UNIVERSIDAD PONTIFICIA COMILLAS

**ESCUELA TÉCNICA SUPERIOR DE INGENIERÍA (ICAI)**

OFFICIAL MASTER'S DEGREE IN THE ELECTRIC POWER INDUSTRY

Master's Thesis

# Optimal placement and sizing of public charging stations for electric vehicles

## taking into account both demand side and network infrastructure

**Author: Lorenzo Simons**
**Supervisor: Prof. António José Pais Antunes**
**Co-Supervisor:**

**Madrid, 4 July 2016**

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# Master's Thesis Presentation Authorization

THE STUDENT:

Lorenzo Simons

……Simons……………………………………

THE SUPERVISOR

Dr. António Pais Antunes

Signed: …………………… Date: ..4../ ..7../ 2016

THE CO-SUPERVISOR

Signed: …………………… Date: ……/ ……/ ……

Authorization of the Master's Thesis Coordinator

Dr. Luis Olmos Camacho

Signed.: …………………… Date: 04/ 07/ 2016

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**Abstract**

The growth of the share of electric vehicles (EVs) over the last years and its contribution to the reduction of greenhouse gases is seen as a positive trend for society. However, with a high penetration of EVs it might become necessary to redesign the distribution grid as these EVs represent significant loads that might cause potential overloads or excessive voltage drops.

In this work we try to take into account these problems in the planning phase rather than in the operation phase as typically has been studied in the literature. Therefore we have developed a bi-level model to determine the optimal locations for electric charging stations. In the upper level we decide in which LV feeder vehicles will charge and at what time of the day they will be connected to charge. In the second level we determine the optimal location and size of the charging stations with respect to the minimal walking distance for the vehicle owners. The optimal locations are determined while taking into account the limits of the network and these results are compared with the optimal solution from a purely customer point of view.

The results show that the minimum number of stations that needs to be installed as well as the walking distance can increase when a solution tries to respect all the limits of the network. Secondly it is shown that in some cases it is necessary to restrict the installed capacity in a low voltage feeder in order to avoid line overloads. Moreover, charging management could significantly improve the reliability of the system while some form of parking management could help to reduce the number of stations that needs to be installed.

# Contents

# 1. Introduction

Over the last decade, the popularity of electric vehicles has increased significantly. Electric vehicles are usually considered as the technology of the future but few people know that electric vehicles have been the top choice of transportation in the past. The history of the electric vehicle started in the nineteenth century with the invention of the electric motor. Between 1832 and 1839, Robert Anderson made a first electric-powered carriage. However, together with the other prototypes invented in this century, the prototypes were not economically viable because the batteries were not rechargeable and the electric motors were not efficient enough. [Guarnieri, 2011]

During the second part of the nineteenth century, the electric motor (DC) and the batteries went through a number of developments. The motors became more efficient and owners were able to recharge their batteries. At the end of the nineteenth century, the first commercial electric vehicles were introduced in the market and the market share increased to almost 30% of the market. [Outlook, 2013]

The market share started growing at the end of the nineteenth century very quickly, but after the introduction of the Ford Model T in the beginning in the twentieth century, the electric vehicles almost completely disappeared from the market. Due to the replacement of the hand crank by an electric starter, the cheap availability of petrol and the limited driving range of electric vehicles, the market was completely taken over by the gasoline-powered vehicles. [Yong et al., 2015]

The electric vehicle seemed not to have any future until at the end of the twentieth century climate issues started to appear and people started to realise that the emissions of gasoline-powered vehicles were damaging our climate. However it took until the second decade of the $21^{st}$ century with the introduction of battery electric vehicles (BEVs) and plug-in hybrid vehicles (PHEVs) before electric vehicles really entered the market again. [Yong et al., 2015]

## 1.1 Motivation

An increasing number of electric vehicles implies that also a lot of charging stations need to be installed. The current types of vehicles have a driving range up to 200 km with one single full charge and it takes them 8 hours to fully charge with a slow charger. These features will be explained in more detail further on in this work. Thus, the proximity of a charging station is an important element when making the decision to buy an electric vehicle. Therefore the placement of these charging stations should aim to satisfy as many people as possible and this is typically the way policy makers make their decision when deciding where to install the charging stations. In the literature many studies concerning the siting and sizing of charging stations start from this policy of satisfying the demand.

However, the growing popularity of electric vehicles has some side effects that should be carefully studied before making policy decisions. One of these side effects is that a high penetration of electric vehicles can cause problems for the electricity grid with respect to voltage fluctuations, system losses and line overloads. [Tikka et al., 2011] The effects on the network strongly depend on where and when consumers charge their vehicles. Not only the local networks are affected, but a high number of electric vehicles charging at the same time can also create overloads on substation transformers and therefore it is important not only to study the effect on a single feeder, but on the whole local distribution network. [Hadley, 2006]

As will be explained in more detail later, a great part of the existing literature is trying to investigate what would be the optimal behaviour of electric vehicles for the electricity grid. Typically the results of this optimal scenario are compared with the worst case scenario in which all the vehicle owners decide to charge at the peak moment of the day. The conclusions from these studies should help policy makers to decide which incentives should be given to stimulate vehicle owners in the optimal way.

In this study, we will combine the urban studies about the placement of charging stations with the studies about the charging behaviour of vehicle owners. We will bring both types of studies together by trying to satisfy the demand for charging stations in an optimal way with respect to the driving/walking distance for the customers and at the same time taking into account the constraints of the network. This should result in a solution where the stations are placed in such a way that charging management can be reduce to a minimal level.

## 1.2 Research Objectives

It is important to understand for the reader of this work what the objectives and the limits are of this work. Therefore it is not only important to mention the objectives, but also to state clearly which research questions are excluded from this work.

**The aim of this work is to investigate what the effect is of the distribution network on the optimal placement and sizing of charging stations for electric vehicles.** This will be done by comparing the solution without taking into account the distribution network with the solution where it is taken into account. This means that the following objectives lay outside the scope of this work.

We are not trying to determine the optimal location of charging stations in the real world for the area considered in the case study in this work. Although the proposed model could be used for that, data about traveling patterns and the electricity network should be more detailed and correspond with the reality. This is not the case for the data we have used in this work. The case study is run with realistic data, and not real data, and results can only be interpreted in the light of the effect of the distribution network on the locations of the stations.

The purpose of this work is also not to determine what the optimal charging pattern would be for the whole system. Consumers are assumed to minimize the total traveling distance of all the consumers together, an assumption that could already be strongly criticized. The base assumption is that vehicle owners start to charge when they arrive at a node and the vehicle stays connected until the owner decides to leave. We will also analyse the effect of what we call 'smart charging', which tries to minimize the demand peaks in the different low voltage feeders given the time that vehicles will be connected to charging stations. This assumption could only be valid in reality if vehicles owner have to determine up front how long they want to be connected and make some kind of reservation. However, the purpose of this smart charging is not to determine how vehicles should charge in reality, but to see the effects on the locations for charging stations if not all vehicles are charging at the same time.

It is also not our aim to determine what the minimal electricity consumption should be given the number of electric vehicles that want to charge. If the amount of produced electricity is taken into account in the objective function, this is only done to make sure that the power flows correspond more or less to what would be a realistic operation of the grid. Therefore we will also assign a marginal weight to this component such that it has no determining effect on the locations of stations, nor on the charging behaviour of the vehicles. Reducing the amount of electricity that should be produced is not a determinant in our model to decide the location of the charging stations.

## 1.3 Thesis Outline

After this introduction, we will discuss the literature that exists about the different aspects that are important for this work. Therefore chapter 2 will start with a description of the different ways of modeling the demand side and the typical technological standards that are in place in reality. After these first two sections, three more specific sections will explain how the distribution network can be approximated, what the optimal charging behaviour should be and what the effects are on the distribution network. Finally we will describe the two approaches that can be found in the literature to decide where charging stations should be installed. Chapter 2 ends with two different technologies that could be considered as an alternative for charging the batteries at charging stations.

The next three chapters of this work will cover the three different models that we will bring together to investigate how the electricity network can affect the optimal placement of charging stations. In the first chapter, chapter 3, we will describe a model that could be used to decide where to place charging stations based on the daily schedule of the EV owners. The objective here could be to minimize the number of charging stations given some constraints or to minimize the walking distance given a number of charging stations. In chapter 4 an approximation of the distribution network is added to the model to analyse the effects on voltage levels and power flows in the network.

As the model becomes quickly too big to be solved in reasonable time, these first two models will be used to determine the charging behaviour on the medium voltage level. To determine the specific locations of the charging stations and the number of charging points that should be installed in each charging station, a second model will be used. This model is described in chapter 5 and the relevance of this second model will be explained in more detail in section 5.1.

We will end this work with a case study to test the model and to analyse the possible effects of taking into account the network in the decision making process. Chapter 6 will describe in detail the background, the data and the results of the case study. Every section of this chapter deals with a different scenario to see the effects of chaging the assumptions on the final outcome.The sections will start with an analysis of the medium voltage network after which we will focus in more depth on certain low voltage feeders where problems might occur. The results obtained in this chapter will be summarized in chapter 7.

# 2. Literature Review

## 2.1 Modeling the Demand Side

The first step when we want to investigate the effect of a high penetration of electric vehicles in the society, is to model the demand. This problem typically can be split into three components. The first two components have to do with drivers' behaviour which determines where and when they are willing to charge their vehicles. In the literature many studies can be found about the maximal deviation from the shortest path, the difference in use between slow and fast chargers and which type of consumers are using fast chargers. The third component is the daily energy consumption of the electric vehicles. In the literature there are studies which try to estimate the average consumption while other studies try to give a more detail estimation based on several indicators.

### 2.1.1 Electric Vehicle Owner Behaviour

All these demographic models focus on installing the charging stations in such an optimal way for consumers. However, it is not easy to adequately represent the way they act in reality. Therefore it is important to investigate how consumers behave and which strategies they follow when deciding where to charge.

Consumers tend to follow the shortest path between their destinations and prefer to either charge when they are parked or eventually deviate slightly from their shortest path to visit a charging station. [Li, 2015] investigated the effect of the willingness to deviate on the placement of charging stations. The author found that if consumers are willing to deviate 50% from their shortest path, the number of stations could be reduced by 50% while the average traveling distance only increased with around 3%. The author also found that for another case study, a decrease in the number of charging stations with 30%, only led to a 2% increase of average traveling distance.

[Morrissey et al., 2016] investigated the behavioural differences between consumers who use fast charging and standard charging, as they call it. They found that most of the people who use standard charging at home, connect in the evening. For fast charging the results were significantly different. The authors found that consumers connect more often to fast chargers in public parkings than to fast chargers in a fast charging stations. However, the amount of energy charged in a fast charging station was usually bigger, which seems to suggest that people use fast charging stations (on the road) when they are running out of battery.

To estimate the demand in the different charging stations, it is not only necessary to know what the preferred schedule is of the different customers, but also how much customers are willing to deviate from their preferred schedule. [Sun et al., 2016] analysed that customers are willing to deviate more during weekdays than during weekends and that the price influence on deviation from their shortest path is not significant. In their case study most of the customers were not willing to deviate more than 1.5 km from their shortest path. However, the authors mention that conclusions from their work cannot be extrapolated to other regions as charging behaviour depends on the maturity of the market and the specific characteristics of the region. Moreover the authors do not investigate the placement of the charging stations which means that the conclusions might not be valid for this study.

It is important not only for the placement of charging stations, but also for the installation of new generation capacity, to know what the effects will be of a high penetration of EVs on the total energy demand. [Gennaro et al., 2015] found that a shift from conventional fuel vehicles to electric vehicles ranging from 10% to 57% would mean an increase in electricity demand between 0.7% and 18%. These results were obtained for the region of Firenze, Italy. The authors also stated that allowing Vehicle-to-Grid interaction would significantly help to avoid that the peak demand would increase accordingly.

Other studies have studied the consumer profiles [Sprenger, 2013] or consumer strategies [Xiong et al., 2015]. The first paper focuses on the demand side for charging stations and investigates how the knowledge about customers can help lowering the costs of the network. The analysis of the information is based on the frequency that consumers use public charging stations, the arrival times, the end-times and how much energy drivers usually buy. According to the survey conducted by the authors, drivers who drive more kilometers use the public charging infrastructure less frequently.

The second paper mentioned above, by [Xiong et al., 2015], focuses on the strategy that drivers apply when choosing a charging station. In this work the authors start with a "bilevel optimization" in which EV drivers make decide where to charge based on their own profit maximizing. On the other hand the second level of optimization takes into account the mutual effect on the road network and the quality of service. The biggest shortcoming of those studies is that technical problems that might occur in the distribution network are neglected.

A more specific study has been conducted by [Bayram et al., 2016] who investigated the charging patterns on a major North American University campus. They found that vehicles typically were charging during the day and that the peak demand correlates with solar irradiation. The authors concluded that installing solar panels close to the charging points on a campus could offer cheap energy to the vehicle owners.

[Miralinaghi et al., 2016] showed that bilevel optimization is not necessary if the objective of the central planner is the same as the objective of the individual customers. This might be the case when the central planner is trying to minimize the total traveling distance of customers, while customers will always minimize their own traveling distance. The authors focus on an Intra-City Network while they assume that travelers could deviate from the shortest path in order to refuel. The authors also assume a multi-period model to represent changes in demand over time.

### 2.1.2 Energy consumption

Many studies have been conducted to measure how much energy an electric vehicle is using when completing its trip. In the literature simple figures can be found with an average consumption per driven kilometer but also more detailed studies exist.

[Abousleiman and Rawashdeh, 2015] investigated the energy consumption based on seven factors. The authors stated that they were able to approximate the real consumption with an error less than of 1.5%. The factors they took into account are elevation changes, friction, regenerative braking, the length of the trip, the speed limit, the ambient temperature, auxiliary loads and traffic information.

[De Cauwer et al., 2015] investigated the energy consumption of one type of electric vehicle based on real world data. The first model they used was based on kinematic parameters over aggregated trips to estimate the energy consumption for an entire trip. Secondly, they added acceleration parameters and more detailed kinematic parameters to predict the energy consumption for micro-trips.

[European-Commission, 2013] made estimations of the energy consumption for different types of vehicles based on empirical curves taken from [van Haaren, 2011]. To estimate the consumption, the curves consider four types of energy usage; ancillary services, tire losses, aerodynamics and the drivetrain.

In general it is found in the literature that the consumption in reality is somewhere between 0.12-0.25 kWh/km. [Peugeot, 2012, RWTH, 2010] More specifically, [Yong et al., 2015] stated that the Nissan Leaf is able to drive up to 160km and has a battery capacity of 24 kWh, which means that the car uses around 0.15 kWh/km.

## 2.2 Technological Standards

### 2.2.1 Types of Vehicles

Electric Vehicles can be typically divided in three types, which are Plug-in Hybrid Electric Vehicles (PHEVs), Hybrid Electric Vehicles (HEVs) and battery electric vehicles (BEVs). The first two types use two types of energy sources, which mean that they run with an internal combustion engine and an electric motor. On the other hand the BEVs use only an electric propulsion system which means that the distance that these vehicles can travel depends on the capacity of the battery. [Yong et al., 2015]

### 2.2.2 Battery Technology

To estimate the demand for charging stations, it is necessary to define the capacity of the batteries. Together with the consumption per driven kilometer, the amount of energy that needs to be charged can be determined. Most of the batteries in the past where Lead-acid based batteries because they are relatively cheap. However, more recent models have started using Lithium-based models because these type of batteries have a high energy density, a high power density and they can accept fast charge. This technology has been used in the Tesla Model S and the Nissan Leaf, which are two of the more popular EV models at the moment on the market. The Nissan Leaf has a battery with a capacity of 24 kWh, which allows a travel range of 160 km with one full charge. In combination with the ability to charge the vehicle in a fast charging station, the vehicle could also be used for longer distances.[Yong et al., 2015]

Car manufacturers have realised that the limited driving range is one of the biggest limitations when customers are deciding which type of car they will buy. Therefore new battery technologies are continuously under development to increase the driving range. New vehicles of Nissan already possess batteries with a capacity of 30 kWh which allows an autonomy of 200 km. Likewise, Volkswagen announced to release a new model at the end of 2016 with a similar capacity. Matthias Müller, president of Volkswagen, stated that new models of the Golf will have an autonomy of almost 500 km by 2020. [Parain, 2016]

### 2.2.3 Charging Stations

Similar to fossil fuel based vehicles, PHEVs and BEVs need be recharged externally when they run out of energy. For this process, a specific charger is needed because the electricity coming from the grid is alternating current (AC) while the batteries of the vehicles are based on direct current (DC). Therefore the chargers need to be able to transform the alternating current to direct current. [Yong et al., 2015]

According to [Foley et al., 2010], there are some common charging standards like Society of Automotive Engineers (SAE) and International Electromechanical Commission (IEC). For the purpose of this work it is not necessary to explain in detail the differences between the charging standards. Nevertheless, it is necessary to explain the differences between what is called "standard" charging in the literature and "fast" charging.

Standard or slow charging uses an on-board charger as it charges directly from AC. Typically these chargers have a power between 1.4 kW (which is rather low and therefore less used nowadays) and 7 kW. With this technology it typically takes between 3.5 hours and 17 hours to fully charge a BEV, depending on the vehicles battery capacity. The most common chargers have 3.3 kW power and charge on a voltage level of 240V and a 80A current which result in a charging time of around 8 hours to fully charge a BEV. [Yong et al., 2015]

Fast charging is based on an off-board charger which rectifies the AC current to DC current before charging. This technology uses typically a higher voltage (between 200-450 $V_{DC}^t$) and depending on whether the charger provides 80A or 200A, they supply a power between 20 kW and 90 kW. This means that it takes from 20 to 80 minutes to fully charge a BEV. Commonly in the literature "fast charging" is assumed to be a 45 kW charger supplying a 200A current, which results in a 30 minutes charging time to fully charge a BEV. [Yong et al., 2015]

Currently Tesla is offering their fast charging infrastructure for free to stimulate the demand for electric vehicles. This infrastructure provides 120 kW when charging which enables you to drive around 270km with 30 minutes of charging. [Tesla, 2016]

## 2.3 Approximating the Electricity Network

To assure that no technical limits are violated when consumers are charging their electric vehicles, the electricity network should be taken into account. When considering the electricity grid, it is important to make a distinction between the Transmission Grid and the Distribution Grid. The difference between both grids is not always clear and is country dependent. However, for the purpose of this study, the following definition of transmission and distribution lines of

[Pérez-Arriaga, 2013] will be followed.

Transmission lines in the electric power industry have the function of transport or shipping in other industries. The transmission lines are high voltage lines which allows transmitting large amounts of electric power over large distances in the most economic way. Distribution lines on the other hand have the function of connecting the substations (the place where the power arrives, typically placed around cities) with the final consumers. The voltage levels in distribution lines are lower and therefore they are called distribution lines. In principle they have the same function as transmission lines, but the lower voltage levels and the radial operation make that the power flows need to be approached differently.

### 2.3.1 Linear Approximation

The power flows between two nodes in a network depend on the difference between the voltages at both end-nodes of a line and the difference in phase angles. According to [Garcia Gonzalez, 2014] and [Trodden et al., 2014] an electricity grid can be approached linearly if the voltage magnitudes are virtually identical, the inductive component of the lines is significantly greater than the resistive part and the differences in the angles of the tensions at each node is small. The assumptions are valid for transmission lines which makes that an AC Power Flow can be approximated by a DC Power Flow, which is a linear model.

However, these assumptions could ignore some problems that could occur in the distribution network as voltage magnitudes could be locally significantly different. Therefore the differences in voltage levels need to be taken into account and also the reactive power needs to be monitored, as the inductive component in some lines might be close to the resistive part. Therefore [Trodden et al., 2014] propose a better Piecewise Linear Approximation of an AC Power Flow. The problem of this approach is that a Piecewise Linear AC Power Flow model is also only valid if the angle differences are small enough as the values cosinus function of the angle differences grows rapidly when the differences grow.

## 2.4 Optimal Electric Vehicle Charging

Minimizing the costs of the distribution network and taking into account all the essential network constraints has not been studied very often in the literature about the placement of charging stations. Therefore it is important to consider other literature which focuses on minimizing the network costs in a distribution network with electric charging stations already in place.

[Li et al., 2014] studied the effect of applying Distribution Locational Marginal Pricing (DLMP) on the charging patterns of electric vehicles and the effect on the distribution network parameters. They show in their paper that introducing DLMP leads to more efficient charging patterns with respect to the total network costs. Moreover the socially optimal charging schedule will be the outcome of individuals who maximize their own net profit. The authors assume hourly data and the locations of the charging stations are fixed.

In [Huang et al., 2015] the authors assumed a distribution network with a high penetration of flexible demand (electric vehicles and heat pumps). Similar to the previous article, they found that EV charging is mainly scheduled during the night. This results in a spread out HP scheduling with a HP peak load just before the peak of the conventional load. The results are interesting to estimate which kind of charging schedule can be expected. However the focus of our work is on locating charging stations which differs from the already assigned locations in their work.

[Alharbi et al., 2014] investigated what the effect on the distribution network is when electric vehicles are charged when customers arrive home. The paper only considers private charging and assumes that consumers either will charge at 6 pm or at 10 pm. Assuming these demand peaks, the effect on the voltage level is measured. The authors concluded that utilities should be prepared to handle these peak loads assuming a high penetration of electric vehicles and that all vehicle owner charge at the same moment. Because these assumptions might not come true in reality and as the conclusions of this paper depend highly on these assumptions, they should be taken into account with the necessary prudence.

[Alonso et al., 2014] analysed what the effect could be of a smarter charging schedule on the distribution network. The authors started from a base case in which drivers would charge immediately when they arrive at home and measure the effect on the distribution network. They found that this kind of behaviour can cause problems with respect to the voltage limits. After applying a smarter charging schedule based on a Genetic Algorithm, they found that this solves the technological constraints. Their model does not take into account electricity prices and the charging stations are already in place.

To model the behaviour of the different agents in the process of charging electric vehicles is not always easy. Therefore [Hu et al., 2014] followed a multi-agent based model and tried to see how the interaction between the different agents can lead to an efficient outcome. The authors assumed that electric vehicle owners share their information about their battery level and about the trips that they will make with an "electric vehicle virtual power plant agent". They presumed that this agent will interact with the DSO market agent which will make sure that the schedule for charging the vehicles will be feasible with the lowest amount of costs. In this process the DSO market agent will take into account the technical limits it received from the DSO technical agent. The authors assumed different prices for every 15 minutes which lead to congestion in the distribution network at moments that the prices were the lowest. However, the authors did not consider the placement of the charging stations. It might not be realistic that the DSO knows the exact schedules of the EV owners and therefore the technical constraints should be taken into account at the moment of planning the placement of the electric charging stations, rather than only in its operation.

[Shuai et al., 2016] made a study about the existing literature about the charging management of electric vehicles. They concluded that Smart Grids can significantly reduce the costs of charging electric vehicles and these systems should give the right signals to consumers to act according to what is the best solution for the system. One example of giving the right incentives to consumers is to apply real time pricing. This was investigated by [Liu et al., 2014] by assuming that consumers will jointly optimize their routing and charging behaviour in case of applying real time prices.

## 2.5 Effect of EV charging on the Distribution Grid

[Farhoodnea et al., 2013] the effect of the placement of a parking lot in a distribution system. The authors assumed a maximum capacity of 230 EV's that could be charging at the same time in the charging station. They found that a peak demand could cause significant voltage drops in the nodes close to the charging station which would cause problems for the system. They showed that in deciding the maximum capacity for the charging station, the distribution grid should be taken into account.

[Shetty, 2015] investigated the effect on a 33-bus distribution grid in case of a high penetration of EVs. The author assumed a 50% to 70% penetration of EVs and assumed that all the vehicles charge when they arrive home from their daily activities. He concluded that such an uncoordinated behaviour would cause serious problems for the distribution grid. This work also analyses what would be the optimal locations of the charging stations in the distribution grid. As only the operation of the distribution grid was taken into account, the charging stations were placed as close as possible (electrical distance) to the electric bus from which the energy was entering the feeder. However, this does not take into account consumer convenience and might not seem very realistic. It is important to mention that the negative effects for the distribution grid will be worse if customers convenience is taken into account with such a high penetration of electric vehicles. Different ways of siting the charging stations are discussed in the next section.

Similar results were obtained in [Olivella-Rosell et al., 2015] but the authors also analysed what the effects would be of smart charging. Four scenarios were considered varying from charging when arriving home to smart charging to minimize their costs. Results showed that the most straight forward way of charging, charging when arriving home, lead to the biggest voltage drops. This additional voltage drop due to charging could almost completely disappear when charging at valley hours. Therefore incentive should be introduced to avoid that the limits of the distribution systems are violated.

[Masoum et al., 2011] did a similar study and found that changing from charging when arriving home to charging at night could reduce the losses significantly. In their test case they found that losses reduced from 3.37% to 2.6%. The authors assumed three types of customers; customers who always want to charge when arriving home, customers which might shift slightly there behaviour when tariffs are lower later on the evening and customers who are willing to adapt completely to what is optimal for the system. It was also shown that thanks to smart charging management, not only losses can be avoid but also voltage limit violations.

## 2.6 Siting and sizing of charging stations

In general there are two approaches to decide how charging stations should be optimally placed. The first approach starts from socio-demographic studies and will build the charging stations based on the demand. On the other hand, there is a purely technical approach in which the placement of the stations is based on the technical features of the electricity grid. In the literature also many approaches can be found that are a combination of both approaches.

### 2.6.1 Socio-Demographic Approach

One of the clearest examples of a socio-demographic study is a paper by [Frade et al., 2011]. In the paper, the authors are installing charging stations within a neighbourhood in the city of Lisbon, Portugal. The important determinant to find the optimal placement is the estimated demand in each point of the area that is studied. This approach results in solutions where consumer demand is usually pretty well-covered, but with an underestimation of the cost for society. Moreover it is possible that the solution from this approach is not practically feasible as the technical constraints of the distribution network are not taken into account.

A similar approach was followed by [Chen et al., 2013]. The method followed by the authors is based on parking information and there the location of the charging stations will be based on demand variables like the availability of parking spots and residential information. The method tries to cover all the demand while it tries to avoid that stations are placed to close to each other. The authors run a case study based on data from Seattle. However, like the previous method, this one also does not take into account the technical features of the distribution network.

Other similar studies have been conducted by [Shahraki et al., 2015], [Wu et al., 2016], [Song et al., 2015] and [Shi and Lee, 2015] but with different methods to evaluate the solutions. The first study uses a linear optimization model to determine what the optimal locations are. The model was tested based on driving patterns of the taxi drivers in Beijing. The study evaluated several criteria and used the PROMETHEE method to decide which were the optimal locations for the charging stations. The third study takes into account the costs of for the vehicle owners, the time cost and the cost of controlling the pollution and the solutions are evaluated on a Voronoi Diagram. The last study focuses on fast charging stations and tries to find the cheapest solution taking into account the cost of installing a station and the cost for consumers. The authors also try to determine the optimal number of charging poles in one station and therefore they try to estimate the marginal utility of each pole. To evaluate these criteria, the authors use a multi-objective evolutionary algorithm, which is called SPEA-II. All these study start from a demand based approach and try to satisfy this demand as good as possible, taking into account several criteria. However, the technical limits of the electricity network are usually not taken into account in an adequate way.

These first two approaches assume an in-the-node demand. This way of approaching the demand for charging stations is typically the easiest way as in most countries data are available about the usage of building. Assuming an in-the-node demand makes it easy to decide where cars will be parked during the day (typically around building where people work) and during the night (typically around building where people live). This information about the demand is very useful if one is investigating the placement of slow charging stations, which typically happens when vehicles are parked over a longer period. For fast charging stations the demand is different as these stations are mainly used as on-the-way charging stations. This means that the usage of this charging does not depend on how many people work or live around the charging stations, but it depends on how many people pass by this charging stations.

Similar to the study of [Chen et al., 2013], [Zhang et al., 2015] and [Li and Cui, 2015] formulated the problem of finding the optimal locations of charging points as a Maximum Flow Coverage problem. However, the aim of their solution is to cover as much demand as possible between two points, and not the demand in each node. [Zhang et al., 2015] developed a greedy algorithm to solve bigger instances in reasonable time. The drawback of their approach is that they take very few elements into account when deciding where to install the stations. The optimal solution for them is based on the demand, without taking into account the influence of electricity prices on the demand, without taking into account hourly differences and without taking into account the limits of the network. [Li and Cui, 2015] also developed a heuristic to be able to solve bigger instance. Their method has the same drawbacks as the method of the first authors: it does not take into account the technical limits, nor does it take into account price sensitivity. The aim of both articles is to install the stations such that the biggest amount of possible demand is covered.

[Zhu et al., 2016] used a combination of the two previously mentioned approaches, by not only allowing to install stations at the nodes, but also on the arc in the middle between two nodes. The objective is to determine where charging stations should be located and how many chargers should be installed at each stations. The optimal solution is the one for which the cost of installation is the lowest while achieving a certain degree of consumer convenience. They concluded that introducing a tolerable distance, the maximum distance that vehicles are willing to move away from their path to charge, is an important factor to consider. Therefore in the model in this work, distance will play an important role as well.

In contrast with the previous Maximum Flow Coverage formulations, and similar to [Zhu et al., 2016], [Miralinaghi et al., 2016] formulated the problem as a cost minimization problem. The authors aim to find the most cost effective way to install the charging stations. Their costs function consists of an installation cost term, a operation cost term and a traveling cost (for vehicle owners) term. This means that the authors assume that consumers will always try to find a charging station and that the demand always will find a way to be "covered". This assumption might be realistic once consumers have an electric vehicle but might limit the possible market as consumers far away from charging stations might not be willing to buy such a vehicle.

[He et al., 2015] used a different objective function to determine the locations of the charging stations than the one used by [Miralinaghi et al., 2016] but tested their algorithm on the same case study. Their objective was to minimize the social cost given a certain budget. This budget allowed them to install four medium and two fast charging stations while the previously mentioned authors only decided to install five charging stations. Considering the total driving and recharging time and the inconvenience of a missed trip to determine the social cost, the authors located three out of six charging stations at the same nodes as the authors of the other study. Even though they consider the option of missing a trip, in their final solution there were no missed trips which coincides with the implicit assumption of [Miralinaghi et al., 2016] that consumers will drive around to find a charging station.

Similar to the study of [He et al., 2015], [Chen et al., 2015] investigated what the optimal placement would be of charging stations given the trips that customers are planning. The aim of their algorithm is to install the stations in such a way that investment costs and transportation costs are covered while considering the user demand and stations capacity. A Genetic Algorithm was used to solve the problem. The authors showed that restricting the distance that a vehicle can travel from one charging stations to another increases the amount of charging stations that need to be installed significantly while the effect on the total costs is rather limited.

Modeling the behaviour of customers when the charging stations have a limited capacity is more complex as customers might try to avoid waiting times. [Liu and Sun, 2014] tried to minimize the waiting time while maximizing the service accessibility when determining the locations of the charging stations. The authors found that their algorithm performs better than the flow-capturing location models (which are similar to the models of [He et al., 2015] and [Chen et al., 2015]) when it comes to waiting time and service accessibility.

[Lam et al., 2013] used a purely mathematical approach to investigate the complexity of the problem. In their paper, the authors proposed a mathematical formulation for Electric Vehicle Charging Station Placement Problem and they proved it is a "non-deterministic polynomial-time hard problem". They propose four solution methods to tackle the problem. However, their approach is probably too simplified and they do not take into account the distribution network.

Moreover they do not take into account the differences between peak and non-peak hours. These limitations will be taken into account in the approach followed in this paper.

One way of making sure that technical logical constraints do not limit the possible outcomes, is to introduce the mechanism proposed by [Bayram et al., 2013]. In this paper the charging stations have the possibility for local energy storage which allows to neglect most of the stochasticity of the demand. Therefore the authors are focusing on minimizing the blocking time in the charging stations and the quality of service. To evaluate their method they use real data from Seattle, during a weekday at rush hour. Their results indicate that more customers can be served with the same amount of energy. Furthermore the probabilities of being blocked were significantly lower than in their base case. The limitations of their work are the communication with the distribution network is simplified by assuming a superior technology. At the same time the paper focuses only on the rush hour moments while in real life charging will happen as well during non-peak moments.

### 2.6.2 Distribution Network Based Approach

[Phonrattanasak and Leeprechanon, 2014] focus in their paper mainly on the distribution grid. They investigate what the layout would be in case of minimizing the total cost, which takes into account the operation cost and the investment cost. The results of this approach are compared with the results in case of minimizing the losses on the network. Their results suggest that fast charging stations should be distributed over the power distribution system. To take into account some demographic elements, the authors include a smooth traffic coefficient. The biggest limitation of this paper is that no hourly differences are taken into account.

[GE et al., 2012] followed a similar approach but the authors take the traffic flow in a different way into account. In contrast with the previously mentioned authors, the traffic is estimated between all the nodes in the network. The traffic and the electricity demand are both taken as an average number. This means that both traffic congestion and congestion in the lines are underestimated.

[Saelee and Horanont, 2016] studied what would be the optimal placement of ten charging stations in the region of Phuket, Thailand. In their study, the authors first estimated the expected load profiles for the charging stations based on 10 000 observed events in the past. Given this expected load for each charging station, the authors analysed what would be the optimal sites for the stations given the technical constraints for the network. Similar to other work, the authors found that a high penetration of electric vehicles could lead to significant voltage drops at peak moments, which should be taken into account when installing the stations. Their conclusions is that a controlling system for EVs charging should be installed to avoid these problems at peak moments.

A different approach is followed by [Neyestani et al., 2014] as the authors are deciding where to install parking lots instead of individual charging stations. They assume that these parking lots are managed by the PL owner who interacts with the market. The PL owner has the right to decide when to buy and when to sell energy as long as he fulfills the contract with its client. The objective of this paper is to site the parking lots in such a way that they minimize the costs of power loss, voltage deviation and network reliability. The behaviour of the PL owner is modeled as if they are profit maximizing. However, our work will focus on the effect of individual charging stations which have a much smaller effect but depend more on consumer behaviour.

In [Pashajavid and Golkar, 2013] the optimal placement of a charging station is determined taking into account a high penetration of photovoltaic panels. The authors used stochastic loads and stochastic power generation for the photovoltaic panels. The objective of their model is to minimize the voltage deviations and the power losses. However, this paper aims to install only one charging station in the whole network and does not take into account the strategical behaviour of EV drivers.

[Mohsenzadeh et al., 2015] went one step further in their research and took into account the technical limits and reliability factors at the peak moment. The authors assumed a peak demand of 800 electric vehicles who want to charge at the same time and investigated what the effect would be on a 33-bus system. In their study, the authors also consider a maximum distance range that a vehicle can travel between two stations which adds another constraint to the model. However, it is difficult to see how the limited driving distance can play a significant role in a distribution network. Another shortcoming of their study is that in a future period where there will be a peak load of 800 electric vehicles in a 33-bus distribution system, the capacity of the batteries will already have improved significantly. The authors also do not consider hourly differences in the network operation or in electricity prices.

## 2.7 Alternative Refueling Technologies

### 2.7.1 Induction Charging

A potential alternative to the installation of charging stations is installing induction charging in the road pavement. Induction or wireless charging uses electromagnetic fields to charge a battery by transmitting power from a source to the battery of the device that needs to be charged. There is not physical connection between the source and the battery. [powerbyproxi, 2016]

To charge the vehicle, alternating current is sent by a transmitter circuit to the transmitter coil. In this coil, the alternating current that is flowing creates a magnetic field which generates current within the receiver coil when it is placed in this field. The current in the receiving vehicle is converted into direct current (DC) and will charge the battery of the receiving vehicle. [powerbyproxi, 2016]

This type of power source can be placed under the road pavement and vehicles passing over this pavement can charge while driving over it. [Rim, 2015] investigated different configurations for the placement of these power source, depending on the types of vehicles. However, the author assumed that the vehicles would drive without any battery, fully relying on the power they receive from the magnetic fields. This would mean that a full circuit would be necessary over the whole trajectory, something that might be worth considering for bus-lines within a city center.

[Shekhar et al., 2015] investigated the economic viability of installing induction charging for one bus line, with for each bus a maximum driving range of 400 km in one day. They concluded that installing such an infrastructure becomes more interesting when the number of electric vehicles increases. At the same time, this allows a smaller battery capacity for each bus, which helps to reduce the costs. They also concluded that the infrastructure becomes more interesting when the charging infrastructure can be installed in road sections where the velocity of the vehicle is lower. The results showed that the batteries account for one third of the total costs. From this last work it can be concluded that the option of induction charging might become interesting when there is a high penetration of electric vehicles.

### 2.7.2 Battery Swapping

This type of "refueling" is different from other types because there is not actual recharging process happening in the vehicle. Battery swapping means that an electric vehicles arrives at a battery swapping station and the battery of the vehicle will be removed from the vehicle and a fully charged battery will be placed in the vehicle. This process has to be a standardized, automatic process as the batteries are too heavy to swap them manually. [GIGAOM, 2013]

The approach has advantages for both vehicle owners and all the electricity consumers in general. The advantage for vehicle owners is that the waiting time to have a fully charged battery is reduced to only three minutes with this approach. This could significantly decrease the range anxiety and could help to attract new customers. More interesting from a theoretical point of view is the possibility to shift the loads to the "valley" moments where the prices for electricity are the lowest. This option strongly depends on the stock of batteries that a charging station has in order not to run out of supply for arriving clients. However, when their stock is big enough, theoretically all the energy consumed by electric vehicles could be charged during the night, when the electricity demand is at its minimum. This creates benefits for the society, as the batteries even could help to reduce the peak demand by offer energy to the system, and stabilize the system during the night by increasing the demand. This would also allow a higher penetration of renewable energy sources in the system as there is always a high potential demand for cheap energy.

Despite all its obvious advantages, this approach also has some disadvantages which have been outweighing the advantages so far. The biggest difficulty companies have been facing is the necessity for standardization as the batteries need to be taken out by a machine. According to [Voelcker, 2014] companies are not likely to install the same battery packages as the design of battery package is related with the design of a car. Adapting the battery package means adapting the car layout and adapting the production process. The author also mentioned that removing a battery package is not easy, as the liquid-cooling pipes need to be disconnected and reconnected. The last problem that the author sees with this technology is the weight of a battery. These type of batteries usually weighs between 100 kg and 450 kg, which means that the process cannot be done manually.

[Sarker et al., 2013] conducted a business case and tried to find the optimal model for a Battery Swapping Station (BSS). Their assumption is that the BSS is not only providing the battery swapping service, but also participating in voltage support, regulation reserves or energy arbitrage. The BSS should provide energy at the peak moments, while being flexible at other moments to stabilize the system. The conclusion of this work was that the swapping station should be able to charge during valley periods, to partially discharge during the peak periods and the interaction between batteries when purchasing energy should be avoided.

[jun Pan and Zhang, 2016] investigated what the benefits could be of a centralized charging station for battery swapping. The aim of their work is to define where a centralized charging station should be placed from a centralized planner point of view. This is the difference with the previously mentioned study, where the objective was to maximize the profits of the battery swapping station.

# 3. Demographic Based Approach

Before defining the model, it is important what we will define as a charging station, a charging point and a connection in this work. We consider a charging station as a set of charging points located at the same place and connected to the same low voltage node. Each charging stations has typically one meter where a client has to pay for the electricity charged. A charging point is a pole with two connections where vehicles can connect to charge energy. A connection is a plug where one vehicle can be connected to the grid.

## 3.1 Relevance

The objective of this work is to compare the optimal solution from a customer point of view with the optimal solution when the technical constraints of the network are taken into account. Therefore we will need a model to determine what the optimal solution is from a customer point of view.

The problem is split into two levels. In this chapter we will describe the upper level, which we will call the model at medium voltage level. All the energy demand is aggregated in medium voltage nodes and also the destinations of the trips of vehicles are assigned to one of the medium voltage nodes. The purpose of the medium voltage is to determine when the vehicles will charge and what the voltage levels are in the medium voltage nodes. In chapter 5 we will describe the lower level of the model which is based on the low voltage nodes in the network. In this lower level we will decide where exactly the charging stations should be installed. In this section we will describe all the constraints and the objective function for the medium voltage model.

We will start with a first set of constraints that will make sure that the vehicle owners can follow their daily schedule. To comply with their schedule, the vehicles will have to move from one place to another which make them use some energy. Therefore we add in the second part some constraints to make sure that the battery level is always high enough such that the vehicle can make all his movements. Secondly the model will determine when and where vehicles will charge and how many stations should be installed in each node.

## 3.2 Formulation

The following formulation is written for the case that individual vehicles are studied. When one wants to study the behaviour of groups of vehicles, the formulation is still valid but in certain equations variables will need to be multiplied by the fleet size. Therefore we have already included this parameter in the formulation with the assumption that the fleet size for every vehicle $v$ is equal to '1'.

### 3.2.1 Sets

i: 1,...,N: set of nodes

t: 1,...,T: set of time periods

v: 1,...,V: set of vehicles

### 3.2.2 Decision Variables

$park_{iv}^t$: binary variable which is 1 if vehicle $v$ is connected in node $i$ at moment t

$ch_{iv}^t$: binary variable which is 1 if vehicle $v$ is charging energy in node $i$ at moment t

$CP_{iv}^t$: power charged by vehicle $v$ at moment t in node $i$.

$a_{iv}^t$: variable which is 1 if vehicle $v$ is in node $i$ at moment $t$ (if $< 1$, the car is between two nodes)

$b_v^t$: battery level at moment $t$

$e_{ijv}^t$: indicates what % of the distance between node $i$ and $j$ vehicle $v$ will do in the period $t$ to $t+1$

$w_{ijv}$: binary variable which is '1' if vehicle $v$ is parked in node $i$ while he has to be in node $j$

$x_i$: binary variable indicates whether a charging station is placed in node $i$ or not

### 3.2.3 Parameters

N: number of nodes

T: number of time periods under consideration

V: number of vehicles under consideration

$TU$: Time unit: the lenght of one period of time

$fleetsize_v$: number of vehicles in fleet $v$

$AD_{ij}$: matrix that takes value '1' if node $i$ and $j$ are close enough

$d_{ij}$: distance in minutes from node $i$ and $j$

$wd_{ij}$: walking distance in minutes from node $i$ and $j$

$maxcap$ : maximum power output of a charging station

$minbat$: minimum level for the battery

$maxbat$: maximum level for the battery

$cap_i$: numbers of parking spots in location $i$

$cons_{ij}$: energy consumption of moving from node $i$ to $j$

$loc_{iv}^t$: binary parameter: indicates if vehicle $v$ has to be in node $i$ at moment $t$

$co_1$: coefficient to determine the weight of the driving distance

$co_2$: coefficient to determine the weight of the walking distance

## 3.3 Constraints

### 3.3.1 Locations of the vehicles

The demand for electric charging stations depends on the battery level of the vehicles and the locations where the vehicles are. Therefore we will model the behaviour of the electric vehicles based on their daily routines. To implement this we introduce the parameter $loc_{iv}^{t}$ which has the value '1' when vehicle $v$ has to be in node $i$ at the beginning of period $t$. We introduce a variable $a_{iv}^{t}$ to indicate the location of a vehicle. To enforce that vehicles need to be in their predetermined locations when they need to be, we introduce the following constraint:

$$a_{iv}^{t} \geq loc_{iv}^{t} \qquad \forall t, \forall i, \forall v \tag{3.1}$$

Variable $a_{iv}^{t}$ can take values between '0' and '1' which means that a vehicle can be located between two nodes. This will be the case when the traveling time is more than the time unit. To illustrate this principle we will give a small example. If vehicle $v$ will travel from node 1 to node 2 and the travel time between both nodes is 60 minutes. If the time unit is 30 minutes, the vehicle will be 0.5 in node 1 and 0.5 in node 2 after one period. After two periods the vehicle will be completely in node 2 and $a_{2v}^{2}$ will have value '1'. Every vehicle needs to have a location at any moment, which results in the following equation:

$$\sum_{i} a_{iv}^{t} = 1 \qquad \forall t, \forall v \tag{3.2}$$

In reality it could happen that vehicles need to park close to the location where they need to be as there are no charging stations available in their preferred location. Therefore we adapt **eq.[3.1]** by introducing an adjacent matrix $AD_{ij}$ which is '1' when nodes are close enough.

$$\sum_{j} AD_{ij} * a_{jv}^{t} \geq loc_{iv}^{t} \qquad \forall t, \forall i, \forall v \tag{3.3}$$

We also introduce another decision variable $w_{ijv}$ which is '1' if vehicle $v$ is parked in node $j$ to walk to node $i$. With the following constraint we indicate if the owner of vehicle $v$ will have to walk or not.

$$a_{jv}^{t} + loc_{iv}^{t} \leq 1 + w_{ijv} \qquad \forall t, \forall i, \forall j, \forall v \tag{3.4}$$

When vehicles move from one location to another, we need to know what the distance is that the vehicles have traveled to determine the energy consumption. Basically we assume that vehicles have fixed routes between any two nodes and that no decisions needs to be taken about which roads they will take to go from point $i$ to $j$. Therefore it is only important to determine whether vehicles are able to go from point $i$ to $j$ in the following period or not. The following equation expresses that the percentage of the path between $i$ and $j$ that vehicle $v$ travels in period $t$ cannot take more time then the length $TU$ of one period.

$$TU \geq d_{ij}^{t} * e_{ijv}^{t} \qquad \forall t, \forall v, \forall i, \forall j \tag{3.5}$$

In the previous equation $d^t_{ij}$ is the length of path $i-j$ in minutes and $e^t_{ijv}$ is a decision variable which is '1' when 100% of the path $i-j$ is completed in period $t$. To express the relation between the location where the vehicles are and the movement variable, we introduce the following equations.

$$\sum_j (e^t_{ijv} - e^t_{jiv}) = a^t_{iv} - a^{t+1}_{iv} \qquad \forall t < T, \forall i, \forall v \tag{3.6}$$

$$\sum_i (e^t_{ijv} - e^t_{jiv}) = a^{t+1}_{jv} - a^t_{jv} \qquad \forall t < T, \forall j, \forall v \tag{3.7}$$

Some additional constraints need to be added to avoid that vehicles try to take roads which are physically not possible.

$$\sum_{ij} e^t_{ijv} \leq 1 \qquad \forall t, \forall v \tag{3.8}$$

$$\sum_{ivt} e^t_{iiv} \leq 0 \tag{3.9}$$

$$\sum_t a^t_{iv} \leq T * \sum_{tj} AD_{ij} * loc^t_{jv} \qquad \forall v, \forall i \tag{3.10}$$

**Eq.[3.8]** makes sure a vehicle cannot travel more than 100% in one period. **Eq.[3.9]** indicates that a vehicle cannot travel to its own node. **Eq.[3.10]** says that a vehicle will not visit nodes where he does not have to be or where he does not go to charge.

A last necessary equation is to introduce a steady state condition which makes sure that the vehicles are in the same position in $T+1$ as in the period 1.

$$a^{T+1}_{iv} = a^1_{iv} \qquad \forall i, \forall v \tag{3.11}$$

### 3.3.2 Charging Behaviour

The first necessary constraint for vehicles to be able to charge is that they need to be in the node where they want to charge. Not only do the vehicles need to be in the node in the beginning of period $t$, they also need to stay in that node until the beginning of the next period. This results in the following equation.

$$2 * ch^t_{iv} \leq a^t_{iv} + a^{t+1}_{iv} \qquad \forall t, \forall i, \forall v \tag{3.12}$$

In this equation the binary variable $ch^t_{iv}$ is '1' when a vehicle $v$ is charging at moment $t$ in node $i$. This variable will be forced to be '1' when a vehicle decides to charge a certain amount of energy at moment $t$ in node $i$.

$$CP^t_{iv} \leq maxcap * ch^t_{iv} \qquad \forall t, \forall i, \forall v \tag{3.13}$$

$CP^t_{iv}$ is a positive variable which expresses the amount of energy (in MWh) that vehicle 'v' will charge. We will replace the inequality by an equality because we assume that the power is not adjustable. This energy needs to be added to the battery level at moment $t$ to have the new battery level at moment $t+1$.

$$b_v^{t+1} = b_v^t + \sum_i CP_{iv}^t * \frac{TU}{60} - \sum_{ij}(cons_{ij} * e_{ijv}^t) \qquad \forall t, \forall v \tag{3.14}$$

In the previous equation $b_v^t$ represents the battery level of vehicle $v$ at moment $t$. If a vehicle is not charging, it could be the case that it is consuming energy by moving around and this energy needs to be subtracted from the current battery level. $cons_{ij}$ is the energy consumption when a vehicle travels from $i$ to $j$. In every period the battery level has to be between certain limits, which are expressed by $minbat$ and $maxbat$.

$$b_v^t \geq minbat \qquad \forall t, \forall v \tag{3.15}$$
$$b_v^t \leq maxbat \qquad \forall t, \forall v \tag{3.16}$$

Because we are assuming a steady state solution, the battery levels need to be more or less the same at the end of every day. This is enforced by the following constraint.

$$b_v^1 \leq b_v^{t+1} \qquad \forall t, \forall v \tag{3.17}$$

**Charge on Arrival**

It is not unrealistic to assume that vehicle owners are not willing to complicate their daily life and that they prefer to connect their vehicle immediatey when they arrive. This can be implemented by adding the following constraint.

$$\sum_i ch_{iv}^t - ch_{iv}^{t-1} \leq T * \sum_{ij} e_{ijv}^{t-1} \qquad \forall t, \forall v \tag{3.18}$$

**Charge only once a day**

Another way of modeling the behaviour of the drivers' more realisticly, is to add a constraint which makes sure that the vehicles will charge during only once continuous period. Therefore we add the following constraints.

$$ch_{iv}^{t-1} - ch_{iv}^t \leq endch_{iv}^t \qquad \forall t, \forall i, \forall v \tag{3.19}$$
$$\sum_{ti} endch_{iv}^t \leq 1 \qquad \forall v \tag{3.20}$$

To make sure that the charging period can also cover the end of the day, the follow variables are added and given the value of the last period.

$$ch_{iv}^0 = ch_{iv}^T \qquad \forall i, \forall v \tag{3.21}$$
$$e_{ijv}^0 = e_{ijv}^T \qquad \forall i, \forall j, \forall v \tag{3.22}$$

#### Vehicles need to be connected when charging

We assume that vehicle owners will only disconnect their vehicles when they do not have to be in that node anymore. Therefore we need a variable that indicates if a spot in a charging station is occupied or not. We introduce the variable $park_{iv}^t$ which should be '1' if vehicle $v$ is occupying a spot in station $i$ at moment $t$. The following constraint makes sure that this variable is '1' when the vehicle is charging in the charging station.

$$ch_{iv}^t \leq park_{iv}^t \qquad \forall t, \forall i, \forall v \tag{3.23}$$

To make sure that the spot stays occupied until the vehicle owner does not have any obligation anymore in node $i$, we also need to add the following constraint.

$$park_{iv}^t \geq park_{iv}^{t-1} * \sum_j AD_{ij} * loc_{vj}^{t-1} \qquad \forall t, \forall i, \forall v \tag{3.24}$$

### 3.3.3 Charging Stations

The total number of vehicles connected at node $i$ at any moment cannot exceed the capacity of that node. Moreover if a vehicle $v$ wants to connect for charging, a station needs to be installed in that node.

$$\sum_v fleetsize_v * park_{iv}^t \leq cap_i \qquad \forall t, \forall i \tag{3.25}$$

$$park_{iv}^t \leq x_i \qquad \forall t, \forall i, \forall v \tag{3.26}$$

## 3.4 Objective Function

The objective of the first model is to satisfy the customers as good as possible. The measure we use to estimate the customer satisfaction is the walking distance and total driving distance that customers of the trips during a day. The lower the sum of the weighted walking and driving distance, the better the solution. Therefore the objective function will try to minimize this sum which looks as follows.

$$\min \quad \sum_{tijv} (co_1 * d_{ij} * e_{ijv}^t + co_2 * wd_{ij} * w_{ijv})$$

# 4. Distribution Network Approximation

In this section the additional constraints that need to be implemented to model the distribution network will be explained. First we will explain in more detail why it is important to take these constraints into account. In the second part we will explain first the theoretical exact constraints which explain exactly what happens in the distribution network. However, implementing these constraints would lead to a non-linear problem. Therefore we will propose a linear approximation to keep the problem linear.

## 4.1 Relevance

The distribution grid should be taken into account for two reasons. The first reason is a technical reason. To provide electricity to the consumers, it needs to be transported by cables. These cables in distribution networks typically have a resistive component which causes a voltage drop when current is passing through it. An excessive voltage drop may damage machines connected to the electricity network and therefore this cannot be acceptable.

Another technical problem that might occur it that lines get overheated. This happens because the power flowing through a line generates heat. When there is too much power flowing, this will generate too much heat which would make a line collapse. In reality security systems, called breakers, have been installed to avoid that a line will collapse by opening the circuit, but this will prohibit that electricity can be transported.

The second reason is an economical reason. The losses in the system, and therefore the amount of energy that needs to be produced, depend strongly on where and when energy is consumed. So if we are able to put the charging stations in those location where the losses are minimal, or if we are able to make people charge their vehicles at moments where it is more beneficial for the system, this would give economical benefits for the whole system.

In this first model we will implement the constraints for the distribution grid to make sure that the technical limits are not violated. The economical reasons will not be considered, as the objective function will be the consumer satisfaction. Later on in this work, we will try to see how the economical benefits could be implemented in the model.

## 4.2 Formulation

In the following equations all the values are assumed to be in per unit. The power base is assumed to be 1 MVA, while the voltage base for a medium voltage network is assumed to be

20 kV. The voltage base for the low voltage network is 0.4 kV. As the power base is equal to 1 MVA, we will not mention the power base in the following equations, as multiplying or dividing by 1 does not change the values.

### 4.2.1 Sets

i: 1,...,N: set of nodes

t: 1,...,T: set of time periods

v: 1,...,V: set of vehicles

k: 1,...,K: set of piecewise linear approximations

l: 1,...,L: set of piecewise linear approximations

### 4.2.2 Decision Variables

$S_{ij}^t$: Apparent power in line $i$-$j$ at moment $t$

$P_{ij}^t$: Active power in line $i$-$j$ at moment $t$

$Q_{ij}^t$: Reactive power in line $i$-$j$ at moment $t$

$L_{ij}^t$:Active power loss in line $i$-$j$ at moment $t$

$COS_{ij}^t$: Variable that approximates the value of $\cos(\theta_i - \theta_j)$.

$u_{ijk}^t$: Binary variable which is '1' when approximation $k$ is binding

$V_i^t$: Voltage level in node $i$ at moment $t$

$\theta_i^t$: Angle out of phase

$GP_i^t$: Active power supply in node $i$ at moment $t$

$GQ_i^t$: Reactive power supply in node $i$ at moment $t$

### 4.2.3 Parameters

$c_t$: cost of 1 MW at moment t

$SLP_k$: slope of a linear approximation $k$

$ICP_k$: intercept of a linear approximation $k$

$\sigma_k$: slope of a linear approximation $k$

$\rho_k$: intercept of a linear approximation $k$

$R_{ij}$: resistive part of line $i$-$j$

$X_{ij}$: inductive part of line $i$-$j$

$DEM_i$: active power demand in node $i$

$DEMQ_i$: reactive power demand in node $i$

$Vmin_i^t$: minimum voltage level at moment $t$ in node $i$

$Vmax_i^t$: maximum voltage level at moment $t$ in node $i$

## 4.3 Constraints

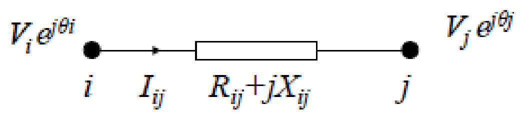
### 4.3.1 Power on the lines

The power that flows from node $i$ to node $k$ is a complex magnitude. The first component is the real part, called active power $P_{ik}$, the second component is an imaginary part, called the reactive power $Q_{ik}$. The reactive power is always presented with respect to the imaginary axis and therefore multiplied by the imaginary number $j$. [Garcia Gonzalez, 2014]

$$S_{ik} = P_{ik} + jQ_{ik} = V_i e^{j\theta_i} \qquad \forall i, \forall k \qquad (4.1)$$

$$= V_i(\cos\theta_i + j\sin\theta_i)\frac{V_i(\cos\theta_i - j\sin\theta_i) - V_k(\cos\theta_k - j\sin\theta_k)}{R_{ik} - jX_{ik}} \qquad \forall i, \forall k \qquad (4.2)$$

In the **eq.[4.1]**, the power flow is represented by a phasor which consists of a module and an argument. In this case the argument represent the angle out of phase $\theta_i$ with respect to a certain reference. The module is the voltage amplitude $V_i$. With this notation, we can present the parameters which determine the power flow between two nodes as follows. [Garcia Gonzalez, 2014]




In the previous expression $R_{ij}$ represents the resistive part of the line, while $X_{ij}$ stands for the inductive component. From **eq.[4.2]** we can retrieve the expressions for $P_{ij}$ and $Q_{ij}$:

$$P_{ij} = \frac{1}{R_{ij}^2 + X_{ij}^2}(X_{ij}V_iV_j\sin(\theta_i - \theta_j) + R_{ij}(V_i^2 - V_iV_j\cos(\theta_i - \theta_j))) \qquad \forall i, \forall j \qquad (4.3)$$

$$Q_{ij} = \frac{1}{R_{ij}^2 + X_{ij}^2}(X_{ij}(V_i^2 - V_iV_j\cos(\theta_i - \theta_j)) - R_{ij}V_iV_j\sin(\theta_i - \theta_j)) \qquad \forall i, \forall j \qquad (4.4)$$

In the previous equation there are no imaginary numbers anymore. Therefore the index $k$ was replaced by $j$, without having any imaginary meaning. It can be seen that these equations are non-linear. To keep our model linear, we will need to approximate these expressions by making some assumptions which do not change the conclusions drastically. A common approximation is to use a DC power flow for the AC power flow. To make this approximation, the following assumptions should be valid.

- $V_i \approx V_j \approx V$
- $X_{ij} \gg R_{ij}$
- $\theta_i \approx \theta_j$

When these assumptions are valid, we can say that $\cos(\theta_i - \theta_j) \approx 1$ and $\sin(\theta_i - \theta_j) \approx \theta_i - \theta_j$. However, these assumptions are only valid for a high voltage transmission network. For a distribution network this approximation could lead to wrong conclusions as the voltage drops are ignored. Typically for medium voltage lines, the resistive and the inductive part have more or less the same magnitude. For the low voltage lines, the resistive part is usually even bigger than the inductive component. Therefore it is important to retain the voltage and the reactive power. The following approximation is based on [Trodden et al., 2014]. The power flows from node $i$ to $j$ in this approximation are:

$$P^t_{ij} = G_{ij}(2V^t_i - 1) - G_{ij}(V^t_i + V^t_j + COS^t_{ij} - 2) + B_{ij}(\theta_i - \theta_j) \qquad \forall i, \forall j \tag{4.5}$$

$$Q^t_{ij} = B_{ij}(1 - 2V^t_i) - B_{ij}(V^t_i + V^t_j + COS^t_{ij} - 2) - G_{ij}(\theta_i - \theta_j) \qquad \forall i, \forall j \tag{4.6}$$

with

$$G_{ij} = \frac{R_{ij}}{R^2_{ij} + X^2_{ij}} \tag{4.7}$$

$$B_{ij} = \frac{X_{ij}}{R^2_{ij} + X^2_{ij}} \tag{4.8}$$

In this equation the variable $COS^t_{ij}$ is an approximation of $\cos(\theta_i - \theta_j)$. This approximation is based on a piecewise linear approximation of the cosinus function. The equations for this approximation look as follows.

$$COS^t_{ij} \leq SLP_k(\theta^t_i - \theta^t_j) + ICP_k \qquad \forall i, \forall j, \forall k \tag{4.9}$$

$$COS^t_{ij} \geq SLP_k(\theta^t_i - \theta^t_j) + ICP_k - (1 - u^t_{ijk}) \qquad \forall i, \forall j, \forall k \tag{4.10}$$

$$\sum_k u^t_{ijk} = 1 \qquad \forall i, \forall j \tag{4.11}$$

In this formulation the index $k$ refers to approximation $k$. Each linear approximation is the derivative of the cosinus function for a different angle. The variables $SLP_k$ and $ICP_k$ represent the slope and the intercept of this function. The binary variable $u^t_{ijk}$ makes sure that the cosinus approximation is equal to the value on the right side for exactly one $k$.

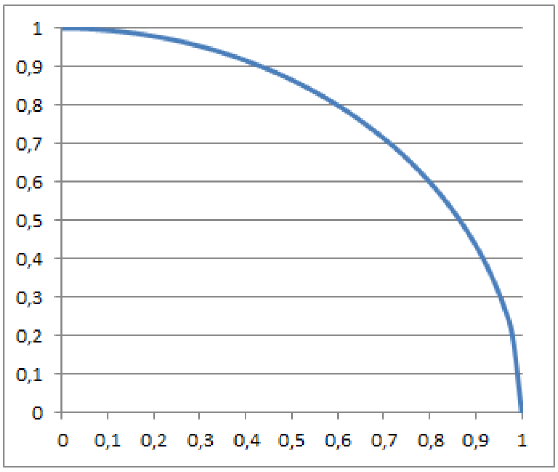
The heat limits of the lines are usually translated into apparent power limits. This means that the combination of active and reactive power should be considered when checking if a line will not be overloaded. In the following equation $S^{max}$ stands for the maximum apparent power that can flow through a line. We are considering the absolute values, so there is no need to put a minimum, as all the number will be positive.

$$S_{ij} \leq S^{max}_{ij} \qquad \forall i, \forall j \tag{4.12}$$

The problem with the implementation of this constraint is the definition of $S_{ij}$, which is non linear.

$$S_{ij} = \sqrt{P^2_{ij} + Q^2_{ij}} \qquad \forall i, \forall j \tag{4.13}$$

Figure 4.1: Theoretical Apparent Power Limit

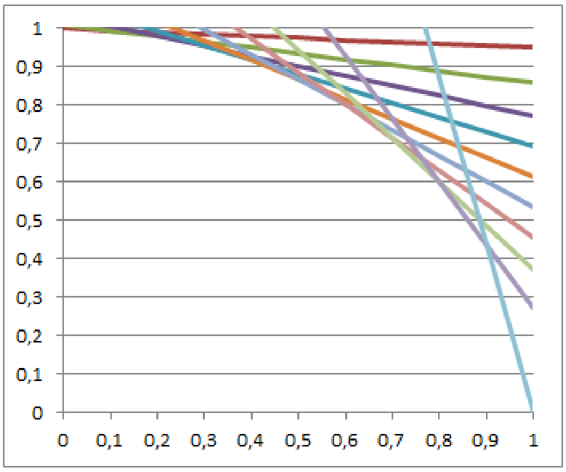



Similar to the approach we have followed to approximate the AC power flow, we will also define a linear approximation fo the line limits. This approximation will restrict the power flows slightly more than is necessary in reality. However, as we are making a long term decision, the actual power flows can differ significantly. Thus limiting the power flows slightly more than is necessary in reality, will make the chosen system more reliable.

$$|Q_{ij}^t| \leq S_{ij}^{max}\rho_k + \sigma_k|P_{ij}^t| \qquad \forall i, \forall j, \forall k \qquad (4.14)$$

In **eq.[4.13]** $\rho_k$ stands for the intercept of the linear approximation of the $k^{th}$ segment, while $\sigma_k$ represents the slope of the approximation of that segment. The allowed power flows can now be represented like this:

Figure 4.2: Approximation of the Apparent Power Limit



### 4.3.2 Demand

The demand has to be equal to supply at each moment in each node.

$$\sum_j P_{ji}^t - \sum_j P_{ij}^t + GP_i^t = DEM_i^t + \sum_v (CP_{iv}^t) \qquad \forall i, \forall t \tag{4.15}$$

$$\sum_j Q_{ji}^t - \sum_j Q_{ij}^t + GQ_i^t = DEMQ_i^t + \sum_v (CQ_{iv}^t) \qquad \forall i, \forall t \tag{4.16}$$

In this equation $DEM_i^t$ represents the demand of other consumers than the electric vehicles at moment $t$ in node $i$. As mentioned before $CP_{iv}^t$ stands for the amount of power that is charged by vehicle $v$ at moment $t$ in node $i$. This total demand needs to be equal to the amount of energy $GP_i^t$ produced in node $i$ at moment $t$ plus the amount of energy entering the node minus the amount of energy leaving the node. **Eq.[4.16]** states exactly the same for the reactive power as **eq.[4.15]** states for the active power.

### 4.3.3 Losses

We need to approximate the losses as the losses are non linear. This is done in the same way as we approximate the apparent power limit. We will use again the approximation of the cosinus function $COS_{ij}^t$ to approximate the losses as the losses are expressed by the following expression.

$$L_{ij} = 2 * G_{ij} * (1 - \cos(\theta_i - \theta_j)) \qquad \forall i, \forall j \tag{4.17}$$

in which we will replace $\cos(\theta_i - \theta_j)$ by $COS_{ij}$. We can assume that these losses are equally distributed over the line and we will therefore add half of the losses to the demand on both sides of the line.

### 4.3.4 Voltage Level

In a feasible solution, the voltage level has to be within a certain minimum and maximum level. Thus, the next equation needs to be added to make sure that these limits are respected.

$$Vmin_i^t \leq V_i^t \leq Vmax_i^t \qquad \forall i, \forall t \tag{4.18}$$

### 4.3.5 Objective Function

The objective of solving an optimal power flow model is to minimize the cost $c^t$ of the energy produced. We assume that the cost of increase the demand with one MW is the same in each node as in our model the power supply will always be located in the HV/MW substation. In the following equation $GP_i^t$ is the power supply in node $i$ at moment $t$.

$$\sum_{ti} c^t * q_i^t \tag{4.19}$$

# 5. Low voltage model

To make sure that no problems occur in the network, it is necessary to know exactly to which low voltage nodes the charging stations are connected. Due to the complexity of the model, it is not possible to analyse this on an aggregated level and therefore we need to use a second model

## 5.1 Relevance

In this chapter we introduce a lower level in our model which is based on the low voltage nodes in the network. In this lower level we will decide where exactly the charging stations should be installed. We will describe all the constraints and the objective function for the low voltage model.

## 5.2 Formulation

### 5.2.1 Sets

i: 1,...,N: set of nodes

t: 1,...,T: set of time periods

v: 1,...,V: set of vehicles

f: 1,...,F: set of fleets

### 5.2.2 Decision Variables

$park_{iv}^{t}$: binary variable which is 1 if vehicle $v$ is connected in node $i$ at moment t

$ch_{iv}^{t}$: binary variable which is 1 if vehicle $v$ is charging energy in node $i$ at moment t

$CP_{iv}^{t}$: power charged by vehicle $v$ at moment t in node $i$.

$w_{ijv}$: binary variable which is '1' if vehicle $v$ is parked in node $i$ while he has to be in node $j$

$x_i$: binary variable indicates whether a charging station is placed in node $i$ or not

$y_i$: integer variable to indicate how many charging points should be installed in stations $i$

### 5.2.3 Parameters

N: number of nodes

T: number of time periods under consideration

V: number of vehicles under consideration

f: number of fleets

$parkstart_f^t$: binary parameter which is 1 if vehicle $v$ has to be connected at moment t

$chstart_f^t$: binary parameter which is 1 if vehicle $v$ has to be charging energy at moment t

$wd_{ij}$: walking distance in minutes from node i to j

$maxcap$: maximum power that can be charged

$cap_i$: numbers of charging points that can be installed in location $i$

$c_t$: cost of 1 MW at moment t

$h_i$: binary parameter: indicates if car v has to be in node i at moment t

$\phi_{vf}$: binary parameter which is '1' if vehicle $v$ is in fleet $f$

## 5.3 Constraints

### 5.3.1 Charging Pattern

The model uses as input parameters the charging patterns of the medium voltage level. Therefore it is necessary to include the following constraint which says that whenever a vehicle needs to be charging, it need to be charging in exactly in one node. The right hand side of the equation is the input parameter $chstart_f^t$ which is '1' for the periods that vehicle $v$ which belongs to fleet $f$ needs to charge in one of the nodes of the low voltage feeder. For the other periods this parameter is equal to '0'. $\phi_{fv}$ is a parameter which is '1' if vehicle $v$ belongs to fleet $f$ and '0' if not.

$$\sum_i ch_{iv}^t = \sum_f \phi_{fv} * chstart_f^t \qquad \forall t, \forall v \tag{5.1}$$

Similarly the connection pattern of the fleets should be respect by each vehicle of that fleet. Therefore we introudce the next constraint where $parcstart_f^t$ indicates whether members of fleet $f$ should be connected at moment $t$ or not.

$$\sum_i park_{iv}^t = \sum_f \phi_{fv} * parkstart_f^t \qquad \forall t, \forall v \tag{5.2}$$

If a vehicle is charging at node $i$, it means that it also has to be connected at that moment in node $i$. Therefore the following equation is necessary because the previous ones do not impose any restriction on the location of the vehicles.

$$ch_{iv}^{t} \leq park_{iv}^{t} \qquad \forall t, \forall i, \forall v \tag{5.3}$$

A vehicle cannot charge more than the maximum power that stations allow, although this constraint will be implemented in our model as an equality. In constraint (5.4) the parameter $maxcap$ is the maximum power drain when charging the vehicle and $CP_{iv}^{t}$ represents the amount of power charged by vehicle $v$ at moment $t$ in node $i$.

$$CP_{iv}^{t} = maxcap * ch_{iv}^{t} \qquad \forall i \tag{5.4}$$

### 5.3.2 Location and Capacity of Stations

The next step is to make sure that when a vehicle is connected, there are enough charging points installed in the place where he is connected. As every charging point has two connections, the number of charging points is multiplied by '2' in the next equation. The number of charging points installed in node $i$ is indicated by $y_i$.

$$\sum_{v} park_{iv}^{t} \leq 2y_i \qquad \forall t, \forall i \tag{5.5}$$

If a charging point is installed in a node, it means that this node has a charging station. The presence of a charging station is indicated with the binary variable $x_i$ which is '1' if there is a charging station in node $i$. The amount of charging points in a charging station can also not exceed the capacity $cap_i$ of a charging station.

$$y_i \leq cap_i x_i \qquad \forall i \tag{5.6}$$

### 5.3.3 Walking Distance

When a vehicle is charging in another node than its destination, it means that the owner will have to walk from his vehicle to his destination. This is enforced by the following constraint where $H_{i,v}$ is a parameter that if node $i$ is the destination for vehicle $v$ or not. $w_{ijv}$ is a binary variable that will take the value '1' when the owner of vehicle $v$ has to walk from node $j$ to $i$ and back.

$$ch_{jv}^{t} + h_{iv} \leq 1 + w_{ijv} \qquad \forall t, \forall i, \forall j, \forall v \tag{5.7}$$

### 5.3.4 Distribution Network

The distribution network will be included in the same way as discussed in chapter 4. The only difference that the nodes are now low voltage nodes.

## 5.4 Objective Function

The objective function for the low voltage model is similar to the objective function of the medium voltage model. However, as each low voltage feeder only covers several hundreds of meters, the driving distance is left out the objective function as the distance are too small. Therefore it is only important where the vehicle will be parked and how far the owner will have to walk to his house.

$$\min \quad \sum_{ijv} (wd_{ij} * w_{ijv})$$

# 6. Case Study

In this section we will discuss a case study run for the center of Coimbra, Portugal. This section will first describe the background of the case study and the data used for the case study. Together with the data we will explain the assumptions that we made while running the different configurations for the case study. In the last section we will discuss the results by always making a comparison between the results without taking the electricity grid into account and the results with the network taken into account.

## 6.1 Background

### 6.1.1 Area

The area for this case is located in the north of the center of Coimbra. The buildings have both a residential usage and a usage for commercial activities. The faculty of economics and some hospitals in the neighbourhood are both important destinations when we look at the typical traveling data.

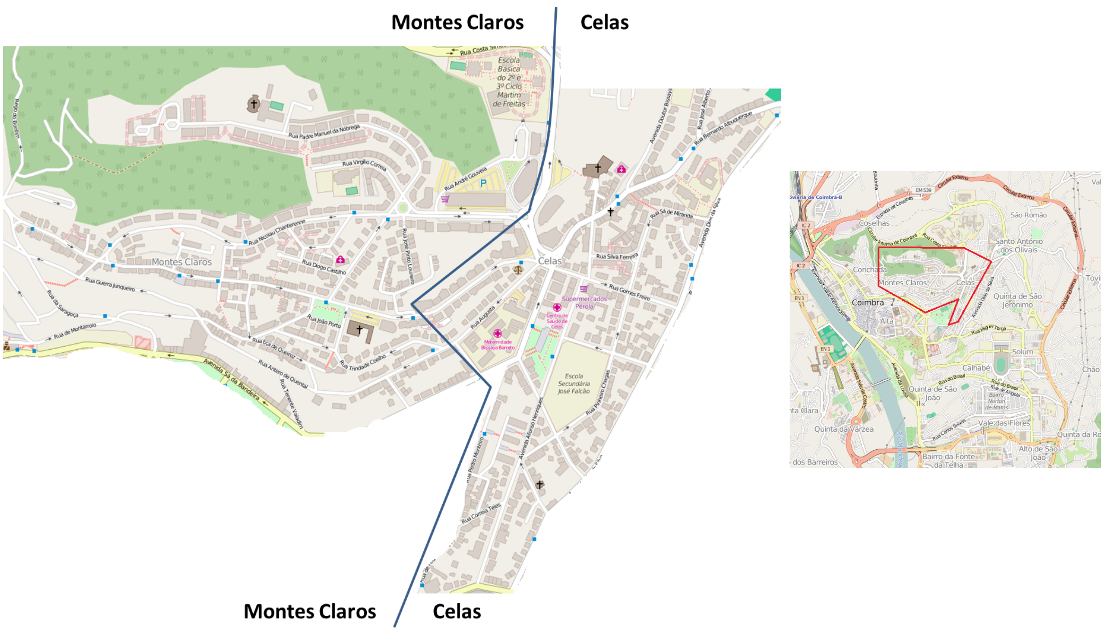



Figure 6.1: Location of the study area

## 6.2 Data

### 6.2.1 Behaviour of Vehicles

The traveling patterns of the vehicles are based on a survey conducted by [MetroMondego, 2008]. However, this survey mainly contains data about people who are visiting the study area during the data, which means that we will mainly focus on the behaviour during the day. As we have mentioned before, the aim of this work is not to determine where to install exactly charging stations in this area, but to see what the effect is of the network on the optimal locations. The purpose of using data of this area is to have a realistic case study.

From this survey we can also deduct information about the size of each fleet of vehicles, as every traveling pattern has a certain weight. Furthermore we will reduce this fleet size to a realistic number of electric vehicles based on the assumptions that we make about the penetration of electric vehicles. In certain cases the number of vehicles in the fleet will be reduced even more when we assume that not all the vehicles will charge every day. This can reduce the fleet size to only 20% if a vehicle is driving a short distance every day and will therefore need to charge for example only every five days.

Based on the starting and ending positions taken from this survey, we assign a start and end node to each vehicle. This node will be the closest low voltage node based on the rectangular distance.

### 6.2.2 Distances

The distances between nodes are expressed in minutes and are based on Google Maps. [GOOGLE, 2016] Likewise the walking distance are also taking from Google Maps. The consumption is based on the driving distance taking from Google Maps and the average speed that one is expected to drive on this segment. The consumption is not a linear function of the distance but as it is calculated before for each segment, this does not cause problems for the model.

Based on these walking distances, we can construct an adjacent matrix for the nodes that are close to each other. Nodes are considered as being adjacent when the walking distance between two nodes is not more than 5 minutes.

### 6.2.3 Electricity Network

The electricity network data are not based on real life data but instead a modeling tool was used to generate a realistic network. This tool was provided by Carlos Mateo Domingo, assistant researcher at the Institute for Research in Technology in Madrid. The tool provides all the necessary information about the network structure based on a map of the study area. Although this information does not correspond to the real data, the data provided by the software allow to analyse in a realistic way what the effects on the network are when electric vehicles are charging.

Since the resulting network has more than 1000 nodes, it almost impossible to solve the problem. Therefore we split the problem in two steps based on the voltage levels. The medium voltage network is reduced until only nodes remain at which a significant number of demand is located while all the electricity demand is aggregated in these nodes. This means that losses are underestimated but the power flows between nodes should be approximately coincide with

Figure 6.2: Selected MV nodes

the power flows in the original network. The aim in this first step is to allocate the demand for charging points to the different low voltage feeders connected to these medium voltage nodes and to have a charging pattern that the electric vehicles will follow. In a second step we investigate the low voltage feeders to determine in which low voltage node the stations should be installed and what the effects are on the walking distance, the voltage levels and the power flows.

Figure 6.2 shows the nodes that were selected from the medium voltage network. These are the nodes that cannot be deleted because they have more than two connections with other nodes, and deleting would violate Kirchhoff's laws. From these 43 nodes, 19 nodes were selected for possible locations for charging stations, while the network is still solved taking into account the 43 nodes. The red dots in the image are the candidate nodes where charging stations can be installed. These points are based on the traveling data and are the once where a significant number of vehicles have their start or end node in one of the low voltage nodes.

### 6.2.4 Electricity Demand

The demand for electricity in each network is based on the estimations of the load profile of [NHEC, 2014]. When we compare the load profile of New Hampshire with the load profiles in [Camus, 2011], we find that the load profiles are very similar to a typical load profile in Portugal. In both cases the peak demand is located around 8 pm which means that the use of these data should lead to realistic results.

The load profiles are taken for each node as a random day in January multiplied by the number of customers in that node. We assume a power factor of around 0.95.

### 6.2.5 Electricity Prices

Electricity prices were taken from [OMIE, 2016] for the Portuguese market. The prices representative for a winter day are taken for 18-01-2016. Although prices might be different from day to day in real life, it is sufficient that prices are congruent with the load profile to draw conclusions.

### 6.2.6 Charging capacity and Batteries

We are assuming that the batteries have a capacity of 35 kWh as we think expect that a high penetration of electric vehicles only will take place when the battery technology has become more mature. We are deciding where to install slow chargers with a capacity of 3.5 kW. This means that the batteries can be 80% charged in 8 hours.

## 6.3 Results

To obtain the results we proceed the following steps:

**Step 1:** We run the MV voltage model with the objective of minimizing the walking + driving distance. Equal weights are attached to both measures assume that vehicle owners try to minimize their daily travel time. An extra term with a small weight is added to the objective function to make sure that the amount of energy produced is also minimized. Interactions between both objectives should be considered as being very low as 1 minute of traveling has the same weight as increasing the production with 10 MW. This is to avoid that a vehicle would decide to charge in another station to avoid losses for the system, something that will never happen in reality without the right incentives.

**Step 2:** For each node we know the voltage level, the amount of vehicles which will be parked at low voltage nodes connected to this node and when and where the vehicles will be charging. This information is taken as data for the LV voltage model in which we will decide how many charging stations we will build connected to each feeder, how many charging points each stations will have and where the vehicles will charge. The objective is now to make sure that everyone is able to charge and to minimize the total walking distance between the place where people charge and their destinations. This second step will be done twice: once with taking the electricity grid into account and once with taking the electricity grid into account.

As will be shown in the results, this two-step approach leads to three types of conclusions.

- the location of the stations does not change depending on the electricity grid
- the location changes and the total walking distance will increase
- no feasible solution exists for the amount of vehicles who want to charge at the same time for the minimal number of charging stations.

Later on we will discuss which measures can be taken to solve this last problem.

### 6.3.1 Low Penetration - Charge on Arrival - No Daily Charge

In all the following cases "Low Penetration" means that 10% of the total amount of vehicles parking in the area under consideration is an electric vehicle. "Charge on Arrival" means that electric vehicles automatically start charging when they are connected. When the battery is fully charged, the vehicle stays connected until the owner manually disconnects the vehicle but the vehicle stops charging automatically. This means that the station is still occupied but the vehicle is not charging any more.

The last assumption for this first case is that vehicle owners prefer to charge only when their battery is low enough. This means that only a certain percentage of the fleet will charge during a day and therefore we will reduce the number of vehicles to this percentage.

#### Medium Voltage Level

The following graphs show how many vehicles are parked and how many vehicles are charging at each node at each moment of the day.

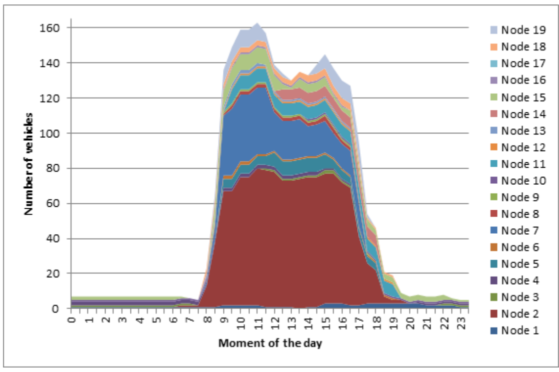



Figure 6.3: Parking behaviour

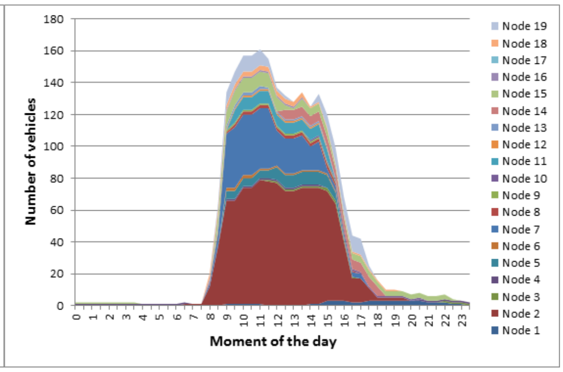



Figure 6.4: Charging behaviour

More specifically we can have a more detailed look at node 2, to see how many of the vehicles are connected without charging. In the following graph the red area represents the amount of vehicles that are charging at each hour of the day in node 2. The blue area indicates how many vehicles are still connected after charging without charging energy. This means that they are occupying available space which cannot be used by other vehicles.

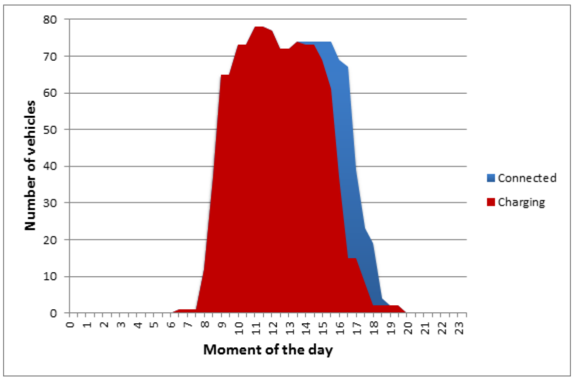
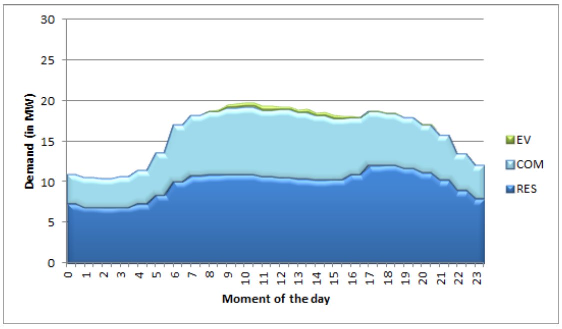
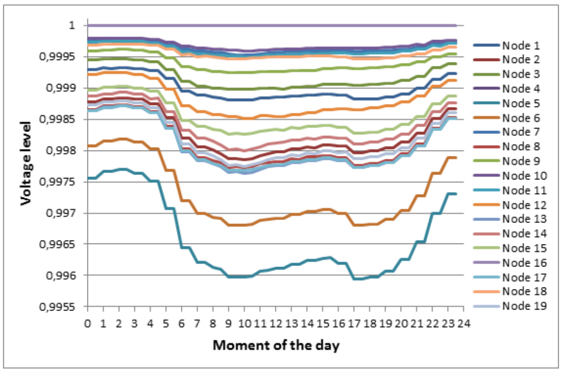



Figure 6.5: Charging behaviour at node 2

To analyse the effect on the distribution network, we also need to retrieve the voltage levels for each medium voltage node, as these are the nodes where the low voltage feeders are connected to the rest of the system. Therefore the following voltage levels are taken as inputs for the low voltage model.




(a) Electricity demand




(b) Voltage levels in the medium voltage network

Figure 6.6: Demand and its effect on the volltage levels in the MV network

### Low Voltage Level

The medium voltage model gave us the moments when people prefer to charge and in which nodes they want to charge. We can now analyse how many charging stations should be installed and connected to each low voltage feeder. The first step is to determine what the minimum amount of charging stations is that needs to be placed to be able to cover all the demand without taking into account the distribution network. After determining the minimum number of charging stations, we compare this result with the minimum amount of charging stations when taking into account the network. When this number is different, we can already conclude that the distribution plays a significant role in that area.

After this process, we will run the model several times to analyse how the stations should be placed to minimize the total walking distance, given a certain number of stations that will be placed. We start the iterations with the minimum required number of stations and increase this number with 1 in every iteration. Also the amount of charging points will increase with one in each iteration. We analyse the effect of increasing the number of stations on the total walking distance, the power flows and the voltage levels in each node. Results will always be compared between taking into account the network and the purely demand based results.

### Node 7 [Medium-Low Voltage Substation 3]

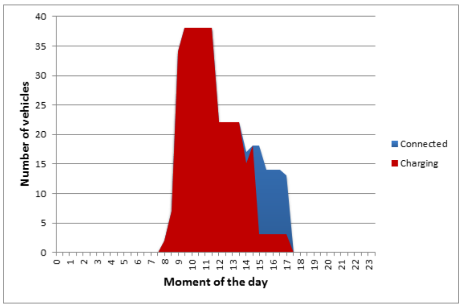
The feeder connected to node 7, is located at the area shown in the next graph. It is important to remind the reader that this network and the assigned demand do not necessarily correspond with the real data, but are only used to perform a realistic case study. Conclusions about the real implementation cannot be drawn from this study.


Figure 6.7: Location of feeder 7 in Celas

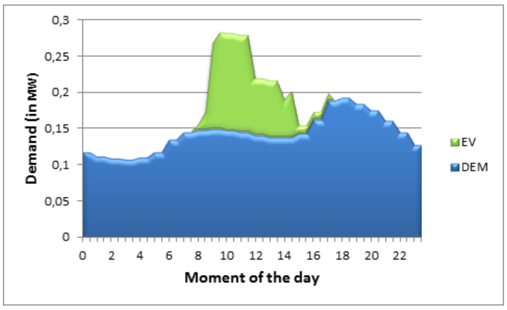
We also assign a capacity to each node, based on empirical observations in real life about how many charging points could be installed at those locations. The number of charging points that can be installed in each node is shown in the next table.

| node | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| cap | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 4 | 1 | 1 | 8 | 2 | 3 | 0 | 2 | 3 | 0 |

The first step is to determine the minimum amount of charging stations that are necessary for this area. As there are at most 38 vehicles parked at the same time, the minimum amount of charging points is 19, as each charging point has two connections. Given the capacity of the different locations, these 19 points will need to be installed divided over at least five charging locations (stations). Solving the model with the objective of minimizing the number of charging stations and charging points while taking into account the limits of the network gives the same results. Then we run the model for ten iterations, starting with five charging stations and 19 charging points and stepwise increasing this number in each iteration to see what the effect is on the walking distance, the voltage levels and the power flows.




(a) Charging behaviour at node 7




(b) Demand at feeder 7

Figure 6.8: Charging pattern and the effects on the demand

The next table shows how the total walking distance decreases when we increase the number of charging points. The walking distance is expressed in minutes, which means that a value of "60" means that the total walking distance is equal to one hour.

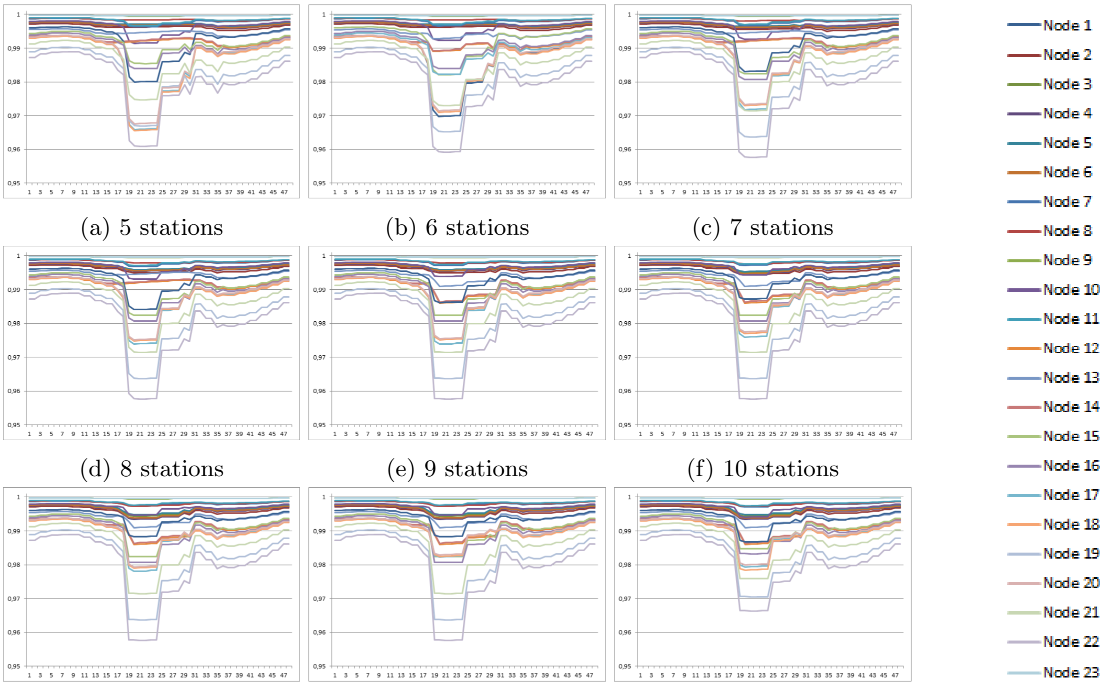
| x | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|
| y | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 |
| WD | 79 | 62 | 54 | 49 | 45 | 41 | 37 | 34 | 32 | 31 |

To give the reader an idea about what the locations are for the charging stations, the next image shows where the stations are placed in case of the placement of 5 stations (figure 6.9a) and 13 stations (figure 6.9b). The charging stations are shown in yellow while the other nodes are shown in purple.

(a) 5 stations (b) 13 stations

Figure 6.9: Results

The analysis of the voltage levels shows that node 22 is the point where the voltage reaches its lowest level, independent of the number of stations in place. The next graphs also show that increasing the number of stations does not affect drastically change the voltage level in the different nodes.




(a) 5 stations (b) 6 stations (c) 7 stations

(d) 8 stations (e) 9 stations (f) 10 stations

(g) 11 stations (h) 12 stations (i) 13 stations

Figure 6.10: Voltage levels

A last parameter that imposes an important constraint on the feasibility of the solutions is the apparent power limit of each line. However, these limits depend on the characteristics of each line and therefore we will show the percentage of the line that is being used at each moment of the day. The highest values occur when the minimum amount of stations (5) is installed and therefore we will only show the values for this configuration in this work. In the following graph it can be seen that the line between nodes 16 and 21 is the line with the highest percentage of usage at the peak moment. The graph shows that the apparent power reaches slightly more than 80% of the line limit at this moment, which suggests that a further increase in the number of electric cars might cause problems.

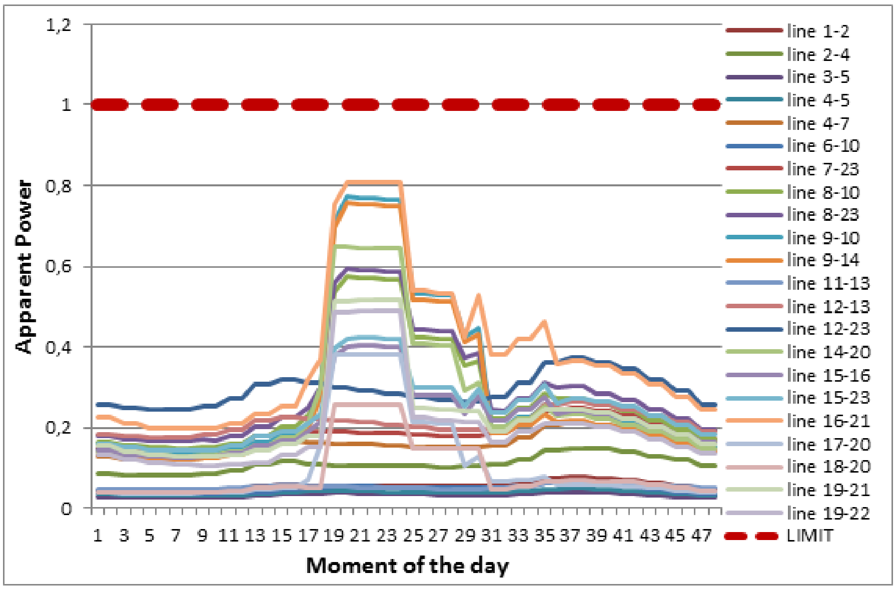



Figure 6.11: Apparent Power

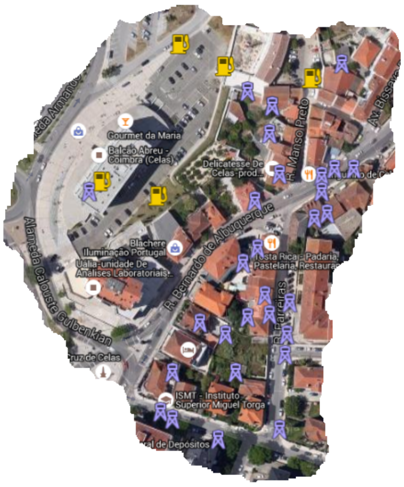
### Node 2 [Consumer Medium Voltage 23]


Figure 6.12: Location of feeder 2 in Celas

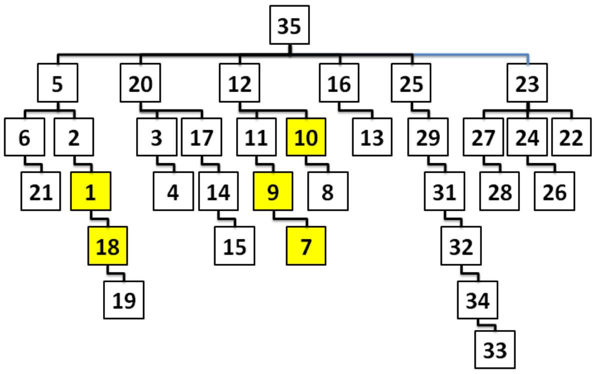
Node 2 of the medium voltage network is located more to the north of Celas. It typically has more vehicles which remain parked during the whole day which is slightly different from node 7 where many people leave around lunch time. Nevertheless the charging pattern at both nodes is very similar. The capacity of the different nodes is shown in the next table.

| node | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| cap | 8 | 0 | 0 | 0 | 3 | 0 | 12 | 0 | 6 | 8 | 0 | 0 | 0 | 3 | 3 | 0 | 3 | 5 |
| node | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | |
| cap | 5 | 3 | 0 | 5 | 2 | 0 | 0 | 0 | 3 | 3 | 0 | 0 | 3 | 3 | 3 | 3 | 0 | |

At the peak moment there are 78 vehicles connected, which means that at least 5 stations need to be installed with 39 charging points. In total 90 vehicles are charging during the day in node 2.



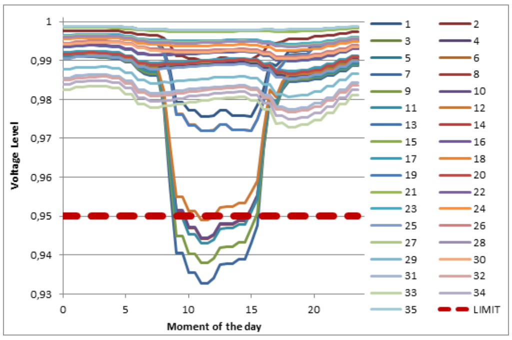
(a) Locations on the map



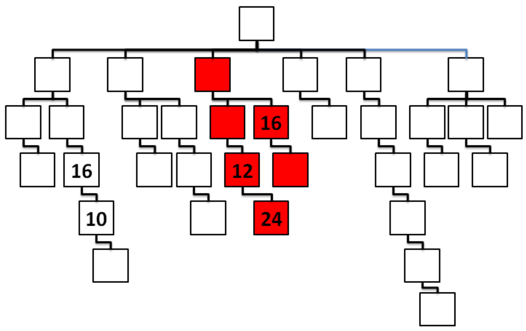

(b) Schematic Representation

Figure 6.13: Solution with 5 stations

The layout of the solution is shown in figure 6.13. The numbers in figure 6.13b are the node numbers. As the voltage levels follow the same trend as the voltage levels in node 7 when the number of stations increases, there is no need to show the voltage levels for the 10 different iterations. Instead we will only analyse the voltage levels in the different low voltage nodes for the minimum amount of stations that need to be installed to fulfill the demand.




(a) Voltage Levels at LV nodes connected to node 2



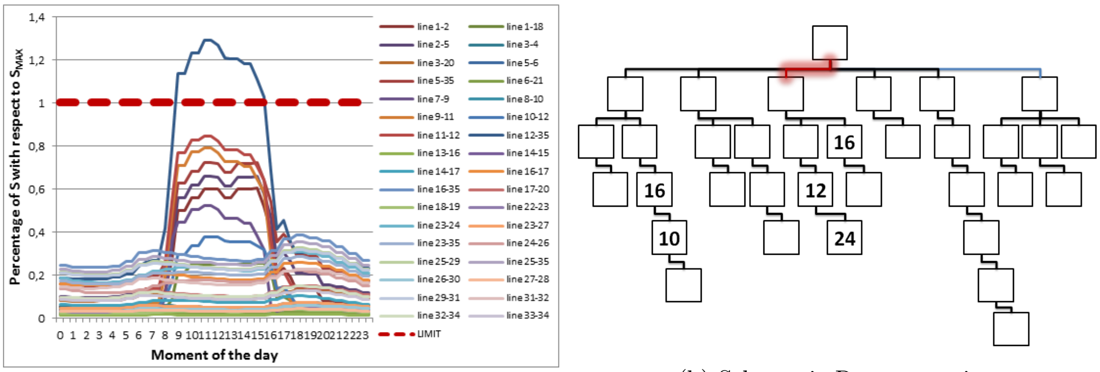

(b) Schematic Representation

Figure 6.14: Results for 5 stations

When we look at the voltage levels, we see that the peak charging during the day causes the voltage to drop below the acceptable limits of 0.95 p.u. Therefore it is not possible to place only 5 stations, although it would be enough to serve all the demand. Figure 6.14b indicates in which nodes the voltage drops below the limit and indicates how many vehicles are charging in that node at the peak moment of the day.

In this section we will see what the effect will be of installing more stations and we will show that this is one way of solving this problem. Later in this work two other possible solutions will be discussed. The possibility of replacing some lines will not be considered in this work, although it could also be a possible solution.

Furthermore we see that not only the excessive voltage drop causes problems, but also the apparent power exceeds the line limits in line 35-12. This can be seen in the next graph where the percentage of usage of each line is shown for each moment of the day. Values bigger than '1' mean that the capacity of the line is exceeded.




(a) Apparent Power in all the lines

(b) Schematic Representation

Figure 6.15: Results for 5 stations

The solution in this case to solve this infeasibility is to add an additional station. This makes sure that the power gets divided over more lines, which avoids that certain lines will be overloaded. However, it is important to mention that the locations of the six stations will not be the same with or without the network. Without taking the network into account, it is preferable to place a station in node 34. This results in a voltage drop below 0.95 p.u. in node 7 at the peak moment and is therefore not a possible solution when taking into account the network. We see that taking into account the network results in a solution with more stations than necessary to cover all the demand and with a bigger total walking distance in comparison to the solution without taking into account the network.

After installing seven or more stations, we find similar trends as what happened in the previous case. When we have a look at the walking distance, we see that the electricity network has no effect on the walking distance when seven or more stations are installed. We also see that the marginal reduction of walking distance is decreasing with the number of stations.

| x | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|
| y | 39 | 39 | 39 | 40 | 41 | 42 | 43 | 44 | 45 | 46 |
| WD without | 125 | 84 | 72 | 63 | 57 | 54 | 51 | 48 | 46 | 44 |
| WD with | - | 109 | 72 | 63 | 57 | 54 | 51 | 48 | 46 | 44 |

Table 6.1: walking distance for the solution with and without taking into account the network

When we take into account the number of vehicles (90) that charge during the day in one of the nodes of this feeder, we see that with the minimum number of charging stations that is technically feasible (6) the average walking distance is slightly more than 1 minute.

### 6.3.2 Medium Penetration - Charge on Arrival - No Daily Charge

For this section we make the following assumptions:

- 25% of the vehicles are electric vehicles
- Vehicles are connected when they arrive to a charging station and start charging immediately.
- The batteries are charged to (almost) their maximum level and therefore vehicles do not need to be charged every day. This means that only a certain percentage of the electric vehicles will charge.

#### Medium Voltage Level

When we have a look at the parking and charging patterns, we see that the higher penetration has a significant effect on the number of vehicles parked at node 7, while this effect is much lower in node 2. There is a double explanation for this. The first reason is that the number of vehicles in each fleet was rounded up and therefore the number of vehicles with a shortest distance daily routine were overestimated. However, this effect is only significant for the small fleets. The most important reason for this shift is the fact that many vehicles decide to charge in node 15 instead of node 2, as the walking distance between these two areas is negligible. This can be seen in the following graph were the share of vehicles parked in node 15 is significantly bigger than its share in 6.3.

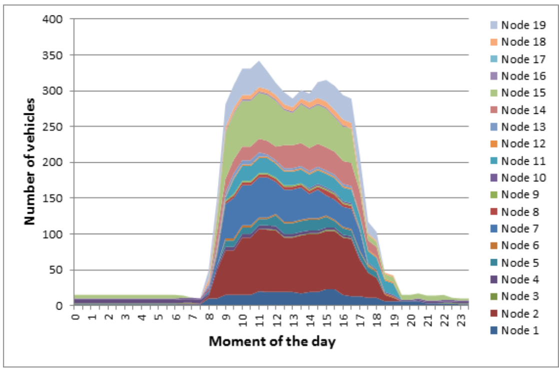



Figure 6.16: Parking behaviour

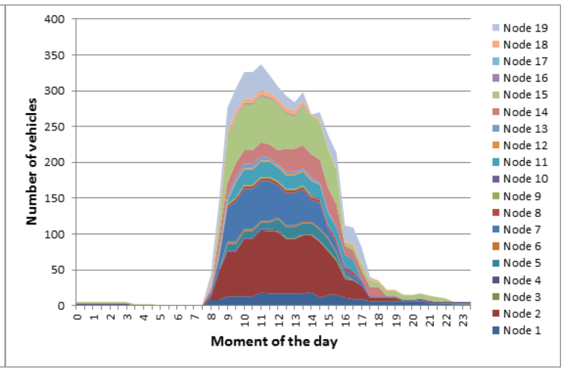
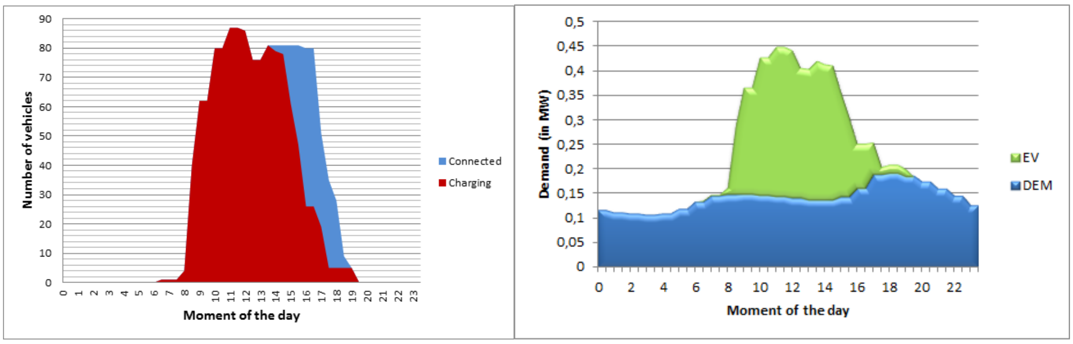



Figure 6.17: Charging behaviour

On the other hand has the number of vehicles parked in node 7 increased from 38 to 56, which is almost the maximum capacity of charging connections that can be installed in that area. In the next section we will first study the effect on node 2 and afterwards analyse the effect on node 7.

#### Low Voltage Level: Node 2 [Consumer Medium Voltage 23]

The first step is again to determine how many stations need to be installed to cover all the demand, without taking into account the electricity network. We see that at most 87 vehicles are connected at the same time, which means that at least 44 charging points should be installed.




(a) charging pattern (b) electricity demand

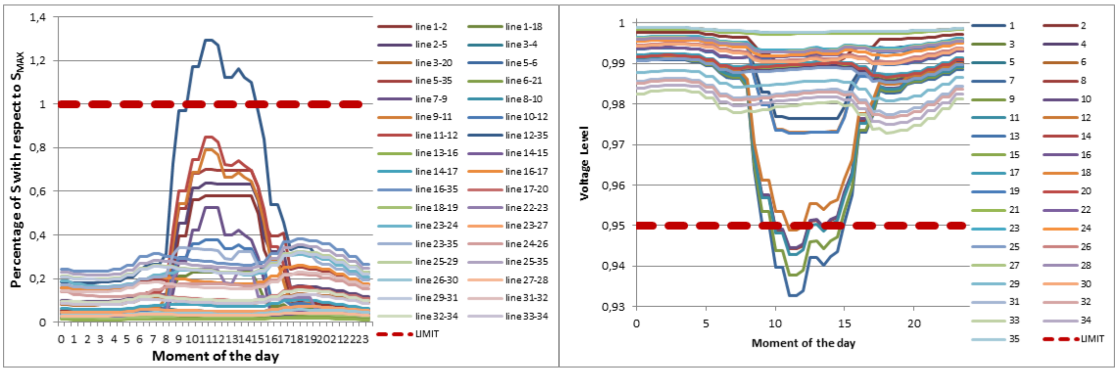
Figure 6.19: Effect of charging behaviour in node 2

Looking at the capacity of the different stations, we see that at least 6 stations need to be installed.

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| node | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
| cap | **8** | 0 | 0 | 0 | 3 | 0 | **12** | 0 | **6** | **8** | 0 | 0 | 0 | 3 | 3 | 0 | 3 | 5 |
| node | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | |
| cap | **5** | 3 | 0 | **5** | 2 | 0 | 0 | 0 | 3 | 3 | 0 | 0 | 3 | 3 | 3 | 3 | 0 | |

Table 6.2: Capacity of the nodes in feeder 2

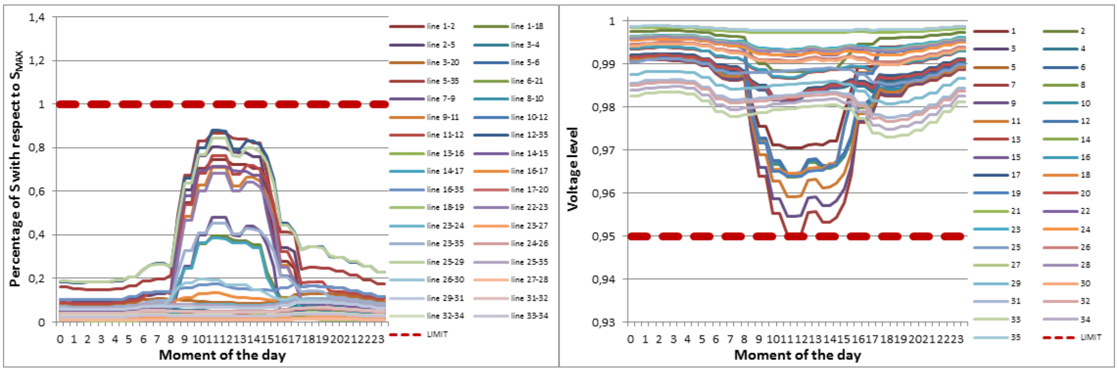
Solving the model for the minimum amount of charging stations (6) results again in an infeasible solution when the distribution network is taken into account. This can be seen when we have a look at figure 6.20 where the voltage levels and the power flows are displayed for each moment of the day.




(a) Power flows (b) Voltage Levels

Figure 6.20: Results for 6 stations

Solving the model for seven stations also gives an infeasible solution which means that a minimum of eight charging stations with a total of 44 charging points is necessary. The voltage levels and power flows through the lines are now within the limits as can be seen in figure 6.21.




(a) Power flows (b) Voltage Levels

Figure 6.21: Results for 8 stations

In the following table we show the effect on the walking distance when increasing the number of stations. In the following table we see similar results as before, but we also see that it is necessary to install more stations before finding a technical feasible solution.

| x | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|
| y | 44 | 44 | 44 | 44 | 45 | 46 | 47 | 48 | 49 | 50 |
| WD without | - | 135 | 97 | 83 | 70 | 60 | 53 | 48 | 45 | 42 |
| WD with | - | - | - | 83 | 70 | 60 | 53 | 48 | 45 | 42 |

Table 6.3: walking distance for the solution with and without taking into account the network

When we compare this to the walking distance with a lower penetration we see that the average walking distance for the minimum number of stations has decreased from 1.2 minutes to 0.75 minutes. However, compared to installing eight stations for the fleet of vehicles in case of a low penetration, the average walking distance has increased from 0.66 to 0.75. This is because there is a certain degree of freedom when we have to decide where to install eight stations for a lower number of vehicles. This effect of limited possible solutions already disappears when installing nine stations.

#### Low Voltage Level: Node 7 [Medium-Low Voltage Substation 3]

Assuming a medium penetration of 25% electric vehicles results in a much higher demand for charging stations in node 7 than in the low-penetration case. As the area only has enough space to place 30 charging points, the capacity of node 7 is limited to 60 vehicles in the medium voltage model. This resulted in a solution where 62 vehicles want to charge in node 7 with a peak of 56 vehicles connected at the same time. It can be demonstrated that the minimum number of charging stations that should be installed is equal to 12 to provide a capacity for 56 electric vehicles. By placing 12 charging stations in the area, the total walking distance is equal to 96 minutes or an average of approximately 1.5 minute for each customer.

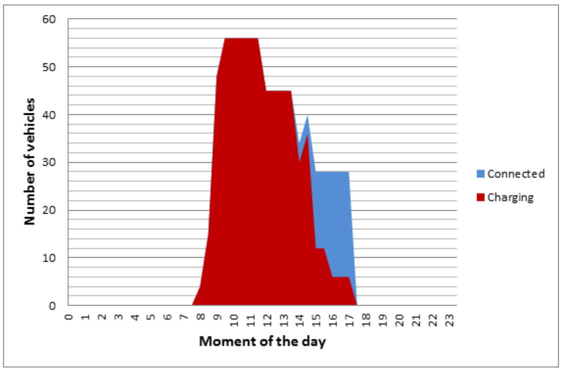



Figure 6.22: Charging behaviour at node 7

However, solving the model shows that it is technically impossible to place sufficient charging stations to allow that 56 vehicles would charge at the same time, given the structure of the network. This can be solved by limiting the number of charging points that will be placed in the area and by doing this forcing the vehicle owners to look for a charging station in another node of the medium voltage network. Another solution would be to disconnect certain charging points at peak moments, but this would create a lot of confusion among users and a certain degree of redundant capacity.

If we allow to only install 27 charging points instead of 28, and therefore limit the capacity of node 7 to 54 vehicles in the medium voltage model, the solution becomes feasible with the installation of 14 charging stations and 27 charging points. This means that two vehicles will have to look for a charging station in another node.

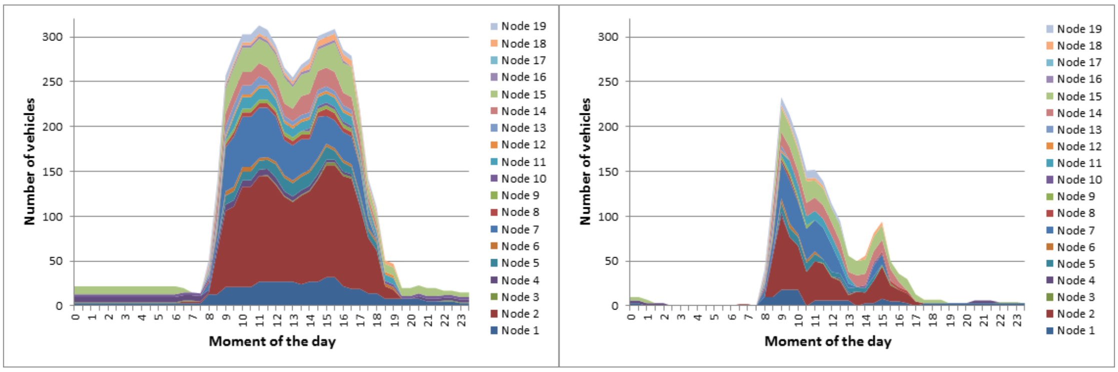
### 6.3.3 Low Penetration - Charge on Arrival - Daily Charge

For this section we make the following assumptions:

- 25% of the vehicles are electric vehicles
- Vehicles are connected when they arrive to a charging station and start charging immediately.
- Vehicle owners only charge the amount of energy that they are using during that day. This creates a steady state in which the same pattern is repeated every day.

#### Medium Voltage Level

Figure 6.24 shows that this type of behaviour requires more stations to be installed as more people are willing to connect their vehicles every day. One can conclude that this kind of behaviour is less efficient for the system because more stations need to be installed to provide the same amount of energy. Policy makers should try to encourage people to change their behaviour by charging a connection fee or eventually provide some kind of connection management in which the same connecting point can be used for several vehicles without moving them.



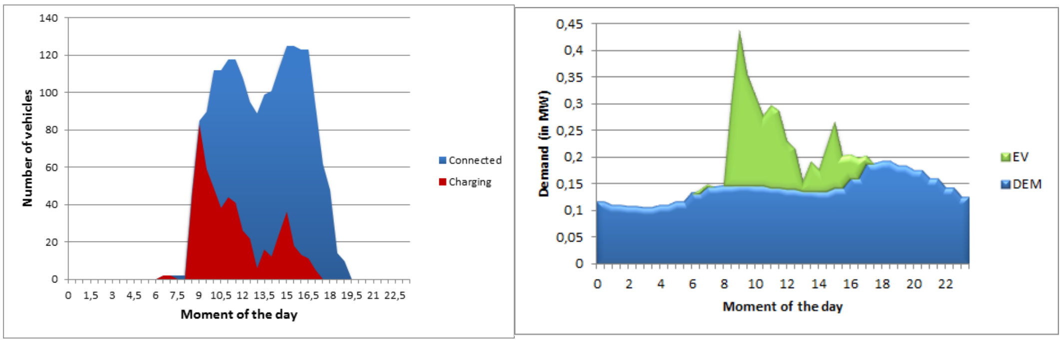

(a) Parking behaviour

(b) Charging behaviour

Figure 6.24: Charging and Parking Behaviour

### Low Voltage Level: Node 2 [Consumer Medium Voltage 23]

The increase in number of vehicles that want to be connected at the same time, also has a significant effect for the solution. When we look at figure 6.25a, we see that the peak of charging does not coincide anymore with the peak of connection. At the moment that the highest number of vehicles are connected (125), only a small part (36) of them are charging.




(a) Charging behaviour at node 2

(b) Demand in feeder 2

Figure 6.26: Share of EV consumption in demand in feeder 2

This affects the number of charging stations that need to be installed. While before 6 stations where enough to cover all the demand, a minimum of 13 stations is now necessary to provide a capacity of 125 connections. When the model is run, we find the following solutions and we see that there is no difference between the solution with or without taking into account the network.

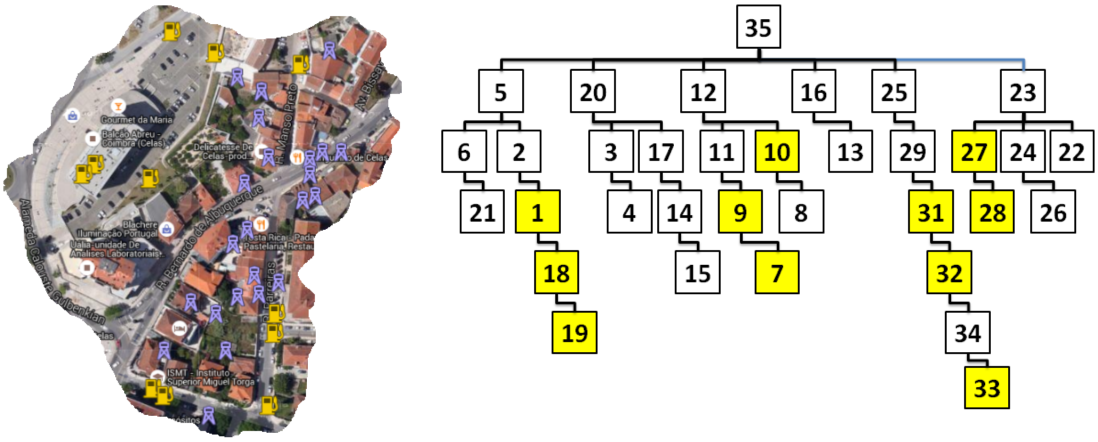



Figure 6.27: Solution with 11 stations

A last measure we would like to mention is the total and average walking distance and compare it with the average walking distance in the scenario where there is no daily charge. In the next tables we see that the total walking distance in minutes is much higher when compared to the solution with the same number of charging stations. However, when we take into account the number of vehicles charging in the feeder, we see that it is only slightly higher. Given the fact that this depends strongly on the random assignment of the destination nodes, it can be concluded that this effect is not significant.

| x | 11 | 12 | 13 | 14 |
|---|---|---|---|---|
| y | 43 | 44 | 45 | 46 |
| WD No Daily Charge | 51 | 48 | 46 | 44 |
| WD Daily Charge | 90 | 81 | 77 | 73 |

Table 6.4: Total walking distance in minutes

| x | 11 | 12 | 13 | 14 |
|---|---|---|---|---|
| y | 43 | 44 | 45 | 46 |
| WD No Daily Charge | 0.596 | 0.536 | 0.51 | 0.483 |
| WD Daily Charge | 0.566 | 0.533 | 0.511 | 0.489 |

Table 6.5: Average walking distance in minutes

**Low Voltage Level: Node 7 [Medium-Low Voltage Substation 3]**

The capacity of node 7 was limited to 56 vehicles as we have shown in the previous section. However we see that even though 56 vehicles are connected at the same time, only 40 of them are charging at the same time. In the optimal solution we find that it is enough to install 28 charging points in 12 different stations. Figure 6.28 shows how the solution looks.

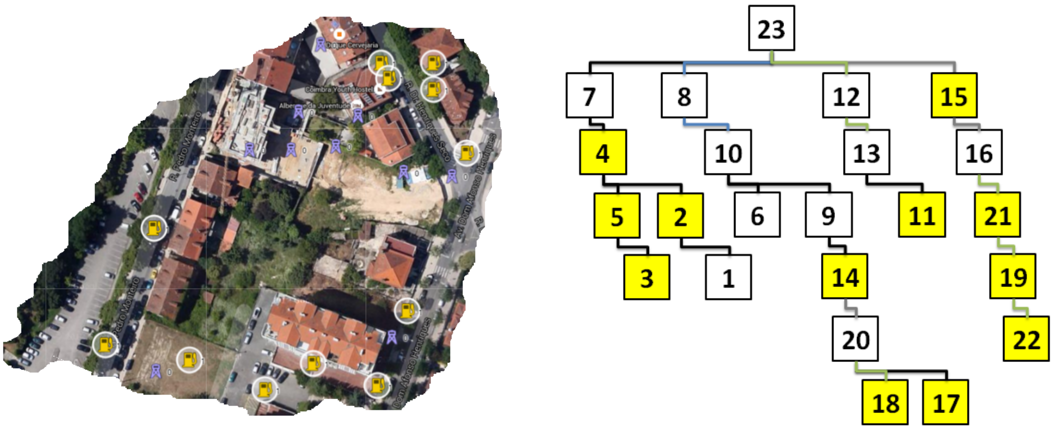



Figure 6.28: Solution with 12 stations

When we have a look at the voltage levels in the different nodes of feeder 7, we see that there is no problem when vehicles are charged on daily basis. The peak that occurs around the time that most of the vehicles arrive at their destination causes a short but sharp voltage drop which could become problematic when the penetration of EVs is higher. In the next figure the voltage levels in case of daily charge and no daily charge are compared.

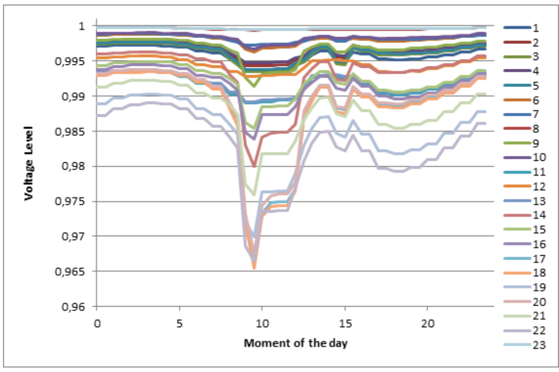



Figure 6.29: Voltage levels [Daily Charge]

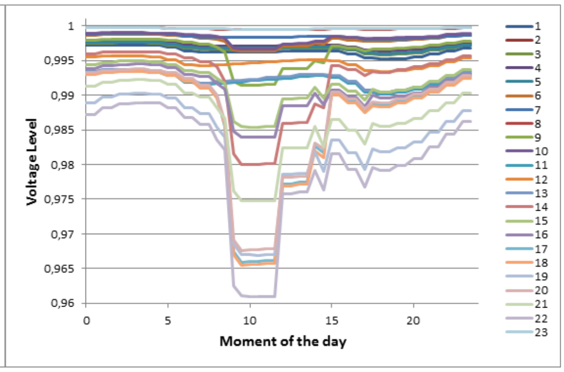



Figure 6.30: Voltage levels [No Daily Charge]

### 6.3.4 High Penetration - Charge on Arrival - Daily Charge

For this section we make the following assumptions:

- 50% of the vehicles are electric vehicles
- Vehicles are connected when they arrive to a charging station and start charging immediately.
- The batteries are charged to (almost) their maximum level and therefore vehicles do not need to be charged every day. This means that only a certain percentage of the electric vehicles will charge.

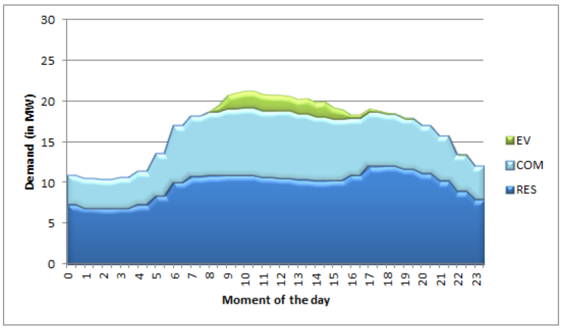
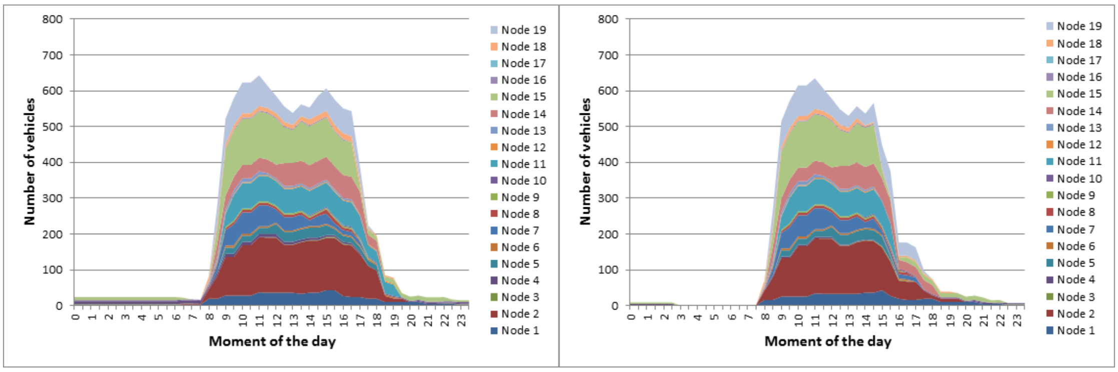



Figure 6.31: Effect on the total electricity demand

As the capacity of the feeder connected to node 7 was already reached with a medium penetration level, we will not investigate the scenario of high penetration for this feeder. Therefore we will briefly discuss the outcomes of the medium voltage level and describe in more details the effect on the feeder connected to node 2.

### Medium Voltage Level

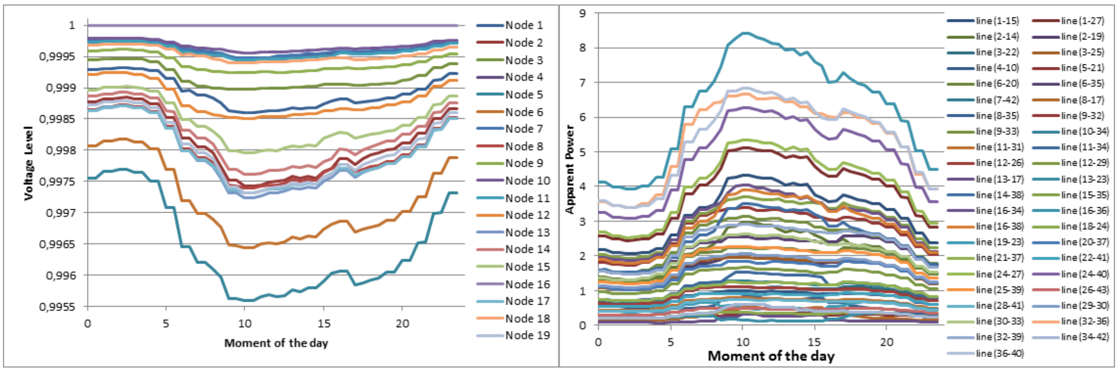
When we have a look at figure 6.32 we see that the peak demand increases significantly when there is a high penetration of electric vehicles. To cover the peak, it is necessary in this case to provide 643 connection points to allow that everyone can be connected at the same time. With a maximum number of 635 vehicles charging at the same time, we see that there is again some capacity that is not used for charging but this number is remarkably less than when vehicles charge on a daily basis.




(a) Parking behaviour (b) Charging behaviour

Figure 6.32: Results for 50% penetration

When we look at the voltage levels in the medium voltage nodes we see that the voltage levels only have dropped slightly in comparison to the low penetration scenario. For the power flows a significant increase in apparent power can be noticed during the peak hours of charging. Despite the increase to almost 9 MVAr in line 16-36, the limits are not reached as this line has a capacity of 17.84 MVAr.




(a) Voltage Levels

(b) Power flows

Figure 6.33: Results within the limits for 50% penetration

### Low Voltage Level: Node 2 [Consumer Medium Voltage 23]

We see that a high penetration of electric vehicles increases the number of vehicles who are willing to charge in node 2 from 110 to 166. This results in a peak demand of 154 EVs charging at the same time at feeder 2.

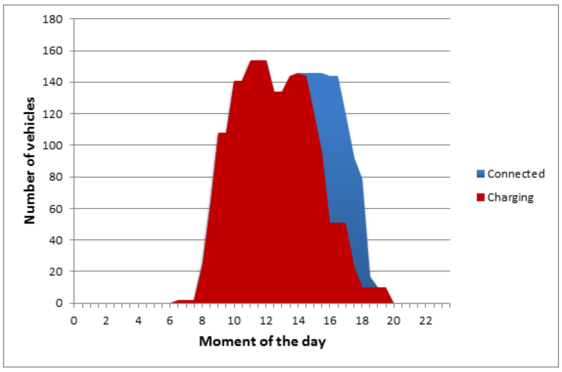



Figure 6.34: Charging behaviour at node 2

We see that this results in a minimum of 17 stations with at least 77 charging points to provide 154 connections at the same time. The locations of the charging stations are shown in figure 6.35

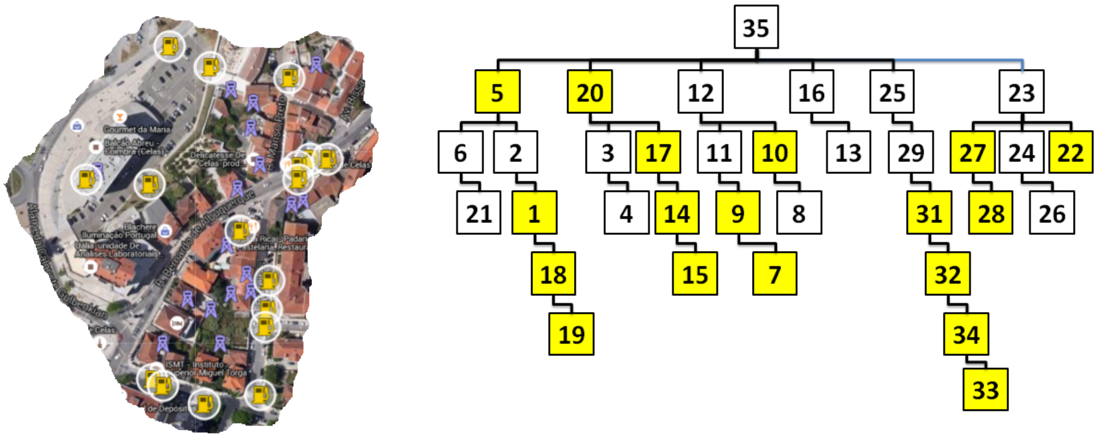
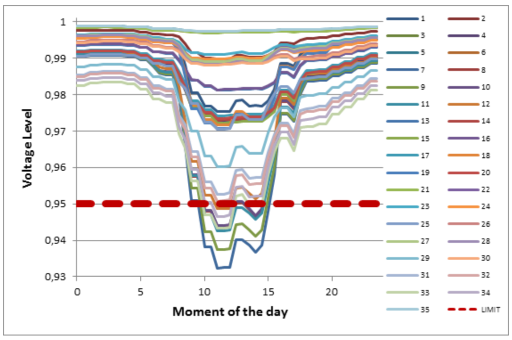
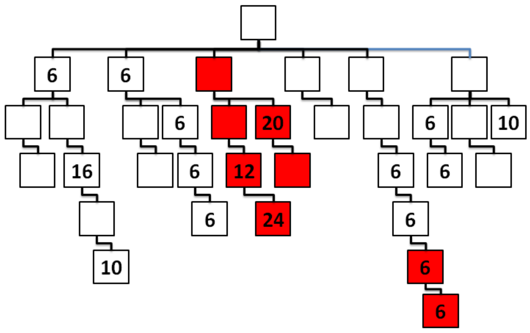


Figure 6.35: Solution with 17 stations

Looking at the voltage levels that occur at the peak moment, we see that this solution is technically not feasible as it causes the voltages to drop below the technical limit. Moreover, we see that increasing the capacity to its maximum by installing the maximum charging points in the last two possible candidates for charging stations, also does not lead to a feasible solution.




(a) Voltage Levels at LV nodes connected to node 2



(b) Schematic Representation

Figure 6.36: Results for 5 stations

The solution here could be to install some distributed generation in the feeder connected to node 12 and node 25 of the low voltage level. However, most of the distributed generation are based on renewable energy sources and are not always available when the demand occurs. Another possible solution could be to upgrade the line 35-12 to lower the voltage drop that occurs over this line. If none of this is possible, the capacity in the feeder connected to MV node 2 should be limited to 134 and therefore at least 20 vehicles will have to find a charging stations connected to another MV node.

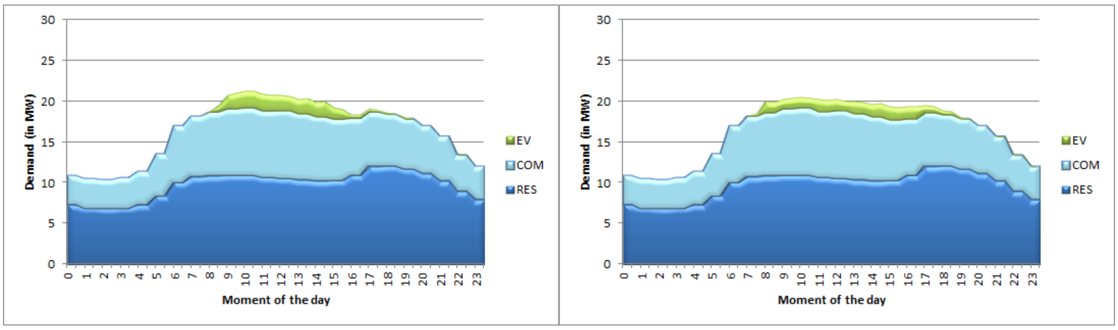
### 6.3.5 High Penetration - Smart Charging - No Daily Charge

For this section we make the following assumptions:

- 50% of the vehicles are electric vehicles

- Vehicles are connected when they arrive to a charging station and we assume that a general planner knows when all the vehicles will be connected during the day.
- The batteries are charged to (almost) their maximum level and therefore vehicles do not need to be charged every day. This means that only a certain percentage of the electric vehicles will charge.

We assume for smart charging that all the vehicle owners have to reserve their charging station and define during which hours they want to be connected. The central planner will determine when a vehicle is connected when it will charge such that the vehicle can leave with a full battery. Implicitly we assume that the central planner knows how much the other vehicles need to charge during the day, an assumption that is not very realistic, unless vehicle owners indicate how many energy they need when they make their reservation. Therefore this scenario is not considered as likely to happen in reality but we will consider this solution as a reference to see what a more ideal configuration would be without changing the daily rhythm of the vehicle owners.

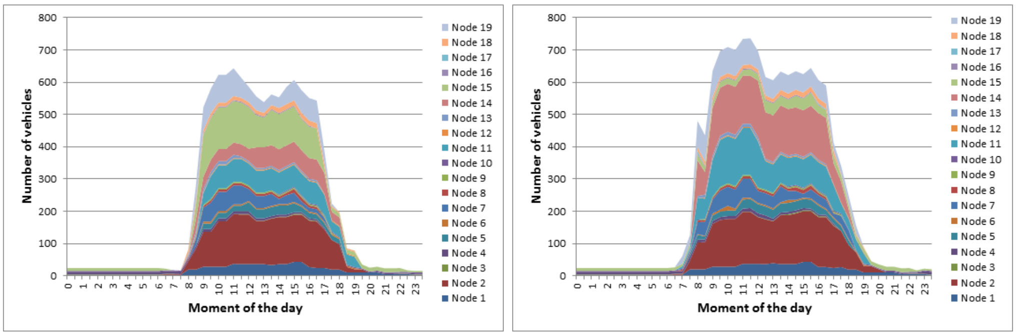



(a) Demand with Charge on Arrival (b) Demand with Smart Charge

Figure 6.37: Effects of Smart Charging

**Medium Voltage Level**

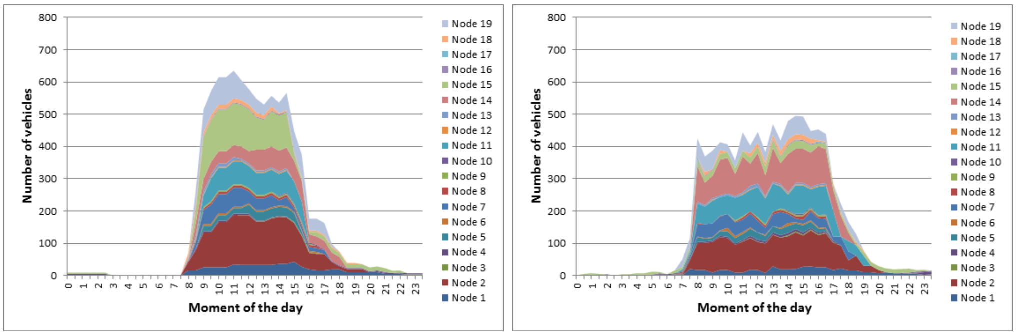
When we analyse the parking behaviour on the medium voltage level we see that it is very similar to the behaviour without smart charging. One important difference to mention is that many vehicles have switched from charging at node 15 to charging at node 14. This is because the traveling time (walking time + driving time) is equal for them in both locations and therefore they are indifferent between both nodes.




(a) Parking without Smart Charging (b) Parking with Smart Charging

Figure 6.38: Comparison of parking behaviour

Even though the parking behaviour is very similar in both cases, the charging behaviour has changed completely. Figure 6.39 shows the parking behaviour in case of smart charging and charging on arrival. We see that local peaks in the low voltage feeders have flatten out to avoid overloads in the power lines. We see that the charging peak occurs more often during the afternoon around moment 30 [around 15:00]. Further research should be conducted to investigate the beneficial effects of installing solar panels to help covering this charging peak.



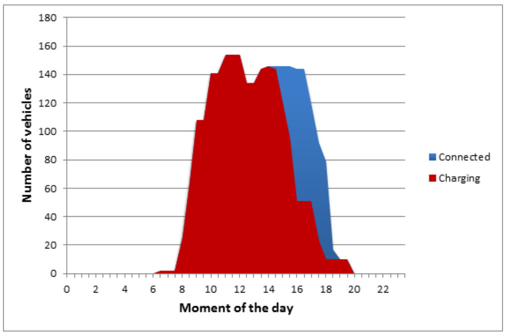

(a) Charge on arrival (b) Smart Charging

Figure 6.39: Comparison of charging behaviour

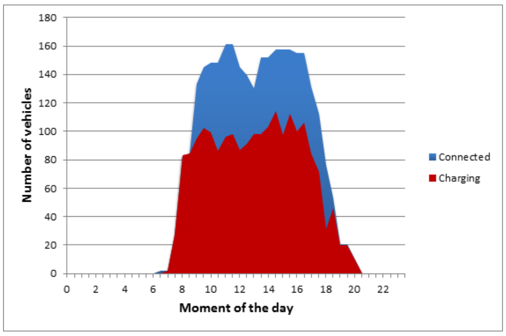
In the previous section we saw that in case of a high penetration of electric vehicles, feeder 2 would also experience problems and 20 out of 166 vehicles would have to be forced to charge in another location. In the next section we will investigate what can be the beneficiary effects of smart charging and if we can increase the number of 146 vehicles that can be dealt with.

**Low Voltage Level: Node 2 [Consumer Medium Voltage 23]**

Looking at the charging behaviour in MV node 2, we see that this pattern has changed completely in comparison to the case when vehicle owners start charging when they arrive. The EV population who are charging in one of the stations connected to this feeder has increased from 166 to 201 while the peak has been reduced from 154 to 118.



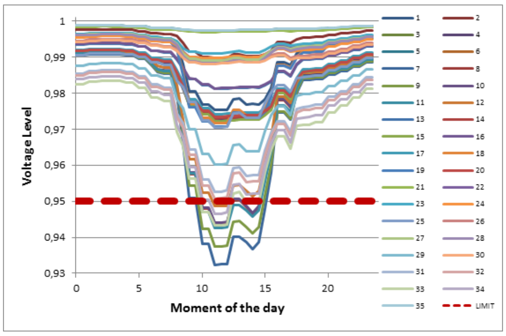

(a) Charge on arrival



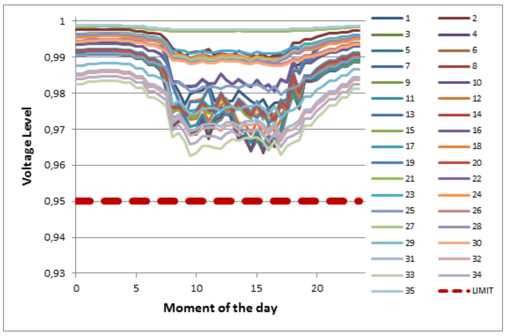

(b) Smart Charging

Figure 6.40: Comparison of charging behaviour in node 2

It is obvious that this charging pattern also has positive effects on the voltage levels in the different LV nodes of this feeder. In figure 6.41a we see that the voltage drops are not within the limits, which means that none of the the vehicle willing to charge in MV node 2 has to move to another LV feeder. When we look at 6.41b we see that due to smart charging this excessive voltage drops can be avoided and therefore the system would not have problems dealing with a high penetration of electric vehicles.



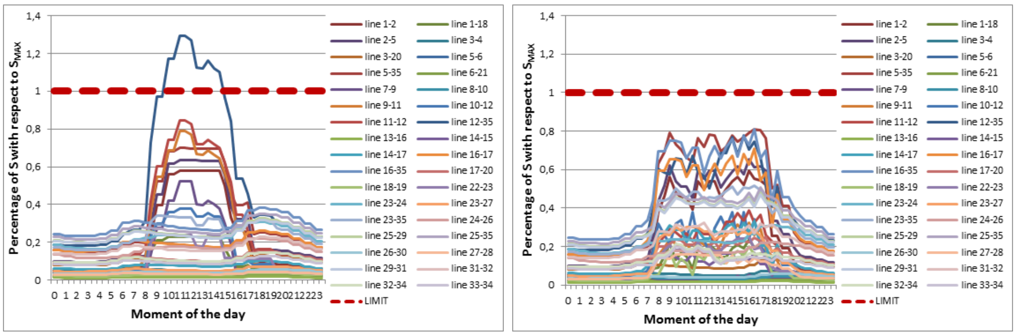

(a) Charge on arrival




(b) Smart Charging

Figure 6.41: Comparison of voltage drop in feeder 2

Also when we look at the power flows in the different lines of feeder 2, we see that nowhere the power flow exceeds the capacity limit of each line.




(a) Charge on arrival (b) Smart Charging

Figure 6.42: Comparison of power flows in the lines of feeder 2

As we have shown in the previous section, sometimes it was necessary to increase the number of stations to avoid overloads in certain power lines. Smart charging helps to avoid that this extra capacity needs to be installed to deal with these peak demands. A second step would be to introduce some parking management, as we mentioned before, to make sure that only 118 stations need to be installed instead of the 162 that are necessary to deal with the parking peak. We see that smart charging is a helping hand for the network while parking management can lower the cost of installing stations.

# 7. Comparison of Results

In the previous section we have analysed several situations in which problems might occur when the electricity network is not taken into account when deciding where to install the charging stations. This usually leads to both unacceptable voltage drops and line overloads. The remedies to solve this problems are very different and therefore a careful analysis of the specific case that is likely to occur is needed.

We have seen that problems can already occur with a low penetration (10%) of electric vehicles. The case described in this work led to a situation where the optimal solution would have been to install only five stations which caused an excessive voltage drop. This could occur because there were too many stations connected to the same branch. The solution for this was to **install one more station**, which made that the demand was more divided among different branches. It is important to mention that we assume that in this case the same amount of charging points gets divided over more stations, which forces some vehicles to charge somewhere else. A similar situation occurred when the penetration increased to 25% at the feeder connected to branch 2. Also here this problem was solved by installing eight stations instead of six.

A second interesting result that we saw was that sometimes it is not necessary to install more stations, but it can be necessary to **install them in locations which are not optimal from a customer point of view**. We used the walking distance between the customers destination and the charging stations to measure the customer satisfaction about the location of a charging station. We saw that due to the electricity network, the walking distance increased with 30% in one specific case (6.1).

When we analysed the effect of medium penetration (25%) on feeder 7, we saw that this could also cause some serious problems. The solution was to force the vehicles to charge in a neighbouring low voltage feeder and to limit the capacity installed in feeder 7. We saw that it was enough to **take away one charging point** (and therefore force two vehicles to charge somewhere else) to have a feasible solution. A similar situation appeared for feeder 2 when we assumed that 50% of the vehicles are electric.

Furthermore we saw that these conclusions depend on the charging pattern that people tend to follow. If vehicle owners prefer to charge on a daily basis more or less the energy that they need for that day, more stations need to be installed for the same degree of penetration. However, due to the fact that more stations need to be installed, it is less likely that problems will occur in the electricity network.

As has been studied excessively in the literature (see Chapter 2), changing the charging patterns by for example implementing a system which allows smart charging, could significantly help to avoid excessive power flows and voltage drops. In section 6.3.5 we showed that shifting the charging pattern could make it possible to cover all the demand in feeder 2 without forcing anyone to move to a charging station connected to another MV node.

We concluded that **charging management** (or smart charging) could help to avoid network overloads while **parking management** is necessary to help to reduce further the amount of charging stations that need to be installed.

# 8. Conclusion

This work aimed to investigate how the optimal locations of charging stations changes when the distribution network is taken into account in the decision making process. We developed two models which should be used jointly to define the optimal locations for charging stations and compare the solution to the optimal solution from a pure customer point of view.

In the medium voltage model we determined in which low voltage feeder (fleets of) vehicles prefer to charge based on the minimization of the total driving and walking distance of all the customers together. The charging behaviour and the voltage level in the optimal solution were taken as inputs for the low voltage model. In this second model we determine where charging stations should be installed based on these charging patterns and we check the stability of the system with respect to voltage levels and power flows. The optimal solution in each scenario is compared with the optimal solution without taking into account the network.

We saw that typically vehicles are parked (and therefore connected to a station when they decided to charge) during more time than is necessary to fully charge their battery. This makes that the capacity of charging stations is not fully used and policy makers should take this into account when deciding about parking pricing. Vehicle owners could be penalized for this or some parking management could be provided by a central planner.

Problems with respect to the stability of the network could already occur in case of a 10% penetration of electric vehicles although these problems are very rare. The solution is usually to install more charging stations and therefore spread the charging points over the network. We saw that the optimal solution when the network is taken into account can force people to walk more to the closest charging stations than in the solution without the network.

In other cases it might be necessary to force some customers to charge in another medium voltage node as covering all the demand would cause excessive voltage drops. This can be done by removing a number of charging points and by doing so, limiting the capacity in that feeder.

The basic assumption for our case study was that people connect and start charging when they arrive at their destination. We also assumed that vehicle owners prefer to charge when their battery is low and therefore they will not be charging every day. When we change these assumptions, we obtained some interesting results.

When vehicle owners charge every day the amount of energy that they need for that day, we see that a higher number of charging stations is required to cover all the demand. At the same time the usage of these charging stations is much lower as many vehicles stay connected when they already finished charging. In this case parking management could significantly reduce the minimum number of stations that need to be installed.

If we assume that a central planner can control the charging behaviour of vehicles when they are connected to the grid, the stability of the grid increases significantly. This type of smart charging can help to avoid local demand peaks and this reduces line overloads and excessive voltage drops.

We conclude that the network should already be taken into account in the decision making process about the installation of charging stations. A well designed charging infrastructure helps to reduce the need for charging management and increases the stability of the system. In this process the daily routines of people should be taking into account as well as structural peaks.

Further work should be conducted on the effect of installing solar panels in several low voltage nodes to see if this can help to reduce the number of stations that needs to be installed. Moreover, if distributed generation starts to become more important, the possibility of nodal pricing in a distribution network could be considered to give incentives to customers about where they should charge.

The model should also be tested for a real life case study and the results should be compared with the actual locations of charging stations that are already in place. This work should help to contribute to reduce the need for charging management as the charging patterns are already taken into account when determining the optimal locations with the model proposed in this work.

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