Thesis Proposal

Investigating operating management and EV behaviour in an over demanded network

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Abstract

The increasing penetration of EVs can become problematic for electricity distribution networks. In this document a research project is proposed to investigate the minimal necessary coordination to prevent a distribution network from overloading due to EV charging. This is done by simulating a distribution network without any coordination between parties and adding coordination measures to investigate their impact. The goal of this thesis is to investigate which combination of measures is needed for and sufficient working distribution system.

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1 Introduction & Background

How many times did you hear or read the word sustainable last week? Sustainability is a hot topic. A movement is going on to make the world more sustainable. A large part of this transition is taking place in the energy system: the energy transition. The energy transition is the change of an energy system based on fossil fuels to a system based on renewable energy sources. This shift has consequences for the supply side as well as the demand side of the energy system and, inevitably, the network connecting these two. This document focuses on the electrical power system as part of the energy system. In this section we will first discuss the current electrical power system, then the consequences of the transition for the production side and lastly the consequences for the demand side of this system. We end with a short description of the problem investigated in this thesis.

1.1 Current Electrical power system

The most relevant parts of the current electrical power system are the network itself, the producers and the consumers. The electrical network is the infrastructure of the system. Typically the network consists of two levels. A transportation network and multiple distribution networks. Both systems are managed by its own operator: the TSO for the transportation network and a DNO for a distribution network. Both the TSO and the DNO are responsible for the performance, safety and quality of the powerflow in their part of the network. When the DNO also delivers system services, the DNO is called a DSO which will be assumed for the rest of the thesis.

The transportation network transports high power over large distances. The voltage in the transportation network is high to minimize the losses in the network. Large power generators are connected to the transportation network where the generated power is transported to distribution networks.

The distribution network distributes the power from the point where it is connected with the transportation network to consumers. It is often a radial network. Such a network has branches from a central point, in this case a substation, without any connections between the branches. These networks are typically designed for unidirectional flows. As the distribution networks have lower voltages than the transportation networks, a transformer is included with the substation to transform the voltage from a high to low level. The capacity of this distribution transformer can become overloaded when the power demand in the distribution network is too high.

Through almost all lines in the network flows an alternating current. Both the voltage and the current have a frequency of alternating. In practice the frequency is regulated to be as constant as possible at a designated value. This is due to the fact that when the supply and demand within a network are in balance, the frequency remains constant. In other words, the frequency is a measure of the balance between the power supply and demand. There is almost no use of storage to balance the supply and demand. Therefore the supply of power must be matched real-time with the demand to keep the network stable. The focus on the supply side is also visible in the difference between the wholesale price of energy and the energy price at the demand side of the market. Wholesale prices are highly fluctuating over the year and even within a day. Peak periods are characterized by higher generation costs, because expensive peaking plants are ramped up to cover demand. During off-peak periods, demand is typically covered by cheaper base load plants. At the demand side however, retail prices are kept constant for months, reflecting average generation costs of that period [1].

1.2 Consequences of the energy transition to the supply side

Due to the energy transition there is a switch to other energy resources. Nowadays new ways of energy production are emerging which are based on renewable energy sources (RES), such as a solar. Between these two there are some significant differences. A first difference is the way they are distributed within the energy network. In the traditional network a relative high part of the produced energy comes from a relative low number of generators. Therefore the most part of the electricity network consists of consumers. The traditional network is therefore for the most part designed as a radialized network where the produced energy is transported in one direction. With the penetration of renewable energy sources however, the picture changes. Renewable energy sources are often distributed energy sources. Meaning that these sources are installed all over the energy system. Further more, these renewable energy sources can be installed at the connection of a consumer. When the RES is producing more than the local consumption, the consumer becomes a producer. With the consequence that the powerflow in the network becomes bidirectional instead of unidirectional.
Another difference between a traditional energy source and a RES is the controllability of the amount of generated power. A traditional energy source often produces a steady amount of power and can be controlled to match the power demand at a certain moment. On the contrary the maximum amount of production of a RES often depends on (for example) weather circumstances. These circumstances vary over time and are not easy to control. Because of this is more difficult to match the power supply with the power demand when the penetration of RES increases. When the supply from RES is larger then the total demand, the supply of the RES can be curtailed. However, as the marginal costs of generating power from an RES is close to zero, curtailing the energy production of RES is just a waste of energy.

1.3 Consequences of the energy transition to the demand side

The energy transition implies two consequences for the demand side of the electricity network. The first consequence is due to the fact that with RES the supply of power cannot be controlled in the same degree. This means that when the penetration of RES is higher, the demand must become more aligned with the supply to match the supply and demand. The second consequence of the energy transition is an increase of the use of electrical devices. More electrical devices will be used instead of devices powered by fossil fuels. A good example can be found in the transport sector. Instead of driving a car powered by petroleum, more electrical vehicles are used. This results in a significant increase in the power demand. The extra demand will often occur on times where there is already a peak demand in the power consumption, increasing the peak demand even further. These increases in demand may not be matched with the supply or lead to congestion in the network. When this happens, the voltage level drops or parts of the network become overloaded.

Summarizing the consequences of the energy transition: First, the demand must become more aligned with the supply when the penetration of RES grows to be able to use all the power which is produced by RES. Second, the demand must be spread more evenly to avoid network congestion.

To tackle these problems the power network must become a smart network where measure and control systems are added to the network to coordinate the power demand. Numerous technical possibilities in coordinating the demand are known. Although, there is no clear policy on how it should be done and who is responsible for what. Meanwhile, the energy transition goes on and one of the main consequences is the increasing penetration of Electrical Vehicles (EVs).

1.4 Problem description

In the previous part of this chapter an overview is given on the impact of the energy transition on the electricity system. The energy transition leads to many challenges for which new solutions must be found and new policies formulated. One of these challenges is for the current DNO which will have to provide system services and become a DSO to regulate the demand response. At this moment there is no clear consensus yet on how the demand response of consumers must be managed in a distribution network. The goal of this thesis is to get a clearer picture on what degree of coordination is needed between actors in an distribution network in the near future. Due to the time available, the scope of this research is limited to the coordination of EV charging. The problem within the distribution network is as follows. The distribution transformers is threatened to be overloaded at the peak times of energy usage due to a high penetration of EVs. To avert overloading the DSO must coordinate the charge behaviour of the EVs. The DSO wants to do this with a simple framework as possible and assuring autonomy of the EV owners.

The focus of the thesis will be the interaction between the actors of the local network, such as the DSO and the different EV owners, who each have their own strategies and objectives and the impact of coordination on this interaction. As an addition , scenarios are investigated where uncertainties are present or actors within the system do no act optimally or as expected.

2 Literature study

The problem of preventing a distribution network from overloading due to EV charging is studied extensively. At first a central question within this topic was whether a high EV penetration would be a problem for distribution networks which was already studied in 1982 [2]. After that, many other network studies on this subject were committed such as [3–6]. For example,Shokrzadeh et al. [7] simulated the impact of the penetration rate of EVs on the overloading of the distribution transformer in Ontario. Concluding that the distribution transformer becomes most likely overloaded in winter months and high income neighbourhoods. Furthermore, Papadopoulos et Al. [3] simulated a typical UK urban distribution network with a high (70%) as well as a low (12.4%) level of EV penetration. They predict with their model that the distribution transformer becomes overloaded for at least once a day per week for both scenarios. Based on these and other papers the consensus arose that a high EV penetration will become a problem for distribution networks.
Meanwhile coordination and planning strategies where proposed to manage these congestion problems in the distribution network. Many of which are centralized. Which means that the relevant information of each car -such as the current battery level and the time when the car needs to be fully charged- are gathered by a central coordinator. With the retrieved information the coordinator plans the charging schemes for all EVs within the technical limits of the network. These central strategies lead to the optimal result for its given objective function [8–10]. The drawbacks of such strategies are however that they often require an extensive communication infrastructure, personal data or charging preferences must be shared and that their is not always an incentive to participate. At this point our research question comes in.
As our goal is to find a minimal coordination framework it would be interesting to know which parts are essential for an effective framework. However, to the best of our knowledge no papers exist investigating this question. In the rest of this section a literature overview will be given on how the DSO and EV owners might behave. This information will be used to build our own model.
The rest of this section will be structured as follows. In section 2.1) papers are discussed when EVs only charge and the DSO uses virtual prices to regulate the charging behaviour. The section is divided in a) pricing strategies of the DSO and b) on the charge behaviour of EVs given these prices. In subsection 2.2 papers are discussed for which EVs can provide ancillary services. This section is divided in the same way as the previous. An overview on how EV drive and charge behaviour should be modeled in discussed in A for the case some data is not present to model this behaviour.

2.1 Papers considering no provision of ancillary services by EVs

In market environments all parties try to optimize their own objective. In our case this holds for the DSO as well as for the EV owners. In the first part of this subsection price setting strategies for the DSO are discussed and in the second charge strategies for EV owners.

a) DSO pricing strategies

There are multiple methods proposed for the DSO to perform congestion management by influencing the charge behaviour of EVs there are multiple scenarios possible. Two different approaches are proposed for the case without provision of ancillary services. In the first approach capacity in the distribution network is sold to the highest bidder. When all the the electricity usage is within the capacity of the network, nothing changes. However, the capacity is sold to the highest bidders when the network becomes overloaded. Both [] and [] propose a market environment for these biddings. In this approach the DSO has no strategic choices to make. This approach might however lead to social undesired scenarios and does not give an incentive for the DSO to invest in new infrastructure when overloading of the network happens often. In the second approach the DSO does not charge a constant price per type of connection as compensation for operating the electricity network, but charges dynamic prices based on the amount energy and time of usage. This is called a Dynamic Tariff (DT). More recently an extension of DP is proposed: Dynamic Power Tariff (DPT) in [11]. In DPT not only the time bus also the power is taken into account. This means that when an EV charges with high power it pays more per KWH. The reasoning behind DPT is that it discourages peaks in demand and these peaks are the main reason for congestion in a distribution network. It is up to the DSO in this case to set the price per timeslot. Based on which information EV owners share with the DSO the the planning problem for the DSO differs.

When no information is shared the price per timeslot is just calculated based on forecasted charging of EVs. The pricing problem can be solved in another way when EV owners share their planned charge schedule with the DSO. In this scenario the problem can be solved with game theoretic methods. Karfopoulos and Hatziargyriou [12] modelled the problem as a single-objective, non-cooperative, dynamic game where the DSO is using virtual pricing to regulate the charging behaviour of the EVs. Each agent has one goal to strive for(single objective), decides on its own strategy (Non-cooperative) and EV users respond to the pricing strategy of the DSO (dynamic). Such a game is played in rounds until the system reaches an equilibrium.

They investigated two scenarios: the system where the EVs only posses their own information and the upcoming virtual electricity prices given by the DSO (uncoupled) and a scenario where the EVs are also aware of the accumulated charging scheme of all EVs (coupled). In these scenarios the DSO is aware of the charging strategies of the EVs. The game is played some time before the actual charging happens. The game starts where the DSO shares prices based on forecasted usage. Each EV calculates its charge schedule and shares it with the DSO. Based on the new responses, the DSO updates its pricing policy in such a way that periods with higher prices reflect periods with high transformer loading. Again, each EV responds to this new pricing policy with its new best response until an equilibrium is found.

b) EV charging strategies

The optimal charging strategy of EV owners depends on their driving behaviour (such as the initial battery level and the period the car is plugged in) and the specifications of the infrastructure such as the maximum charging rate. The discretized optimization problem for a single EV has the following form:

$$\min F = \sum_{t=t_0}^{t_0+T} p(t)P(t) \tag{1}$$

$$\text{s.t.} \quad \sum_{t=t_0}^{t_0+T} P(t) = (SOC_{out} - SOC_{in}) \times \frac{C_{bat}}{C_{eff}} \tag{2}$$

$$0 \leq P(t) \leq P_{plug} \qquad \forall t \in T \tag{3}$$

where t_o is the starting time of charging, T is the charging period, $p(t)$ is the electrical price including the price strategy of the DSO at time t, $P(t)$ is the charging power at time t, SOC_{in} is the initial battery SOC when the EV plugs in, SOC_{out} is the final battery SOC, C_{bat} is the energy capacity of the EV battery, C_{eff} is the charging efficiency and P_{plug} is the maximum charging power. This problem can easily be solved with a simple greedy algorithm where the time slots are sorted based on their corresponding price level obtaining the best response of an EV to the DSO pricing strategy. The model assumes variable rate charging (VRC) where the charge rate of an EV can take each value within 0 and the maximum charge rate. However, the efficiency of a charger is lower with VRC, also most current EVs are only equipped with a much cheaper on/off control which can either charge at full power or not at all. With this discrete rate charging (DRC) an interrupted or an interrupted [13] schedule can be used. When using an uninterrupted schedule the number of the on/off switches should not be too high as it deteriorates certain batteries [14]. However, when more constraints are added the complexity of the problem quickly increases.

The model can be extended by taking into account the power losses during charging. The power loss for a charging current $I(t)$ at time interval t and a internal resistance R is given by $RI^2(t)$. When the voltage level is assumed constant the following term is added to the objective function of equation 1:

$$\frac{R}{V^2} \sum_{t=t_0}^{t_0+T} p^2(t).$$

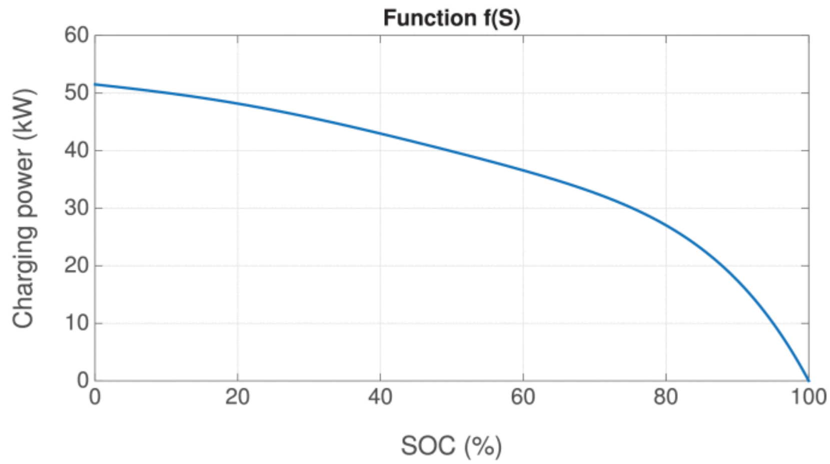

Figure 1: Typical SOC charging curve [16]

Cao et al. [15] consider a more realistic scenario where the maximum charging power depends on the state-of-charge (SOC) of the battery. This phenomenon is based on the fact that a battery can charge at a lower rate the more energy it has stored. The authors derive its dependence using Mass theory resulting in a maximum current $I = I_0 e^{-\alpha t}$ where I_0 is the maximum charging current at the start time, α is the acceptance rate and t is the SOC-rate . An example of such a SOC-curve is showed in figure 1.
There is some debate if this function should be linearized. Cao et al. use the original function where Sundström et al. [17] investigated the decrease of complexity of a linear approximation with respect to its loss in accuracy. They concluded that a linear approximation is preferred. Besides that, more recent Korolko et al. [16] developed a significant faster way of solving the optimization problem with a general SOC-curve using a tailored cutting plane technique. First the problem is solved without taking into account the constraint imposed by the SOC-curve, finding the test point $\mathbf{p}^*$. Then the algorithm checks if the solution violates the SOC constraint and if so a hyper plane is defined which separates $\mathbf{p}^*$ from the feasible region. After this $\mathbf{p}^*$ is projected on this new boundary and the process is repeated until the optimal solution is found. Because the cutting procedure is specifically designed for this problem, the running time of the algorithm is greatly decreased with respect of an off-the-self solver.
Until now we have looked at models where all information was available. However in reality there will be uncertainty about the electricity prices and departure times of EVs. In the same paper Korolko et al. use robust programming where possible ranges of the prices are defined and the algorithm finds the best solution for the worst pricing circumstances.

2.2 Papers considering provision of ancillary services by EVs

Besides regulating the EV charge behaviour by virtual prices, as discussed in section 2.1, another control strategy can be used. A DSO can offer money to parties which deliver ancillary services in turn. Ancillary services are defined as all those activities on the network that are necessary to support the transmission of power while maintaining reliable operation and ensuring the required degree of quality and safety[18]. Examples of ancillary services are the provision frequency regulation by ramping a power generator up or down or providing reactive power to control the power quality at a certain point in the network. In this scenario the most relevant ancillary service is to provide vehicle to grid (V2G) support. With V2G support, the battery of an EV is used to prevent overloading of the network. V2G support can be given unidirectional or bidirectional. With unidirectional V2G support the charging of the an EV is regulated up or down to support the network, where with bidirectional V2G support the EV can also discharge its battery to provide power to the grid.
In scenarios where a EVs can provide ancillary services, the role of aggregators becomes more important. An aggregator is an party which is in between the network operator or wholesale market and a group of consumers. In the current situation utility companies are an example of aggregators. Where consumers do not have direct access to the wholesale market but buy their energy from a utility company. When the network operator asks for ancillary services it is assumed that an aggregator is needed to coordinate vehicles. As one EV produces power to the network will not have a large impact on the network. Other motivations are that it might be too much of a hassle for most EV owners to make specific decisions on their charge and discharge behaviour of their EV.

a) Pricing strategies

For the case of bidirectional V2G the interaction between an aggregator and different EVs can be modeled as an Stackelberg game. In this game the aggregator can be seen as a leader who sets the prices and the demand for V2G and the EVs react to this offer. Chen and Leung [19] propose a game theory model where every information is correctly forecasted and a real time model. The aggregator is in this case an combination of an utility company and an coordinator of ancillary services. Its objective is in this case to sell as much energy as possible to EV owners and to let the EVs provide ancillary services. The aggregator receives a share of the compensation EV owners receive for their provision of ancillary services. In the models of Chen and Leung the grid operator sends the aggregator a regulation request. At this point the aggregator determines the price of the electricity for the charging of the EVs, which in their turn determine their charge strategy. The utility function of the EVs has a price term and a charging satisfaction term. The satisfaction term of an EV n is defined as:

$$\gamma_n \log \left(S_{b,n} + S_n(t_{n,out})\right) \tag{4}$$

where γ is the parameter which couples the economic benefit and the charging satisfaction. $S_{b,n}$ is the basic satisfaction of EV n and $S_n(t_{n,out})$ is the final satisfaction based on the charge level when the vehicle is leaving. In [20] a robust Stackelberg game is proposed where uncertainty in demand is considered. The model takes into account primary and secondary EVs where the primary EVs have priority and the remaining energy is sold to the secondary EVs.

b) EV charging strategies

An optimal charging strategy of an EV when being able to provide bidirectional V2G support is proposed by Dahmane et al. in [21]. The problem is in some ways comparable to the problem described in section b). However a distinction is made between charging P_c and discharging P_d and their corresponding prices p_c and p_d. In this situation, the objective function becomes:

$$\min \sum_{t=1}^{T} \alpha P_c(t) \cdot p_c(t) - (1-\alpha) P_d(t) \cdot p_d(t)$$

where α is a parameter to tune the personal preference of the EV owner. The complexity of the problem is comparable to the problem with virtual prices. Except that a constraint has to be added to prevent charging and discharging at the same time:

$$P_c(t) \cdot P_d(t) = 0. \tag{5}$$

This results in a non-linear problem. The problem can be written as an integer linear programming (ILP) problem when two binary decision variables $y_c(t)$ and $y_d(t)$ are introduced. These are 1 if the EV is (dis)charging at time t and 0 otherwise. Equation 5 can now be rewritten as

$$y_c(t) + y_d(t) \leq 1. \tag{6}$$

To ensure that the values of $P_c(t)$ and $P_d(t)$ actually correspond with the values of $y_c(t)$ and $y_d(t)$ we also need the following forcing constraints:

$$P_c(t) \leq C_{max}\ y_c(t) \tag{7}$$
$$P_d(t) \leq D_{max}\ y_d(t) \tag{8}$$

Less study has been performed on the planning of optimal charging with unidirectional V2G support. When planning the EV charging with a possibility to perform ancillary services, the goal is to minimize the charging cost and at the same time be flexible enough to ramp up or down when regulation can be provided. The scheduled charging rate is called in this case a preferred operation point (POP). Ansari et al. [22] presented an optimal charging strategy for an aggregator using fuzzy linear programming. The objective of the aggregator is to maximize its revenue which is generated by selling energy to EVs and by earning a fraction of the compensation EVs receive for providing ancillary services. The aggregator schedules all vehicles.

3 Research question

As described in section 1.4 the goal of this thesis is to answer the question 'What is minimal amount of coordination needed for a proper working future distribution network?'. To answer this question the following research question is formulated:

> *What is the performance of different scenarios in which multiple actors with different stakes and optimization strategies interact in a power system that becomes stressed by high EV penetration?*

Let us go into more detail about some aspects of this research question, starting with the different actors. The actors in the system are: 1) the DSO which wants to avoid (the risk of) overloading of the distribution transformer and the cables at a minimal cost. The performance measures of the DSO are: the duration and the amount the parts of the network are overloaded, the total price the DSO pays to execute its strategy and how predictable and robust the effect of its strategy is. 2) The EV owners who want their EV sufficient charged in an as cheap as possible manner. The way the insurance of a high charging level relates to the desire to optimize the charging cost can differ per EV owner. The performance measures for charging strategies is the height of their objective function (price paid and/or satisfaction level) and the robustness of their strategy against uncertainty in both the current situation and their predictions of the future.

The performance of an whole scenario is measured by a combination of the performance of the DSO, the EV owners and the amount of coordination within the scenario. Coordination will be defined as the amount of information which is shared and the degree of autonomy of each actor.

The scenarios which are believed to be the most interesting to be investigated are the following: the first scenario will be the current situation with an increased penetration of EVs. This will be the base case. After that the scenario where dynamic prices are introduced, where EVs start optimizing their charge behaviour and where the DSO regulations using virtual prices will be investigated. In the third scenario V2G support is enabled and the DSO regulates using pricing for ancillary services. The scenarios are discussed in more detail in section 5.

The research question will be made more specific by dividing it into the following sub questions:

1. What happens in the current situation when a high EV penetration rate leads to overloading of the network? (base case)

2. What are the effects on each actor of the degree of coordination to prevent overloading of the network?

3. What is the effect of the interaction of different strategies on the performance for the different actors?

4 Relevance of research question

EVs are more and more adopted by the public as green alternative to gasoline vehicles. Charging this increasing amount of EVs will become problematic for the current distribution network, where feeders and transformers can become overloaded when peaks in power demand occur. To support the choice for a proper solution, in the form of coordination or perhaps regulation, understanding the dynamics in an overloaded system is needed. This thesis focuses on understanding these dynamics. The goal of this thesis is to improve the understanding of these dynamics.

5 Methodology

To find an answer to the research question, the power network of a neighbourhood will be simulated. The base model will be basic model to answer the first sub question. Further features will be added gradually to the base model to answer the other sub questions.

5.1 Framework

The model will be a Discrete Event Simulation. In this type of simulation the moments on which an interesting event happens is calculated. An event is interesting if the event changes the state of the simulation, for example the arrival of an EV or a price change by the DSO. Instead of using predefined time steps to calculate the new state, the state will be calculated for the next event. The model will be programmed in Python. DNV-GL prefers that the model is programmed in Python or Matlab to be able to use the model in the future. The choice for python is made from a practical point of view, as it is more similar to other programming languages. The PyPSA package will be used to perform the powerflow calculations in the network.

5.2 Base model

At first the model consists of a low voltage distribution network, an independent system operator, EVs and households which consume power. This model will be a simplified version of a electricity network to produce a base case to investigate what happens when a distribution network becomes overloaded by EV charging. The supply of power is assumed to be matched with the demand. The only bottlenecks are the power capacity of the transformer and the cables. The network will be the network of the a neighbourhood in Amsterdam called Republica, which is an experimental sustainable neighbourhood planned to be build in 2022. Republica is part of European union funded project called ATELIER. The electricity will be modelled as simple as possible. The network will be modelled as alternating current with one phase. The system operator will not take any action in the base model. The non-EV power usage of households will be modelled based on the data obtained by NEDU. NEDU is an association which represents all the different rolls in the energy sector in the Netherlands The penetration rate of the EVs is chosen in such way that the distribution net is likely to become overloaded. The driving and charging data will be preferably used from Elaad, a dutch company which was responsible for setting up public charging points, but is now a knowledge centre for smart charging. By analyzing the data, stochastic arrival, departure and charging times will be determined. When the data is not available distributions from other papers will be used such as in appendix A. The maximum charging power will be modeled with a so called SOC-curve.

Scenario 2.1 One of the ways a DSO can influence the charging behaviour of EVs is by using virtual prices. To be able to introduce this, dynamic electricity prices will be implemented first. In this scenario the prices will become dynamic and EVs will try to optimize their charging costs based on the basic charge algorithm described in section 2.1. The prices change every quarter and the cars will determine their charge strategy on arrival.

Ik zie het verschil tussen Scenario 2.1 en 2.2 niet helemaal.

Scenario 2.2 This second scenario will be extended with an active DSO. The DSO will try to regulate the load on the transformer by regulating the prices. The DSO will use virtual prices to influence the charge behaviour of EVs, which is done by adding or subtracting money to/from the wholesale electricity prices. The DSO will check every minute if the load of the transformer is overloaded and increases the electricity price gradually until the targeted load on the transformer is obtained. Depending on the computational effort, the cars will adjust their strategy with every change of the electricity price.

Scenario 3 The other option the DSO has to influence the charging behaviour of EVs is to offer money for ancillary services. In the third scenario the DSO will offer money for bidirectional V2G support instead of using virtual prices. The EVs will use the charging strategy for bidirectional V2G described in section b).

5.3 Possible extensions to the model

The previous three scenarios are the core of the simulation. When these scenarios are implemented different extensions can be made to the model. For scenario 2 a more complicated charge algorithm can be implemented such as proposed by Koralko et al. including a soc curve. Also a satisfaction term as described in equation 4 can be added where the γ parameter differs per EV so that each EV reacts different to pricing changes. For the third scenario unidirectional V2G support and a satisfaction term can be added. It is also possible to let the EVs sell their stored energy to other EVs. Other extensions are:

- Letting charging algorithms take into account the uncertainty in prices and departure time. This can be done with robust, stochastic or fuzzy programming

- Adding coordination between EVs (Aggregator)
- Adding non-ideal behaviour of EVs or the DSO
- Add solar panels/ distributed generation
- Add technical incentives instead of price incentives such as power curtailing of households
- Implementing a communication blackout or EVs receiving outdated price signals
- Implement DRC instead of VRC

Waarom is DRC moeilijker dan VRC?

6 Planning the second part of the thesis

The first part of the thesis consisted of writing this proposal. For the second part of the thesis I will work with an agile work style with sprints of 3 weeks. Every new sprint will start with a meeting with all supervisors. The first sprint will start on the 6th of April. The most relevant extensions to the model will be determined during sprint reviews. A planning of the first 4 sprints is shown in table 1. The work which is described per sprint will also be written in the report.

Planning		
Sprint #	Date	Work
sprint 1	6 April -27 April	Implementing the base model.
sprint 2	27 April - 15 may	Implementing the base model.
sprint 3	18 May - 8 June	Implementing scenario 2 & 3.
sprint 4	8 June - 29 June	Adding extensions to the model.
sprint 5	29 June - 12 July	Adding extensions to the model.

Table 1: Sprint planning

Event	Date
Vacation	15 July - 8 Aug
Deadline	2 October

Table 2: Other data

References

[1] B. Dupont et al. “Short-term consumer benefits of dynamic pricing”. In: *2011 8th International Conference on the European Energy Market (EEM)*. May 2011, pp. 216–221. DOI: 10.1109/EEM.2011.5953011.

[2] J. A. Orr, A. E. Emanuel, and K. W. Oberg. "Current Harmonics Generated by a Cluster of Electric Vehicle Battery Chargers". In: *IEEE Transactions on Power Apparatus and Systems* PAS-101.3 (Mar. 1982), pp. 691–700. ISSN: 0018-9510. DOI: `10.1109/TPAS.1982.317284`.

[3] P. Papadopoulos et al. "Impact of residential charging of electric vehicles on distribution networks, a probabilistic approach". In: *45th International Universities Power Engineering Conference UPEC2010*. Aug. 2010, pp. 1–5.

[4] Sanchari Deb et al. "Impact of electric vehicle charging station load on distribution network". In: *Energies* 11.1 (2018), p. 178.

[5] LG González, E Siavichay, and JL Espinoza. "Impact of EV fast charging stations on the power distribution network of a Latin American intermediate city". In: *Renewable and Sustainable Energy Reviews* 107 (2019), pp. 309–318.

[6] Mohamed A Awadallah, Birendra N Singh, and Bala Venkatesh. "Impact of EV charger load on distribution network capacity: A case study in Toronto". In: *Canadian Journal of Electrical and Computer Engineering* 39.4 (2016), pp. 268–273.

[7] Shahab Shokrzadeh et al. "A simplified control algorithm for utilities to utilize plug-in electric vehicles to reduce distribution transformer overloading". In: *Energy* 133 (2017), pp. 1121–1131. ISSN: 0360-5442. DOI: `https://doi.org/10.1016/j.energy.2017.04.152`. URL: `http://www.sciencedirect.com/science/article/pii/S0360544217307284`.

[8] Mingming Liu et al. "Residential electrical vehicle charging strategies: the good, the bad and the ugly". In: *Journal of Modern Power Systems and Clean Energy* 3.2 (2015), pp. 190–202.

[9] J. Zhang et al. "Fast Solving Method Based on Linearized Equations of Branch Power Flow for Coordinated Charging of EVs (EVCC)". In: *IEEE Transactions on Vehicular Technology* 68.5 (May 2019), pp. 4404–4418. ISSN: 1939-9359. DOI: `10.1109/TVT.2019.2904464`.

[10] Farukh Abbas et al. "A heuristically optimized comprehensive charging scheme for large-scale EV integration". In: *International Transactions on Electrical Energy Systems* (2019), e12313.

[11] Shaojun Huang, Qiuwei Wu, Mohammad Shahidehpour, et al. "Dynamic power tariff for congestion management in distribution networks". In: *IEEE Transactions on Smart Grid* 10.2 (2018), pp. 2148–2157.

[12] Evangelos L Karfopoulos and Nikos D Hatziargyriou. "A multi-agent system for controlled charging of a large population of electric vehicles". In: *IEEE Transactions on Power Systems* 28.2 (2012), pp. 1196–1204.

[13] Chao-Kai Wen et al. "Decentralized plug-in electric vehicle charging selection algorithm in power systems". In: *IEEE Transactions on Smart Grid* 3.4 (2012), pp. 1779–1789.

[14] Akshay Malhotra et al. “Impact of charging interruptions in coordinated electric vehicle charging”. In: *2016 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*. IEEE. 2016, pp. 901–905.

[15] Yijia Cao et al. “An optimized EV charging model considering TOU price and SOC curve”. In: *IEEE Transactions on Smart Grid* 3.1 (2011), pp. 388–393.

[16] N. Korolko and Z. Sahinoglu. “Robust Optimization of EV Charging Schedules in Unregulated Electricity Markets”. In: *IEEE Transactions on Smart Grid* 8.1 (Jan. 2017), pp. 149–157. ISSN: 1949-3061. DOI: 10.1109/TSG.2015.2472597.

[17] Olle Sundström and Carl Binding. “Optimization methods to plan the charging of electric vehicle fleets”. In: *Proceedings of the international conference on control, communication and power engineering*. Citeseer. 2010, pp. 28–29.

[18] Jin Zhong. *On some aspects of design of electric power ancillary service markets*. Chalmers University of Technology, 2003.

[19] X. Chen and K. Leung. “A Game Theoretic Approach to Vehicle-to-Grid Scheduling”. In: *2018 IEEE Global Communications Conference (GLOBECOM)*. Dec. 2018, pp. 1–6. DOI: 10.1109/GLOCOM.2018.8647357.

[20] Helin Yang, Xianzhong Xie, and Athanasios V Vasilakos. “Noncooperative and cooperative optimization of electric vehicle charging under demand uncertainty: A robust Stackelberg game”. In: *IEEE Transactions on vehicular technology* 65.3 (2015), pp. 1043–1058.

[21] Yassir Dahmane et al. “Decentralized Control of Electric Vehicle Smart Charging for Cost Minimization Considering Temperature and Battery Health”. In: *2019 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*. IEEE. 2019, pp. 1–6.

[22] Muhammad Ansari et al. “Optimal charging strategies for unidirectional vehicle-to-grid using fuzzy uncertainties”. In: *2014 IEEE PES T&D Conference and Exposition*. IEEE. 2014, pp. 1–5.

[23] Nima H Tehrani and Peng Wang. “Probabilistic estimation of plug-in electric vehicles charging load profile”. In: *Electric Power Systems Research* 124 (2015), pp. 133–143.

A Stochastic modelling of charging behaviour EVs

When predicting the impact of EVs on the network or to show the effectiveness of an control algorithm, the charging behaviour of Evs is often simulated. Very different approaches to do this have been used. The charging behaviour of EVs consists in general of three different variables: the departure time, the traveled distance and the arrival time. Therani et al. [23] performed an extensive data study on the charging behaviour of EVs to investigate which distribution functions and their parameters correspond the best with realistic charge behaviour. Based on a dataset of more than 260,000 vehicle trips, the authors selected the parameters which are shown in table 3.

Random Variable	Fitted Distribution	Parameters
Departure time	Weibull	$a = 7.67$ $b = 21.83$
Travelled distance	Weibull	$a = 32.04$ $b = 1.23$
Arrival time	generalized extreme value	$k = -0.06$ $\mu = 17.3$ $\sigma = 0.85$

Table 3: Selected parameters obtained from [23]

Both [9, 10] also modelled EV charging behaviour. In both papers the departure and travel time is modelled with a Markov chain model. Abbas et al. even modelled the EV behaviour for five different time scales, ranging from behaviour within an hour to a year. The distributions they used are shown in Table A.

Data Type	Distribution Type	Parameters
Daily travel frequency	Gamma	a = 3.71 b = 0.64 mean = 2.39 variance = 1.24
Driven Mileage	Birnbaum Saunders	$\beta = 10.57$ $\gamma = 0.97$ mean = 15.52 variance = 15.09
Travel duration	Gamma	a = 1.87 b = 18.35 mean = 34.4 variance = 25.12
Departure time	Location scale	$\mu = 8.36$ $\sigma = 1.08$ v = 2.16 variance = 3.98
Absolute Arrival time	Normal	$\mu = 18.2$ $\sigma = 2.84$

Table 4: Selected parameters obtained from [10].