profitable fast chargers can be allocated, and the more demand will be served.

Finally, the following effects are plotted in one graph:

- Charge behaviour (25% and 75%)
- Market share of the EV fleet (1%, 1,5% and 2%)
- Profitability (5 /7 charges/peak hour)
  -5 is top of the area in the graph-

This is done for a driving range of 80km in Figure 71.

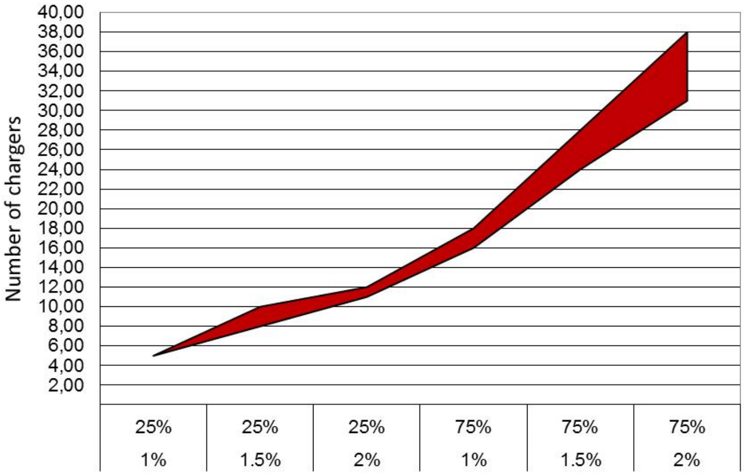


Figure 71, overview of findings sensitivity analyses (driving range 80 km)

It can be concluded that the required number of fast chargers cannot be determined until there is more information available about how some scenarios will change in the future. The locations are however robust. The three locations (south-A10, A10-west and A1-A9) that are determined for Amsterdam in chapter 5 do not change significantly.

7 CONCLUSIONS

The main research theme in this thesis is developing a method that can be used to find the optimal locations and the corresponding number of fast chargers. This final chapter summarises the main results of this thesis. First, the main research findings are given. These include the answers on the sub questions and the main research question. This is followed by recommendations for further research and some specific actions for the municipality of Amsterdam. Finally, a reflection is given on this thesis.

7.1 *Main research findings*

This thesis has given insight into the possibilities that may contribute to better charge infrastructure for electric vehicles. By answering the sub questions, an answer is obtained on the following main question:

Main research question
What is the optimal configuration of fast chargers to reach the highest potential of electric vehicles usage?

The following main research findings are derived:

7.1.1 Total distance travelled on a day is indicative for the use of fast chargers

Electric vehicles (EVs) have different properties compared to the common used ICE vehicles. These differences are studied to find the potential user group that will use fast chargers. The following sub-question is answered:

Who are the potential users of fast chargers and which aspects are relevant for determining the optimal locations and the corresponding number of fast chargers?

The most important element is the distance that can be driven on a fully charged battery. This distance, named the driving range, varies per vehicle, per weather condition and travel behaviour (inc. the fear of getting an empty battery (range anxiety)). Car manufacturers often report a driving range which corresponds to a situation with optimal conditions. This will, however, never happen in reality. Therefore, the actual driving range is much shorter. The current EVs have a driving range of approximately 80 kilometres.

In this thesis, it is assumed that every EV owner can charge their EV at home. Therefore, the battery will be fully charged in the morning. Whether an extra charge en route is required depends on the total distance to be driven on a day. This is studied by analysing daily patterns. If the total distance of a daily pattern is larger than the driving range a charge is required. On the other hand, from the user's point of view is not desirable to charge two times a day. The following conclusion can be drawn:

A potential user is an EV user that makes a daily pattern with a total distance between the driving range and twice the driving range on a certain day.

Analyses of the MON/OViN show that 12.1% of the daily patterns are relevant. How many drivers of this group will actually use fast chargers depends on many aspects. In addition, the presence of slow chargers will decrease the percentage of relevant daily patterns.

The driving range, charge behaviour and presence of slow chargers are relevant parameters to determine the demand for fast chargers.

7.1.2 The TAGA-(Two-point Approach Greedy Algorithm)method is best, dataset point of improvement

In this thesis three datasets, four methods to translate data into a spatial presentation of demand and several allocation methods are studied and compared. Those steps will provide an answer on the following sub-question:

What methods can be used to determine the expected demand for fast chargers, and what methods can be used to find an optimal configuration that meet the demand?

A combination of the steps results in the best method, the newly developed TAGA-method: The Two-point Approach Greedy Algorithm-method.

The studied datasets in this thesis did not satisfy the requirements set (quality and quantity). Therefore, the dataset that is supposed to be best is a combination of a traffic model and a dataset that contains information about daily patterns. Using this input, tours are generated on the basis of probability. The first trip of a tour is derived from an O/D morning matrix of a traffic model and the subsequent trips are estimated by means of data from daily patterns. In this way, tours up to four trips are generated for a specific area.

The potential interval is determined for each relevant tour; this interval indicates where a fast charger is required to make the tour possible with an EV. To determine this interval, two points have to be defined (two-point approach):

- The first possibility is the point on the route where (after a full charge) the battery is empty on arrival at the final destination
- The last possibility is the point where the driver drives until the battery is empty.

Between these two points a fast charger can be installed to ensure that the tour can be ‘electrified’ (can be made with an EV). However, the demand is not spread evenly over the interval. It is safer to use the fast charger in the middle of the area; the probability of getting a flat battery is here the smallest. Hence, a triangular distribution is preferred to divide the demand of the tour (weight). The potential interval of all tours can be added and plotted to create a total spatial representation. The result shows differences between potential areas (more demand) and less potential areas (less demand).

This distribution of demand is used to find the best possible configuration of fast chargers; this is done by allocating fast chargers to the area. A Greedy algorithm is used to allocate the chargers one-by-one to the area with the greatest demand. An optimal configuration has been found as the addition of a new fast charger will lead to loss. In other words, the additional fast charger is unprofitable.

In summary, the following steps are executed in the TAGA-method:
1. Generate tours using an O/D matrix and a dataset that contains information about daily patterns
2. Estimate the weight of each tour
3. Define the potential interval of each tour
4. Distribute the weight over the links in the potential interval
5. Assign the link scores to cells
6. Add up the cell scores of all tours
7. Convert the scores to real demand
8. Find the cell with the highest demand
9. Allocate fast chargers as long as they are profitable
10. Repeat step 8 until no profitable locations (cells) are left

The TAGA method can be used in the following cases:
- Determine the optimal configuration of fast chargers within a certain area.
- Evaluate and rank planned fast chargers on profitability.
- Find the best existing fast charging stations to upgrade to a hubs.

The TAGA-method has some weaknesses:
- Not all possible kind of tours/daily patterns are generated.
- Not all generated tours might be realistic due to general assumptions.
- The Greedy Algorithm will not guarantee a global optimum.

Nevertheless, it is assumed that the dataset and the TAGA-method will provide reasonably reliable results.

7.1.3 Fast chargers are required on at least three locations in Amsterdam

The TAGA-method is applied to Amsterdam. Two issues are studied, namely:

- What are the optimal locations for fast chargers within the municipality of Amsterdam?
- What are the optimal locations for fast chargers for EV users who live in Amsterdam?

In both cases, the year 2020 is studied. This corresponds to the following sub-question:

Should the municipality of Amsterdam install extra fast chargers to meet the expected demand in the future and where should it be placed?

To answer this question, some parameters have to be assumed. The tours are generated using VENOM (2020), a traffic model that focuses on the north wing of the Randstad, and (stacked 2004-2010) data of the Dutch National Travel Survey (MON/OViN). The other parameters are shown in Table 17.

Table 17, Adopted parameters for the application to Amsterdam

Driving range	Market share of the EV fleet	Users that will use fast chargers
80 km	2%	50%

Fast chargers within the border of Amsterdam

Target: Promote EV usage and reduce emissions in Amsterdam

The distribution of the demand is depicted in Figure 72 and the corresponding configuration in shown in Figure 73. The red dots indicate the locations and the number is the number of fast chargers required.

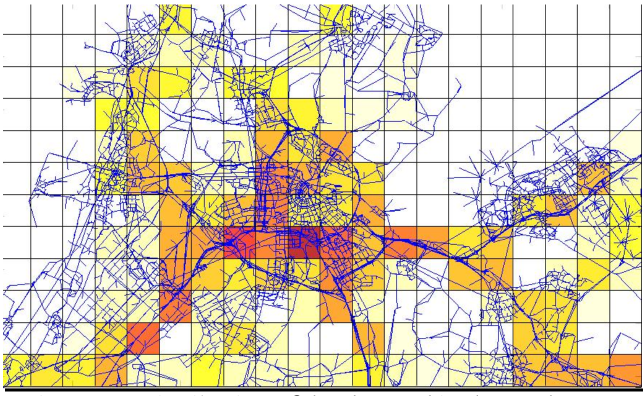


Figure 72, Distribution of the demand in the study area (2020)

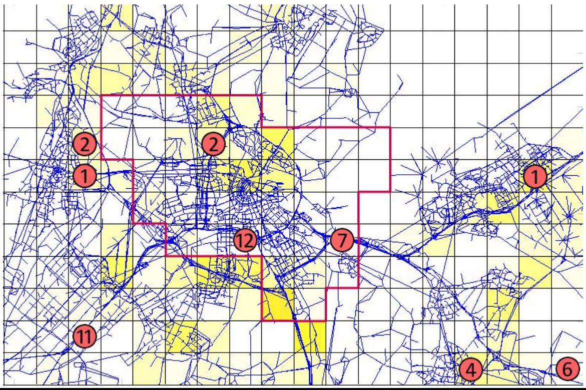


Figure 73, Optimal configuration of fast chargers in the study area (2020)

The result indicates that the most potential locations are situated along the busiest roads. There are three fast charge locations required within the borders of the municipality of Amsterdam. All three locations are situated near a junction of highways. In this way, the fast chargers are easily accessible from several directions making detours unnecessary. In total, 21 fast chargers are required. This is only 14 more than currently present. In total, 80.2% of the expected demand is served with this configuration.

The number of locations can be increased by using another greedy algorithm. This will provide a more ubiquitous network. However, clustering locations has the advantage that it is more cost efficient and offers opportunities for economic activities. See reflection for more information about this difference.

Residents in Amsterdam

Target: Make a larger part of the Netherlands accessible for EV users living in Amsterdam

The distribution of the demand is depicted in Figure 74 and the corresponding configuration in shown in Figure 75.

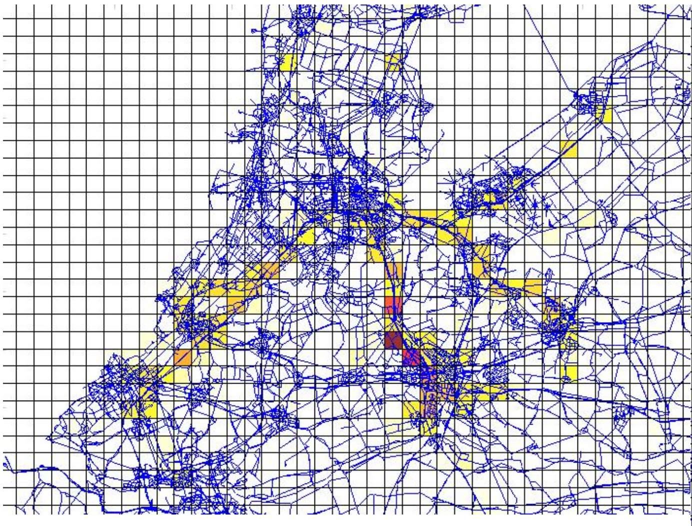


Figure 74, Distribution of the demand for the residents of Amsterdam (2020)

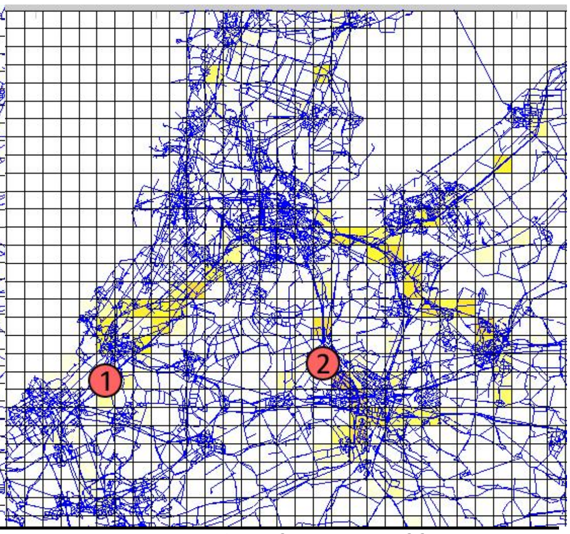


Figure 75, Optimal configuration of fast chargers for the residents of Amsterdam (2020)

The EV users departing Amsterdam in the morning require fast chargers at a distance of about 50-70 km from the city centre. Instead of the limited range of 40 kilometres, now cities situated within a range of 60 kilometres can be visited using an EV. Especially Utrecht, a city located at 40 kilometres from the city centre of Amsterdam, is better accessible due to the presence of fast chargers. The possibility to charge will cope with the uncertainty to get a flat battery. The same effect can be seen on the A4 between Leiden and The Hague. Here, a fast charger required to reach the city of Den Hague with an EV. The expected demand on those locations is however low, therefore only 1 and 2 chargers are required to meet the demand of Amsterdammers. However, not only residents of Amsterdam want to charge over there. Hence, the number of required chargers is unknown.

7.1.4 The locations are robust, the demand is uncertain

To determine how reliable and robust the results are, a sensitivity analysis is performed. The following sub question is answered:

What is the influence of the assumptions on the results, are the results reliable and robust?

The number of expected charges and the associated number of fast chargers is uncertain. The driving range of an EV, the market share of the EV fleet, the number of people that actually wants to use fast chargers, the distribution of the demand over a day, the presence of slow chargers at activity end and the profitability of a fast charger will influence the expected demand in a certain year. These variables are very uncertain and will change over time. In addition, the TAGA-method itself has some uncertain assumptions which are mainly related to the dataset (input). Therefore, it is not yet possible to estimate the expected demand in a certain year. The following conclusions/relations can be drawn:

- The size of the driving range has minimal influence on the potential locations
  The locations of fast chargers within the border of Amsterdam will slightly change if the driving range is chosen larger. The fast chargers on the north side of Amsterdam will slightly displace and one location will switch from the A2 to the A1.

- The larger the driving range, the fewer fast chargers are required
  The driving range is one of the most important variables to determine the demand. The further can be driven on a full battery, the less relevant daily patterns. Assuming a driving range of 80km 12.1% is relevant and for a driving range of 120km this percentage is reduced to 8.2%.

- Market share and the number of users that will actually use fast chargers has a linear relation with the expected demand
- The more (slow) chargers are present, the less fast chargers are required
- The more charges are required to make a fast charger profitable, the less potential is served

The number of profitable fast chargers within the border of Amsterdam in 2020 varies from 5 up to 38. In the worst scenario, only five fast chargers will be profitable. Therefore, it is debatable whether fast chargers are a good investment at all (from a commercial perspective). The locations of the fast chargers in corresponding configurations are robust: only in some cases, a location will change.

It can be concluded that the sensitivity analysis shows that increasing the driving range hardly influences the potential locations for fast chargers. The other aspects, market share of the EV fleet, presence of slow chargers and profitability of a charger, affect mainly the number of required fast chargers. This implies that the locations are robust.

7.1.5 Answer to the main research question

The sub-questions provide insight in the steps that are performed to find an answer on the main question. Using these answers, an answer can be formulated to the main research question:

What is the optimal configuration of fast chargers to reach the highest potential of electric vehicles usage?

In this thesis two situations are studied:

- What is the optimal configuration of fast chargers within a certain area?
- Where do EV owners prefer a fast charger when they depart from home with a full battery?

The developed method, the TAGA-method, is used in both cases. This method translates daily patterns into a spatial distribution of demand for fast chargers in a certain area. The method determines for each daily pattern where a fast charger can be placed. This fast charger makes it possible to 'electrify' the daily pattern: this implies that the pattern can also be made with an electric vehicle. The optimal locations for fast chargers are the locations where as much as possible patterns will be 'electrified'.

In the first case, the optimal configuration of fast chargers is determined for all traffic driving through a certain area. Results show that the optimal locations are along the busiest roads. This thesis shows that only a few locations are required to serve most of the demand. Because only a few locations are sufficient, opportunities will arise to develop (desired) economic activities nearby the chargers.

In the second situation, it can be concluded that fast chargers are desired at a distance of 60% -100% of the driving range. In this way, the EV user can reach destinations that are further away than the driving range. The large variation is related to the number of possible destinations (attraction) within the areas just outside the driving range.

The exact locations can be determined by finding a spot in the cell which meets the wishes of the users. EV users prefer to do something while waiting. The most desired facilities are: wireless network, a shop or cafe to get something to eat/drink coffee. The locations must be attractive enough to spend a half hour, the maximum time required to charge. Activities that take longer than half an hour are not desirable; this may cause unnecessary occupied fast chargers.

The number of required fast chargers in a future year is uncertain. However, it can be concluded with any certainty that the number of planned fast chargers is rather an overestimation than an underestimation. The percentage of relevant daily patterns, the daily patterns that require a fast charger, will greatly decrease if more slow chargers are present in combination with an improved driving range. For example, if a driving range of 120 km is assumed and slow chargers are present at 50% of the destinations at activity end this percentage drops below 5%. From a commercial point of view, fast chargers are therefore a risky investment without subsidy. From the perspective of the government, placing (unprofitably) fast chargers will take away the anxiety range. This will ensure people have the idea that they can always reach a fast charger, which promotes EV usage.

7.2 Recommendations

7.2.1 Application to a large area

An optimum configuration of fast chargers is established when the largest possible area is studied. The potential interval, the road segments where a fast charger is required within a daily pattern, is so large (42km at a driving range of 80km) that a good optimization for an area like Amsterdam is difficult. Therefore it is recommended that the TAGA-method should be applied for the entire country. A simplification, for example to generate tours with only two or three trips, might be useful to avoid long computation times.

In addition, the study area is dimensioned for a maximum driving range of 100 kilometres. If a greater range is analysed, two problems will emerge. First, some EV users that live in Amsterdam desire a fast charger outside the area of influence. Because destinations (postal codes) outside this area can't be chosen as destination, not all possible tours are plotted. This will lead to a distorted result. The same counts for the study area, since EV users from outside the area of influence are not included.

7.2.2 First spatial distribution, then upgrade to hubs

The results show that approximately 80% of the demand is served with a certain number of locations and chargers. The conclusions showed that the number of chargers in a given year is difficult to estimate. Therefore it is not advisable to place the number of predicted fast chargers at a location in one time. It is better to install one fast charger at each location to create a ubiquitous network. The TAGA-method can rank the locations in the optimal configuration to determine which fast chargers have to be placed first. In this way, the available money will be spend as efficiently as possible and a ubiquitous network is created as soon as possible.

7.2.3 Monitoring demand and parameters

The parameters that have been adopted to estimate the number of expected charges in a certain year contain a high degree of uncertainty. Many scenarios have been devised, but it is unknown which scenario will approach the developments best. The development of electric vehicles depends, as CEDelft (2011) has described, on many aspects such as price, subsidies and the development of batteries (driving range). Another effect that is unknown is whether EV users will actually make use of fast chargers. Currently, no data is available because the current fast chargers are not monitored. To make more reliable estimations it is recommended to monitor fast charger usage from time to time in order to calibrate the input parameters.

Furthermore, the demand for a fast charger is not evenly distributed over the potential interval. The shape of the distribution is assumed a triangle. This implies that in the middle of the area, the desire for a fast charger is greatest and this evenly decreases to the sides. The shape of the distribution influences the results. Therefore, it should be further elaborated which distribution fits the charge behaviour best.

7.2.4 Improving the quality of the generated daily patterns

The dataset, the input of the TAGA-method, is a point of improvement. The created dataset contains some assumptions that simplify the world, namely:

- The destinations chosen from every zone (interzonal traffic)
- The number of possible destinations from every zone (interzonal traffic)

Many destinations that are chosen are situated nearby the departure area. To achieve a more realistic distribution of destinations, the purpose of travelling has to be further analysed. The kind of facilities in each zone can, for example, be implemented to make more reliable choices. This, however, concerns only a small proportion (73% is homebound after first trip) of the intensity.

The second assumption ensures that not all possible kind of daily patterns are generated. This can be solved by using faster computers.

7.3 *Reflection and discussion*

7.3.1 Reflection on results: Profitability versus ubiquitous network?

In this thesis it is chosen to cluster as many as possible for the following reasons:

- Probability of finding a free fast charger is greater
- Less expensive: only one connection to the three-phase network per location is required
- Opportunities for economic activities related to EVs/meeting point

This choice will strongly influence the number of locations. The greedy algorithm that is applied throughout this thesis will find an optimal configuration with three locations in within the borders of Amsterdam. This is depicted in Figure 76. Those three locations will ensure that all EV users passing Amsterdam can easily find a fast charger without making an unacceptable detour. From that point of view, more locations are not necessary.

The configuration (Figure 77) obtained with the alternative algorithm, introduced in 4.4 and further elaborated in appendix F, will find of more locations with fewer chargers. This will contribute to a better ubiquitous network. Again, all EVs travelling through Amsterdam will encounter a fast charger.

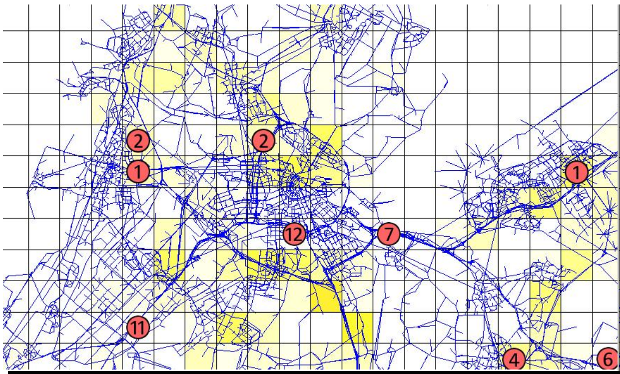


Figure 76, Optimal configuration with clustering

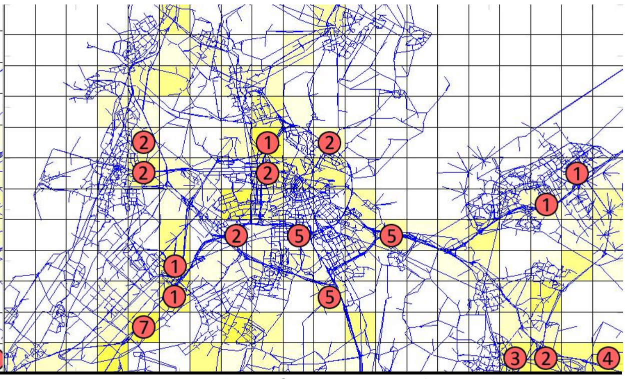


Figure 77, Optimal configuration without clustering

The differences between both configurations are shown in Table 18.

Table 18, Differences greedy algorithms

Aspect	**Greedy Algorithm A**	**Greedy Algorithm B**	**Difference**
Number of locations within the municipality of Amsterdam	3	7	+233%
Number of chargers within the municipality of Amsterdam	21	22	+4.7%
Percentage of demand served	82%	83.9%	+2.5%

The preference for the kind of optimal configuration depends on the purpose of the client. Clustering will lead to more profit due to the reduced installation costs and more locations will provide a better ubiquitous network which will reduce range anxiety.

7.3.2 Market functioning and competition

An optimal configuration will, unfortunately, never be achieved because of the different market parties that are installing fast chargers. These parties do not consult with each other, because they are only installing fast chargers on their own ground. For example, the oil and gas company Total installs their fast chargers alongside their own fuel stations. Achieving an optimal configuration is therefore not feasible. The municipality or government can, however, place their own fast chargers or help companies to provide an optimal network.

The TAGA-method can also be used to provide advice about the order of installation.

7.3.3 Regular and incidental daily patterns: will the potential user group increase?

Regular daily patterns and incidental daily patterns

In this thesis the number of expected charges per period of time is calculated and the corresponding optimal configuration is determined. From a policy perspective, fast chargers are installed to promote EVs. It makes it possible for more drivers to complete their travel behaviour with an EV. This report doesn't include information about how a person travels over time. However, this element is relevant to determine whether a person might switch to an EV. To clarify this, two weekly patterns (how someone travels over a day) are depicted in Figure 78.

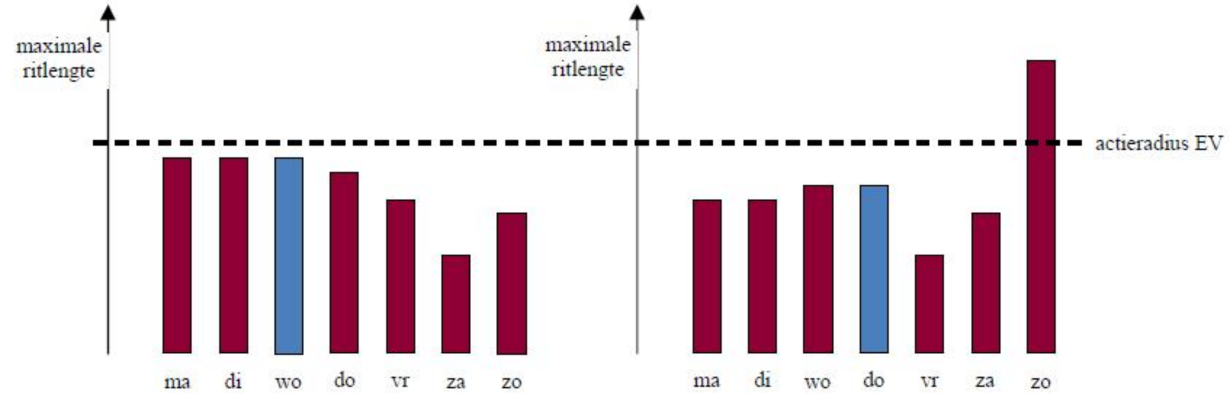


Figure 78, Two different weekly patterns (Goudappel Coffeng, 2011)

Suppose the blue bar indicates the daily pattern which is filled in by a respondent in the Dutch National Travel Survey. Both daily patterns are not relevant, the total distance is shorter than the driving range. According to this day, both users can switch to an EV without making use of a fast charger. However, the weekly pattern showed on the right requires a fast charger on Sunday. These weekly patterns show that incidental daily patterns are the difference between a relevant or non relevant daily pattern and a potential user. If someone will/can switch to an EV depends on the amount of daily patterns in a period of time that are larger than the driving range.

Extra potential due to fast chargers

Potential replacement without fast chargers

The TAGA-method assumes that the market share is an input to determine the number of chargers. However, increasing the market share is also a target (output). Thus, there is a mutual relation. The percentage of drivers that can switch to an EV can be determined by analysing a period of time. Goudappel Coffeng (Brink, 2011) has studied the potential replacement of EVs without fast chargers by using LVO[21] data. This study shows that 80% of the drivers can switch to an EV when one day is analysed and only 15% as a longer period is studied (8 weeks). In other words, 15% of the drivers doesn't make a daily pattern longer than 80km during 8 weeks. Here, it is assumed that everyone can charge at home. This percentage will increase if another (conventional) car is available.

Potential replacement with fast chargers

The same kind of analyses can be made for a situation in which fast chargers are available. In this way, it can be determined how many extra potential users might be added to the percentage calculated in the report of Goudappel Coffeng (15%). However, this will be more difficult. The following aspects are relevant:

- The probability that a driver makes a daily pattern with a total distance larger than twice the driving range for 8 weeks.

  This aspect can be determined by using the LVO data. This percentage is approximately 50%. This implies that 50% of the drivers doesn't make a daily pattern longer than 160km during 8 weeks. Those daily patterns might be made with an EV.

[21] Longitudinaal Verplaatsings Onderzoek

- Location of the fast chargers: The probability that the driver passes a fast charger on the day he or she makes a relevant daily pattern.

  This aspect is more difficult to determine. The results in this thesis have shown that 82-87% of demand is served by the configurations calculated. The probability that the driver encounter a fast charger depends on the route driven. It is unknown how many times during the 8 weeks a driver will encounter a fast charger when he or she makes a relevant daily pattern.

  For example, a driver makes four times a daily pattern with a distance between the 80km-160km during the 8 weeks and no daily patterns longer than 160 km. It is unknown whether this driver can change switch to an EV without changing his travel behaviour. The probability that a driver will be served by a fast charger at all four daily patterns can be calculated, but will result in a very uncertain conclusion. If the driver doesn't encounter a fast charger during a daily pattern, he or she can't make it with an EV and won't be a potential user.

- Charge behaviour: willingness to use a fast charger

  In contrast to the study of GC, behaviour is an important aspect. The time required to charge at a fast charger increases the travel time. It is unknown how many users which are currently driving a regular car would actually want to use fast chargers. This will probably depend on the frequency of usage: someone who makes an incidental relevant daily pattern in 8 weeks will probably switch easier than someone who requires a fast charger every day.

  The market share of 2% will therefore probably be achieved among those drivers who make an incidental relevant daily pattern. This will affect the demand for fast chargers and might affect the locations.

  The maximum potential will be achieved if everyone who needs a fast charger would use it. However, this will not be the case.

It can be concluded that more research is needed to determine to what extent fast chargers will contribute to a larger potential group/market share of the EV fleet.

7.3.4 Has the development of fast charging infrastructure the priority?

Improving fast charge infrastructure is, in my opinion, not the key to the wide acceptability of electric vehicles. Many EV users will have a conventional car that can use be used for longer distances. The EV will be used as a car for short distances. Despite the fact that the EV is able to drive long distances by fast chargers, the normal vehicle (for the majority of the drivers) is preferred. In other words, only a small group that owns an EV will also use it for longer, relevant, distances. To serve their demand, only a few fast chargers are required.

In the future, a greater driving range and the presence of more slow chargers at activity end will ensure that fewer fast charges are required. On the other hand, fast chargers will be less expensive to install and the charging time might reduce due to technical developments. For example, if the charging time drops below 5 minutes it can compete will fuel tanking. This contradiction makes investing in fast chargers a difficult issue regarding future prospects.

Therefore, it is difficult to make a decision whether large (unprofitable) investments should be made to provide a ubiquitous network. There are also other options that can help to make electric vehicles more attractive. For example, by installing slow chargers at attractive destinations.

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APPENDIX

APPENDIX A: Electric vehicles on market

Electric Vehicles on the market according to AgentschapNL (2011) ZerAuto, ANWB, fuelswitch.nl and elektrischeauto.nl

Manufacturer	Type	Kind of car	Fast charge ability
Citroen	C-Zero	City car	
	Berlingo Electrique	Van	X
DFM	Mini bus	Van	
ECE	Qbee	City car	
FAAM	Jolly 2000	Van	
Fisker Karma	Ecostandard	Sportscar	
Mega	eCity	City car	
Mitsubishi	i-MiEV	City car	X
Nissan	Leaf	City car	X
Peugeot	iOn	City car	X
Plaggio	Porter Elektro Glass	Van	
Tazzari	Zero	City car	
Tesla Motors	Roadster	Sportscar	
Think	City	City car	
Chevrolet	Volt	City car	X
Opel	Ampera	City car	X
Volvo	Electric	City car	X
Smart	Fortwo Electric Drive	City car	

Expected Electric Vehicles 2012 (not sure if also in the Netherlands)

Audi R8	e-tron
Fiat	500
Ford	Focus Electric
Hyundai	i10
Renault	Fluence Z.E.
	Kangoo X.E.
	Twizy
	Zoe Preview
Tesla	Model S
Toyota	iQ EV
Volkswagen	E-Up!

Top 5 registered Evs in the Netherlands according to AgentschapNL (2012)

#	Type	Number
1	Nissan Leaf	294
2	SMART FORTWO Electric Drive	257
3	Peugeot ION	82
4	Mitsubishi I-MIEV	61
5	Mercedes E-Cell	34

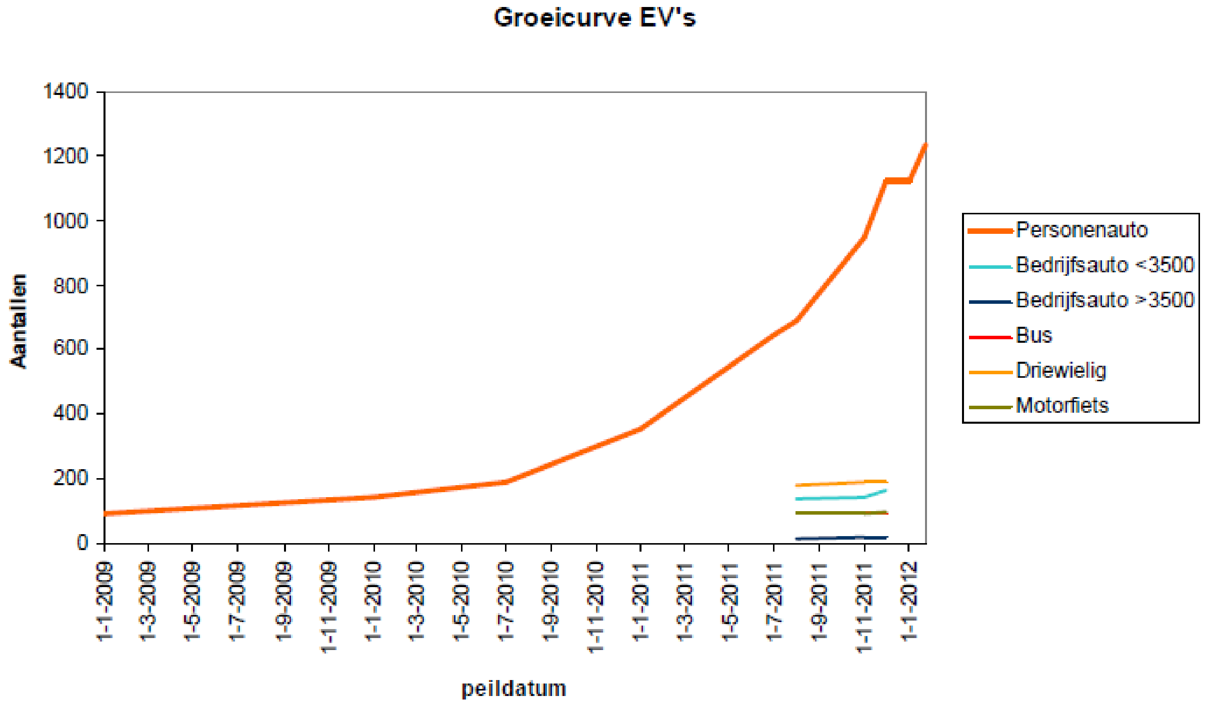


Figure 79, Number of EV's in the Netherlands (2009-2011) (AgentschapNL, 2012)

APPENDIX B: Driving range and battery developments

Driving range

The driving range is a much debated topic. There is considerable uncertainty about the range of an EV: the driving range is often suggested larger than it actually is. To determine a realistic value to use in this study, various scenarios are examined. The driving range of the Nissan Leaf has been studied in different conditions. The results are shown in Table 19.

Table 19, Driving range of the Nissan leaf under varying conditions (Nissanusa.com)

Condition	Average Speed	Temperature	Air conditioner	Range (in km)	Range anxiety factor	Realistic range[22] (in km)
Cruising (ideal condition)	61	20	Off	222		**200 km**
City traffic	38	25	Off	169		**152 km**
Highway	89	35	In use	110	10%	**100 km**
Winter, stop-and-go traffic	24	-10	Heater on	100		**90 km**
Heavy stop and go traffic	10	30	In use	76		**69 km**

Battery

The Nissan LEAF (12-volt lead-acid battery) and the Mitsubishi iMiEV (16-kilowatt-hour (58 MJ) lithium-ion battery) are not using the latest technology. Battery innovations are expected to be key in making hybrid and electric vehicles more widespread. Electric car batteries can be further improved by combining and developing different techniques that will boost the energy density. Experts and car companies are making small steps on different aspects, like costs, weight and lifetime. However, the driving range hasn't strongly improved in recent years.

The three most potential kinds of batteries for EV applications are lithium cobalt or lithium manganese oxides, lithium iron phosphate and lithium titanate.

Lithium cobalt or lithium manganese oxides (LiCO, $LiMn0_2$)

This is the 'standard' battery has been adopted by both BMW (mini E) and Tesla Motors. An improved battery can be a solution due to the relative low costs and very high specific energy. However, safety and performance reasons are limiting the development.

Lithium-titanate battery ($LiTi0_4$)

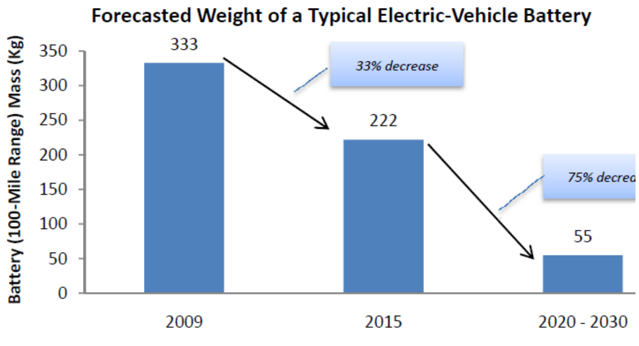
Tobisha, a company specialised in batteries has already developed a battery that can recharge way faster than other batteries (Toshiba Corporation, 2011). This lithium-titanate battery, named Super Charge ion Battery (SCiB), can charge up to 80% in 15 minutes. The technique is currently used for construction equipment, electric bikes and other industrial machines, but there are plans to bring the battery to electric vehicles. The SCiB combined with other improved techniques (regenerative braking) will extend the driving range by 1.7 times the current driving range (270 km).

Lithium iron phosphate battery ($LiFePO_4$)

Another development is the usage of lithium iron phosphate, the ideal material for the production of lithium car batteries in the near future according to chemists. Advantages of Lithium Iron Phosphate Batteries (LIPB) are the longer cycle life over standard lithium ion cells and superior thermal and chemical stability. In May 2007 the first LIPB with cells large enough for electric vehicle (Aptera cars) usage was made. The breakthrough of this kind of battery is that the power density increases without increasing the energy density. In other words, the driving range doesn't increase, but the charge time decreases. This means that the battery is full again in a few minutes; disadvantage is that the high voltages can be dangerous. The major problem is, despite its efficiency, the costs of the lithium material. To make this kind of battery more widely used, studies have to be done to lower the production costs.

[22] The effects caused by electronics (radio, navigation system, mobile phone etc) are not yet included

The department of energy[23] (USA) set targets with respect to ingenuity, innovation and manufacturing. The investments in batteries alone should help to lower the costs, produce more and create jobs. This must lead to the results that are shown as graphs in figure Figure 80 and Figure 81.



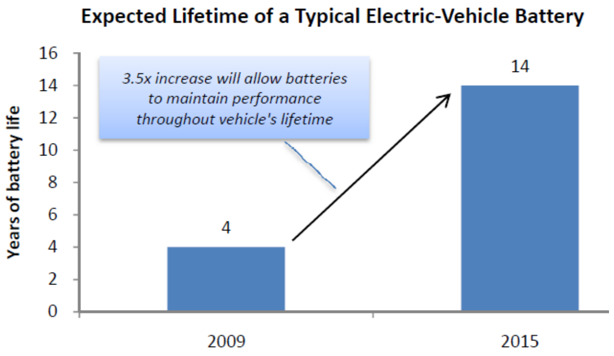
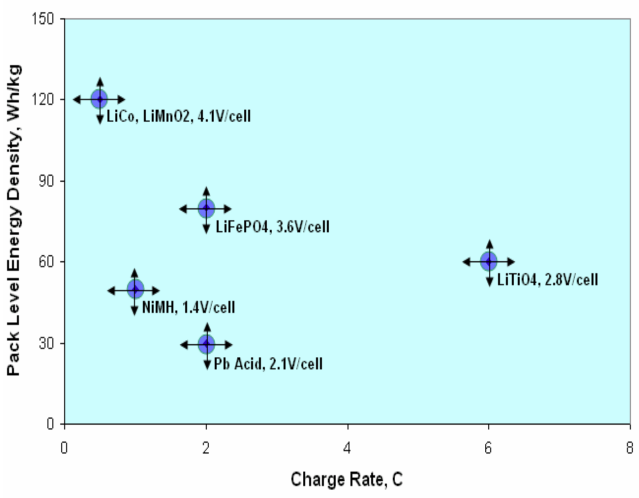


Figure 80, forecasted weight of a typical electric-vehicle battery (U.S. DOE Vehicle Technologies program, 2010)

Figure 81, Expected lifetime of a typical electric vehicle battery (source: U.S. Vehicle Technologies Program, 2010)



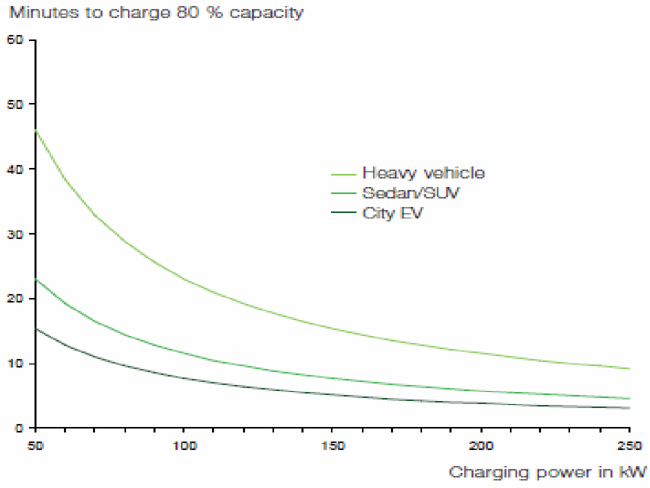


Figure 82, Energy density (Wh/kg) as function of Charge rate for different types of batteries (source: EVS24)

Figure 83, Charging time versus the charging power. Minutes required to charge 80% of the capacity (ABB)

[23] Transforming America's Transportation Sector, Department of energy

APPENDIX C: Comparison MON/OViN - VENOM

The dataset MON/OViN probably contains too less daily patterns to find reliable results. To verify this, a comparison with another dataset is performed. In the first step, the amount of data and the spatial distribution is compared using the data of a traffic model.

More data and more spatial distribution
The matrix that is used in this comparison is the morning matrix of VENOM. This matrix contains more data and less unfilled O/D pairs. To demonstrate the difference, both O/D matrices (first trip MON/OViN and O/D matrix morning VENOM) are compared on some criteria. The results are shown in Table 20.

Table 20, Comparison of spatial distribution and amount of entries (based on all first trips)

Criteria	**MON 1st trip**	**VENOM morning**	**Difference (VENOM/MON)**
Number of trips in matrix	40,404	1,070,573	x26.5
Number of areas (pc3)	260	260	
Number of O/D pairs	67600	67600	
Percentage of filled cells (flow >=1)	14,42%	37,25%	**x2.6**
Percentage of filled cells (flow >5)	2,36%	19,92%	**x8.4**
Percentage of filled cells (flow >20)	0,44%	9,45%	**x21.5**

This table clearly shows that in the VENOM matrix much more cells are filled (x2.5) and with higher flows. This is logical since the MON/OViN is a sample (which can be increased by multiplication factors) and VENOM is based on calculated (realistic) flows/intensities. The difference will increase when higher intensities are analysed (factor 21.5 by intensity higher than 20).

To see if the number of daily patterns is sufficient for analysis, a pre-analysis is performed. The result is shown in Figure 84 on the next page.

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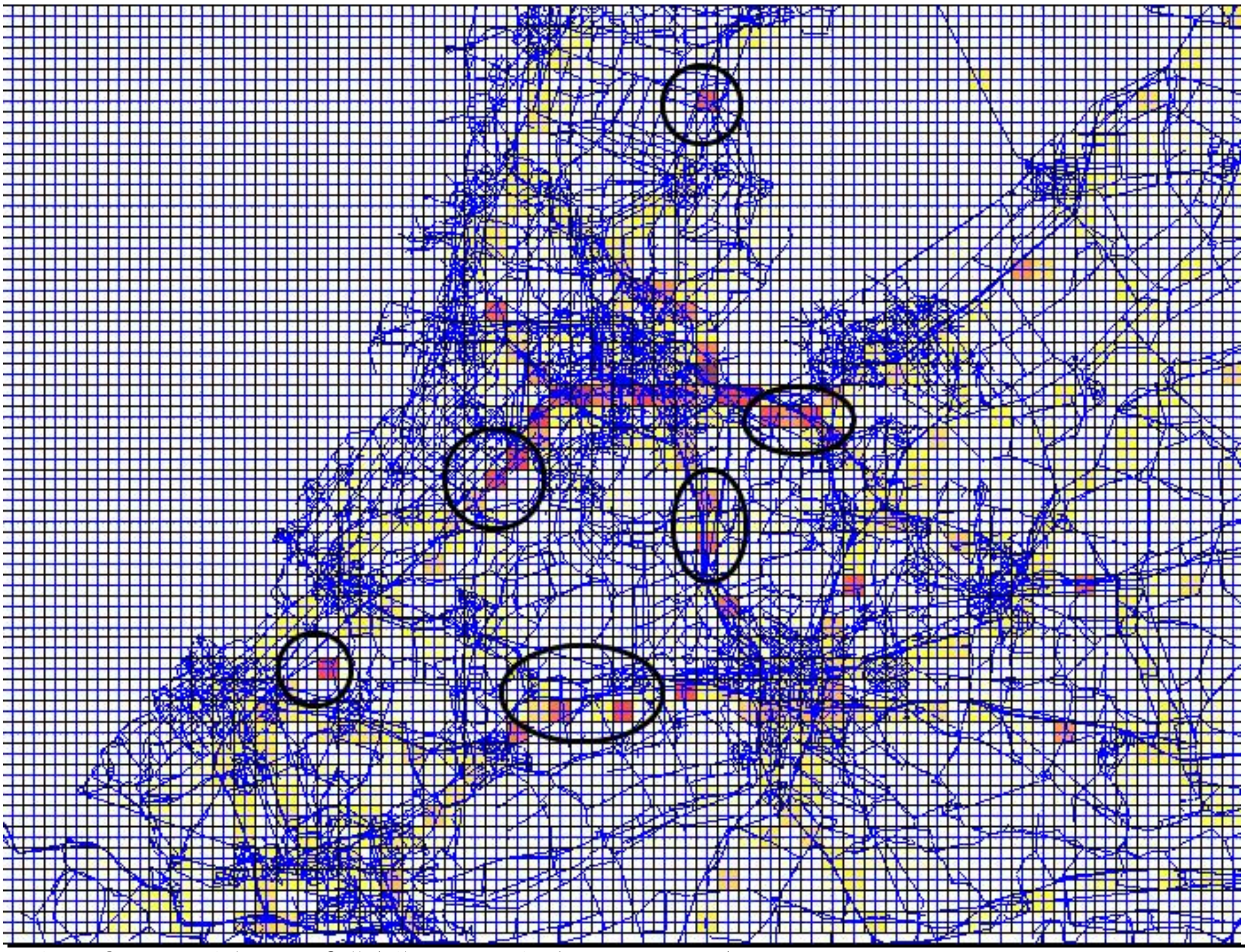


Figure 84, Potential areas of all daily patterns in the MON/OVIN dataset

The number of relevant daily patterns that is used as input is 7500. Because there are many possible relationships between all postal code zones, some cell scores are based on only a few trips. This implies a very low level of robustness; a tour with a small potential interval will give a high score to links and thus also to the related cell(s). The few trips per O/D pair route will cause an unbalanced distribution. In the figure it is clearly shown that the daily patterns that have a relation with Amsterdam are overrated. Most of the red cells are situated in and around Amsterdam.

APPENDIX D: Estimation of the cell size

When a fast charger is placed in a cell, it can affect surrounding cells. Traffic that is driving in the other cells will eventually make a detour to use the charger; the consequence of this is that the demand of those tours is served and the demand of their original potential interval will drop. The allocation method chosen cannot cope with detour factors. Therefore, this effect has to be minimized by making use of the appropriate cell size.

If it is assumed that an EV user wants to make a detour with a maximum distance of **10%** of the trip distance, an estimation of the cell size can be made. To determine this, two aspects have to be taken into account:

- First of all, the distance associated with a detour factor of 10% varies per trip distance. The absolute detour distance for a short trip is shorter compared to a longer trip (e.g. 5km: 0.5km, 50km, 5 km). To find an average, the detour distance per trip length is multiplied with the degree to which the trip occurs. This distribution of the maximum detour lengths for the area of influence is depicted in Figure 85.

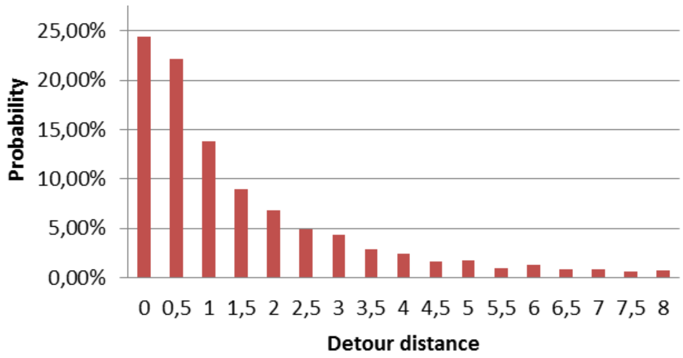
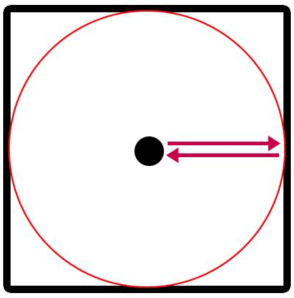


Figure 85, Distribution of detour lengths

- The other aspect that plays a role is how this distance is driven. There are two extreme situations to consider: the situation in which the fast charger is on a location where the EV users should drive to the fast charger and go back on the same way. In the other situation, the fast charger is located closer to the route (Pythagoras).



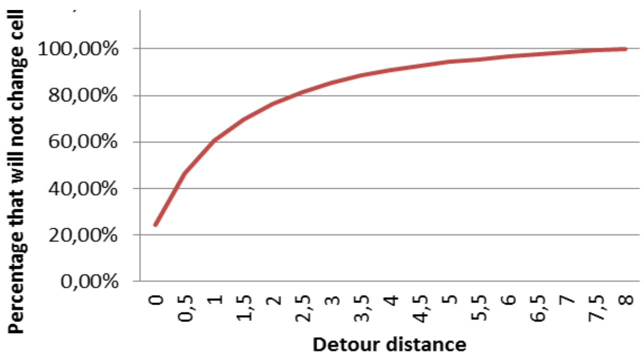


Figure 86, 'Minimum' maximum detour

Figure 87, Percentage of EV users that will not make a detour

Using this information, an estimate can be made about the cell size. If a car is situated in the centre of a cell, then a 'minimum' maximum detour (Figure 86) that can be driven is straight to the side of the cell and back. The detour distance is equal to the cell width (2*0.5 cell width). The distribution of the detour distances is used to determine how many percentage of the EV's will not change cell at a certain cell size. This is shown in Figure 87. This graph shows that when a cell size of 3.5km is assumed, 90% won't change cell in the most extreme case.

Because the mentioned network configuration (a straight road perpendicular to the cell side) is rare, the cell size is assumed a bit smaller. The cell size used for the application of Amsterdam is **3x3 km**. Despite the fact that many exceptional situations can be devised and the value is based on an average (cell centre), it is considered to be an appropriate assumption.

APPENDIX E: Estimation of profitability

The minimum number required charges per unit time to make a fast charger profitable can be determined by cost-benefit analysis. This value is difficult to estimate because the conditions in 2020 may be highly variable. Therefore, some assumptions are made:

- This calculation does not take into account interest rates
- The calculation assumes an average demand. The market share will increase during the life time and the demand will therefore also change. The implantation of this is, however, to difficult.
- The distribution of the demand over a year is based on an estimate.
- The values used are based on sources of ABB and experiences of the DIVV (2011).

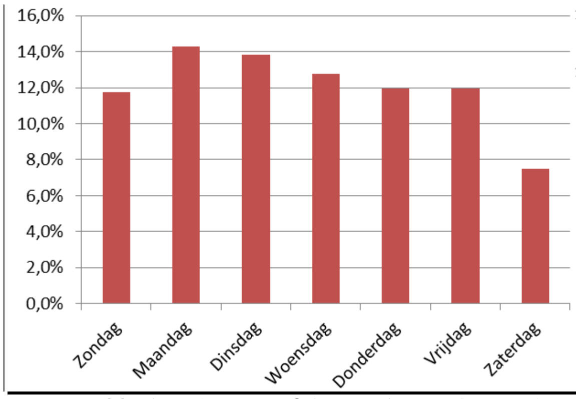


Figure 88, distribution of demand over the week (source: OViN 2010)

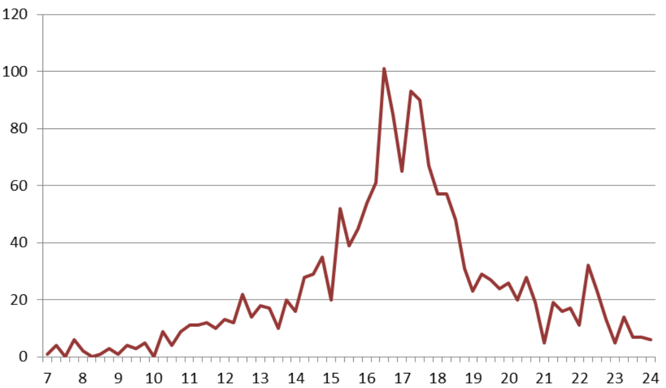


Figure 89, distribution of demand over the day (source: OViN 2010)

Table 21, Estimation of the minimum required number of charges to make a fast charger profitable

Explanation	**Amount**	**Unit**	**Source**
Life time fast charger	10	year	Epyon Terra (ABB)
Investment costs	75000	euro	Epyon Terra (ABB): 25.000 without connection to electricity network Haas, R de 100.000 based on Amsterdam (2 sockets)
Depreciation expense	7500	per year	
Maintenance costs	2000	per year	8% of the hardware costs with full SLA (Service Level Agreement) (ABB)
Total costs per year	9500	Per year	
Charge Revenue	8	euro	The green motion
Charge costs	5	euro	Essent
Profit per charge	3	euro	
Number of required charges a year	Apr. 3200	Per year	
Conversion factor to relevant days	0.004		250 days in a year
Conversion factor to peak hour	0.5		Derived from Figure 89 (OViN, 2011)
Required number of charges per day	12.7	Per day	
Required number of charges per two peak hours	**6.3**	**Per peak hour**	

The effect of a change of the minimum required number of charges is included in the sensitivity analysis.

APPENDIX F: Greedy Algorithm B: More locations with less chargers

The greedy algorithm used in the TAGA-method finds an optimal configuration based on the fact that it is preferred to find minimal number of locations. This choice was made by comparing the pros and cons of clustering the number of locations. These are shown in Table 22

Table 22, Pros and cons of clustering locations

Pros	**Cons**
Probability of finding a free fast charger is greater Less expensive: only one connection to the three-phase network is required Opportunities for economic activities related to EVs / meeting point	More locations will further reduce the range anxiety

It is also possible to use a Greedy Algorithm that finds more locations, introduced as Greedy Algorithm B in 4.4. This Greedy algorithm is presented and executed in this Appendix.

The alternative Greedy Algorithm will search for the most potential location (highest cell score) every time a single fast charger is allocated, while the earlier used algorithm allocated as many profitable chargers as possible to a location.

The flow chart corresponding to this alternative algorithm is depicted in Figure 90. The steps are briefly described:

The fast charger is allocated to the cell with the highest cell score. The demand served by the fast charger is calculated in the same way as the algorithm used in the main report:

1. Selected tool will distribute the capacity over the related cells
2. The scores will be subtracted from the initial cell scores
3. All negative values will be set to 0
4. The difference is the actual use of the fast charger

If the actual use is sufficient to make the charger profitable, another charger will be allocated. In contrast to the algorithm that was used in the main report, the additional charger will be allocated to the location that is most potential. This implies that the location does not have to be the same as the location where previous fast charger is placed. As a result, there will be multiple locations with fewer chargers.

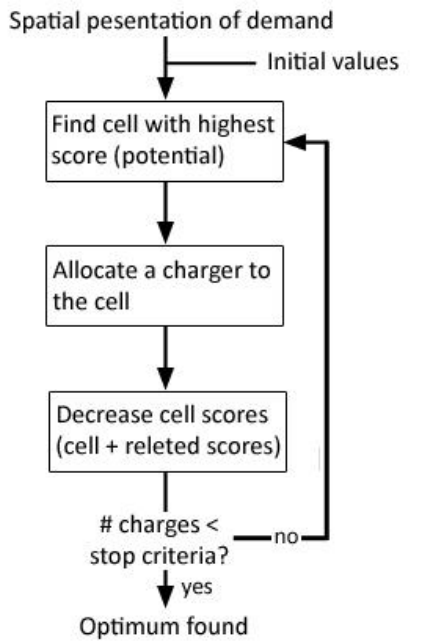


Figure 90, Flow chart associated with the alternative Greedy Algorithm

This effect can be observed after application of the algorithm on the same study area as used for the Amsterdam case. In this comparison, the parameters shown in Table 23 are used.

Table 23, Parameters used as input for the alternative greedy algorithm

Area of influence	Cell size	Factor tours-daily patterns	Market share of fleet & charging behaviour	Peak factor	Presence of slow chargers	Capacity	Profitability
260 3-digit postal code areas	3x3 km	1.84	0.02 & 0.5	0.5	0	8	7

The optimal configuration is shown in Figure 90. The red dots indicate the locations, the numbers the amount of fast chargers.

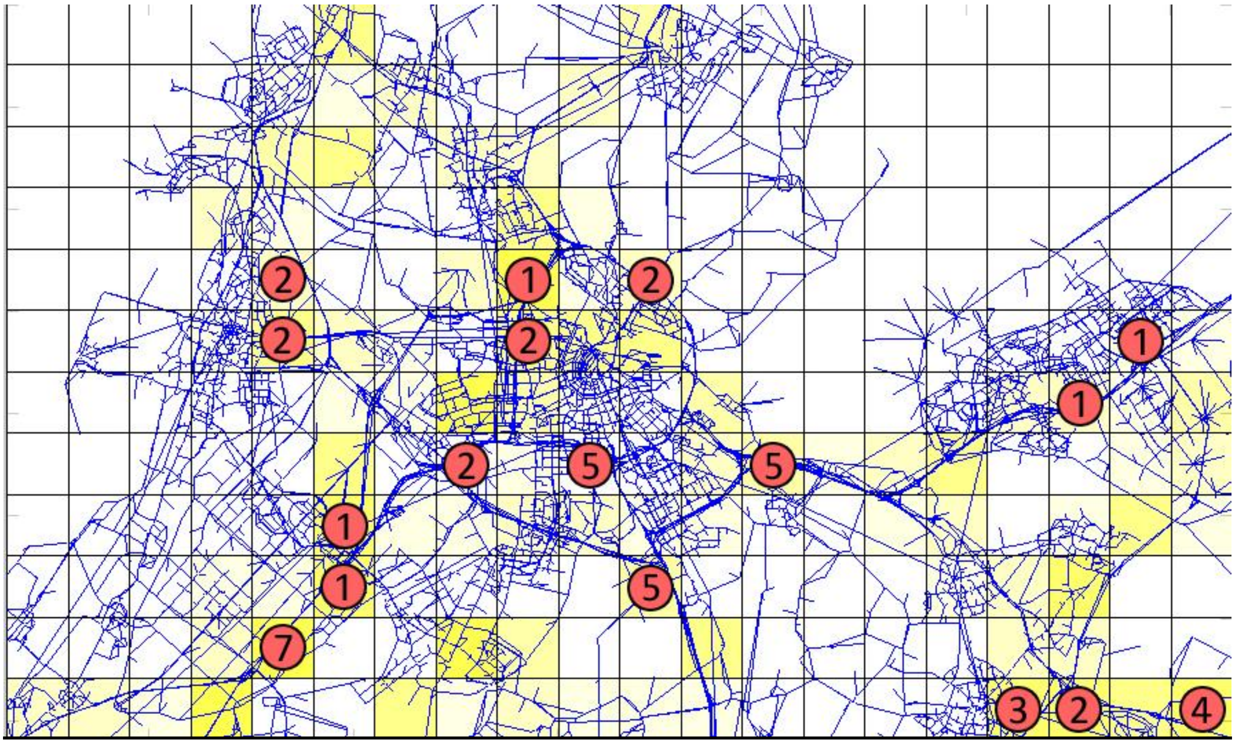


Figure 91, Optimal configuration found by the alternative greedy algorithm (7 locations, 22 chargers)

The difference between the two algorithms is summarized in Table 24.

Table 24, Differences greedy algorithms

Aspect	Greedy Algorithm A (used in the main report)	Greedy Algorithm B	Difference
Number of locations within the border of Amsterdam	3	7	+233%
Number of chargers within the border of Amsterdam	21	22	+4.7%
Percentage of demand served	82%	83.9%	+2.5%

APPENDIX G: Survey results

Number of respondents: 45

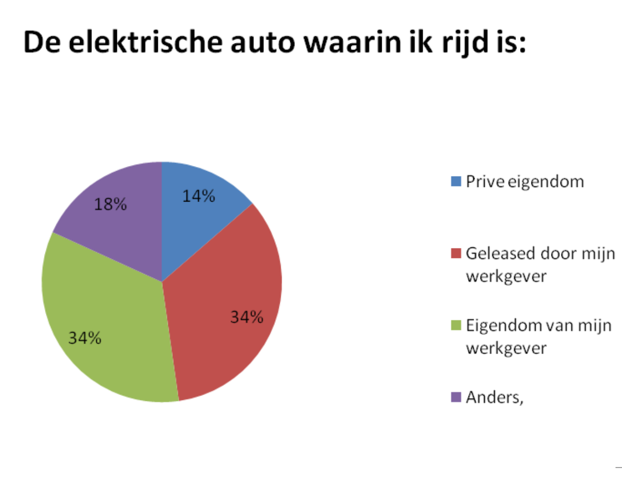
This survey is held among EV users and is filled in by using internet. Because of privacy data, the survey is distributed by means of the following resources:

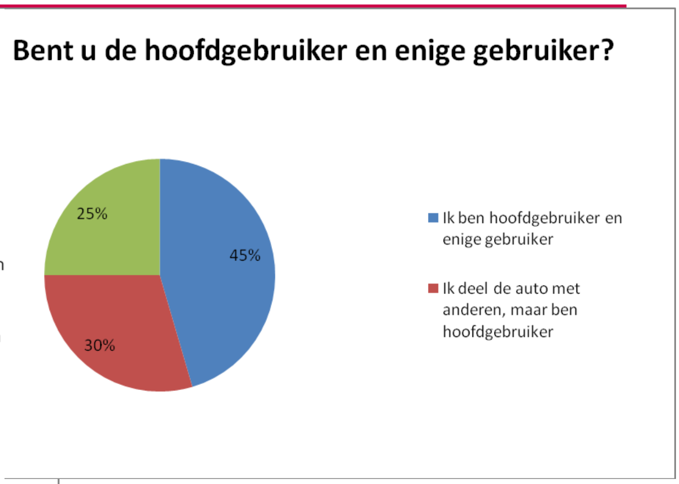
- Internet
- Forums
- LinkedIn
- Twitter

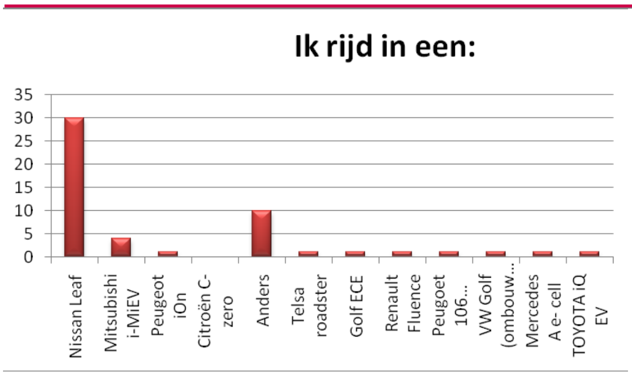
The respondents are mainly early adapters; this might provide a distorted picture

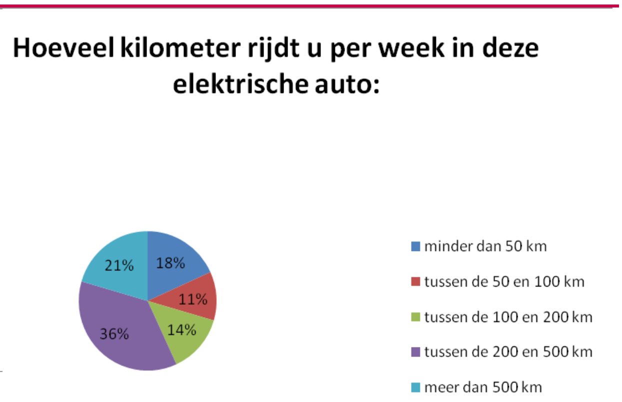
This survey is conducted in collaboration with:

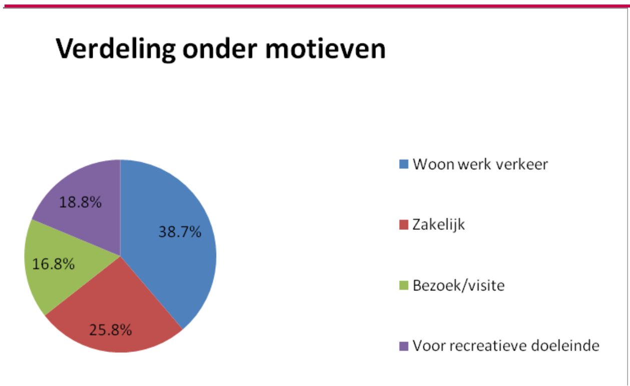
Goudappel Coffeng	*AgentschapNL*	*Dienst Infrastructuur Verkeer en Vervoer*

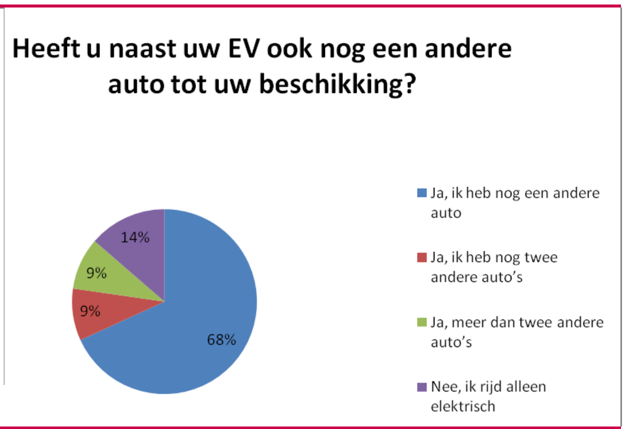

De elektrische auto waarin ik rijd is:
14%
34%
34%
18%
Prive eigendom
Geleased door mijn werkgever
Eigendom van mijn werkgever
Anders,


Bent u de hoofdgebruiker en enige gebruiker?
45%
30%
25%
Ik ben hoofdgebruiker en enige gebruiker
Ik deel de auto met anderen, maar ben hoofdgebruiker

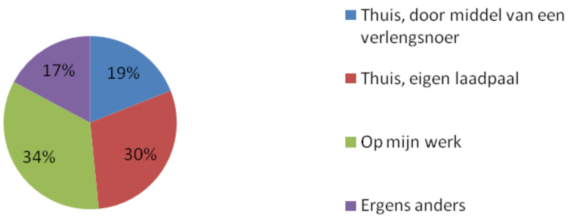

Ik rijd in een:
35
30
25
20
15
10
5
0
Nissan Leaf
Mitsubishi i-MiEV
Peugeot iOn
Citroën C-zero
Anders
Telsa roadster
Golf ECE
Renault Fluence
Peugoet 106...
VW Golf (ombouw...
Mercedes A e-cell
TOYOTA iQ EV


Hoeveel kilometer rijdt u per week in deze elektrische auto:
18%
11%
14%
36%
21%
minder dan 50 km
tussen de 50 en 100 km
tussen de 100 en 200 km
tussen de 200 en 500 km
meer dan 500 km

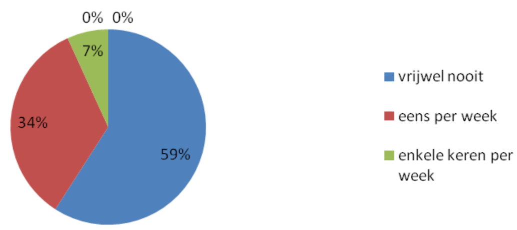

Verdeling onder motieven
38.7%
25.8%
16.8%
18.8%
Woon werk verkeer
Zakelijk
Bezoek/visite
Voor recreatieve doeleinde


Heeft u naast uw EV ook nog een andere auto tot uw beschikking?
68%
9%
9%
14%
Ja, ik heb nog een andere auto
Ja, ik heb nog twee andere auto's
Ja, meer dan twee andere auto's
Nee, ik rijd alleen elektrisch

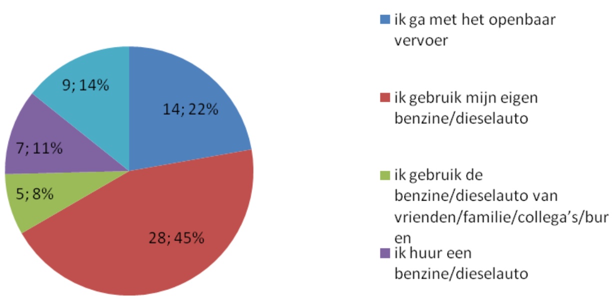
Waar en hoe vaak per week laadt u uw elektrische auto?



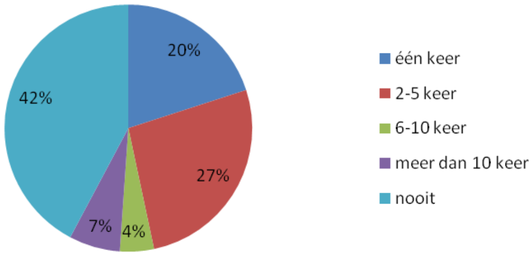
Hoe vaak komt het voor dat u afziet van een rit met de elektrische auto omdat u deze rit niet met uw elektrische auto kunt maken of bang bent met een lege accu te stranden?



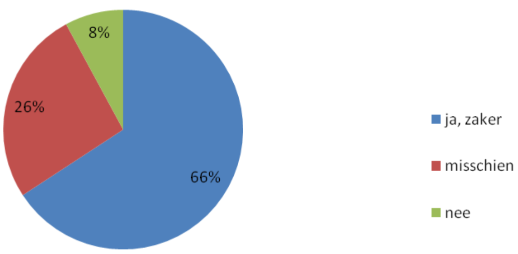
Hoe lost u dit dan op (meerdere antwoorden mogelijk)?



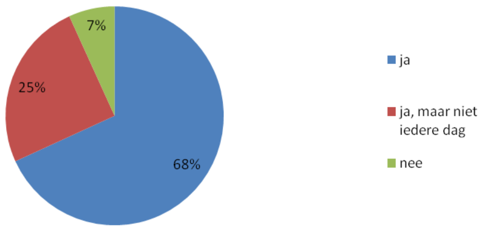
Hoevaak maakt u per maand gebruik van een snellader?



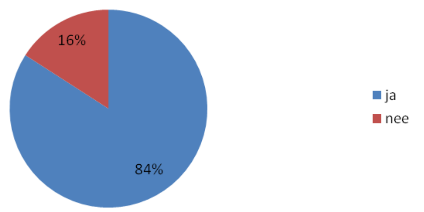
Zou u meer van snelladers gebruik maken als er meer van zouden zijn?



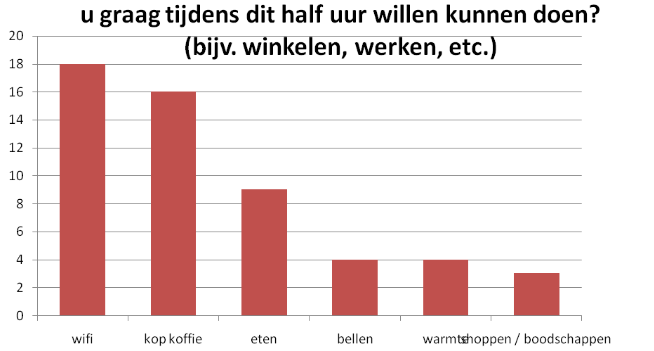
Stel dat uw elektrische auto onvoldoende bereik heeft om een zakelijke rit te maken, zou u dan gebruik maken van een snellader?



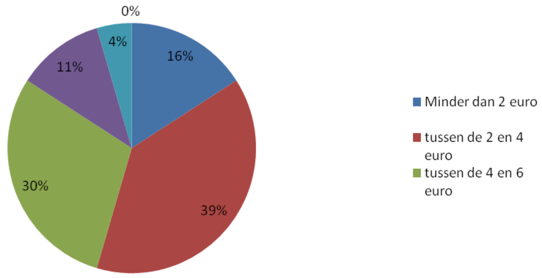
Stel dat uw elektrische auto onvoldoende bereik heeft voor het afleggen van een bezoek aan familie of vrienden, zou u dan van een snellader gebruik maken?



Snelladen kost maximaal een half uur. Wat zou u graag tijdens dit half uur willen kunnen doen? (bijv. winkelen, werken, etc.)



Hoeveel zou u maximaal willen betalen voor een laadbeurt (80% volle accu) bij een snellader?



Vraag 12: Wat vond u van het snelladen?

kosten hoog, locaties te weinig, tijdsduur mag iets korter, maar acceptabel
Veel logischer dan langzaam laden. Geen gedoe met kabels, werken meestal wel in tegenstelling tot het "stopcontact palen van e-laad", tot voor kort geen gedoe met pasjes (waarvoor iemand hopelijk ook iets beters verzint)
werkt goed, nog gratis.
de verwachting is 2 tot 5 keer per week snelladenivm beperkte actie radius van iQ EV (max 50 ~ 80km)
Ze zijn er nog veel te weinig!
locatie nog een problemen. zwolle, den bosch vooral.. werking prima. verwarming werkt niet tijdens laden.. tijd is meestal ok. life saver
positief, het maakt mijn langere rit mogelijk en een keer weigerde de paal in Vianen de pas te accepteren en stond ik dus stil.....
Locatie was verborgen op industrieterreinen Tijdsduur 30-40 minuten is te lang voor snelladen. 10-15 min voor een volle lading zou ik acceptabel vinden. Kosten via laadpas van TheNewMotion
Met name snellader bij Nissan Visscher in Amsterdam ZO gebruikt: locatie is gunstig langs vaak gebruikte snelwegen, vaak is vijf minuten voldoende om thuis te komen, en gebruik is gratis.
Goed alternatief om bij te laden. Vaak is locatie niet aangenaam (dealer, taxiondernemer, etc). Voorlopig nog nooit moeten betalen voor snelladen
super!
Super! 8 Euro per laadbeurt is een fors bedrag in deze fase van de markt.
27 januari ANWB Naarden; was daar de eerst gebruiker en werd daar enthousiast ontvangen. zo'n 30 min gestaan, kon weer 95KM verder terwijl acciradius op 6KM stond Kreeg kopje koffie en enthousiaste vragen kosten nul omdat 1ste half jaar gratis is.
Antwerpen, 20 minuten, € 4,= Goes, 15 minuten, gratis

Op dit moment zijn de snelladers nog redelijk geconcentreerd rond utrecht en amsterdam. Er is nog geen sprake van een landelijk dekkend netwerk. De onzekerheid dat je niet weet of je terecht kunt bij een snellader (in gebruik, defect) of dat er op een dubbel punt al iemand staat te laden waardoor je 2x zoveel tijd nodig hebt om te laden is een beperking bij inzet. Op het moment dat je aankomt bij een snellader en er kan geen (/niet meteen) gebruik van gemaakt worden kun je vaak niet verder rijden om ergens anders te laden. Je bent dus volledig afhankelijk van dit laadpunt. Tot eind 2011 was het snelladen gratis. Momenteel is het tarief rond de 8 euro (4 euro voor korte tijd). Gezien de energie-inhoud van bij de Leaf is dit een forse prijs per kWh (3x zo veel als privé-tarief). Voor zakelijk gebruik is dit wel te rechtvaardigen maar privé zijn dit forse tarieven. Het laden zelf werkt prima, de aansluiting moet in sommige gevallen wel met enig "beleid" g gehanteerd worden (anders breekt er een palletje af) maar dat zal wel merk-specifiek zijn en snel opgelost worden.
weinig problemen tot nu, maar enige zorgen om toekomst - slijtage, bezetting, kosten, commercie, technische problemen, etc
Prima, zolang er niemand voor je staat en er een mogelijkheid is om je te vermaken, bijv. door wifi of een horeca gelegenheid.
De wildgroei aan laadpassen is vreselijk. Kostenloos, new motion, e-laad. En een overzicht ontbreekt
Kost natuurlijk teveel tijd maar kan nuttig worden gevuld met bel en mail. 8 euro is vrij veel
Over het algemeen positief. Ik vind de tarieven van Total te hoog (eur 6/10 min.) Tijdsduur prima
amsterdam, tijdsuur prima, kosten geen delft , tijdsuur prima, kosten geen leusden , tijdsuur prima, kosten geen
snel bereikbaar, altijd plek dus meteen laden, gratis
Prima, alleen veel te weinig laadpalen. Geen mogelijkheid door het land te rijden. Palen bij Zwolle, amersfoort, apeldoorn zoude MEER dan welkom zijn. Zodra dat het geval is kan ik mijn benzine auto laten staan.
Was gratis. Nu enkele palen in amsterdam Te duur voor stroom die je aftopt. Laadtijd redelijk. Kosten per tijdseenheid ipv volledige lading.

TUDelft
Goudappel Coffeng
Municipality of Amsterdam