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Table of Contents

| | |
|--|----|
| Contents..... | 3 |
| 1. Introduction..... | 6 |
| 1.1 Electromobility-grid interaction | 6 |
| 2. The impact of e-mobility on the electricity system | 7 |
| 2.1 Decarbonising energy use through electrification | 7 |
| 2.2 Generation of variable renewable energy | 8 |
| 2.3 Impact of electric mobility on the energy balance | 10 |
| 2.4 Integration in the electricity network | 10 |
| 2.5 Private vs public charging | 11 |
| 3. The impact of smart charging on the local grid..... | 12 |
| 3.1 Methodology | 12 |
| 3.1.1 EV Charging Strategies | 14 |
| 3.1.2 Grid | 14 |
| 3.1.3 Simulation | 16 |
| 3.1.4 Performance Indicators..... | 17 |
| 3.2 Results..... | 18 |
| 3.2.1 Scenario 1 | 18 |
| 3.2.2 Scenario 2..... | 20 |
| 3.2.3 Scenario 3..... | 20 |
| 4. Conclusion and Discussion | 23 |
| 5. References | 24 |
| 6. Appendices..... | 25 |
| 6.1 Description of task 4.7.1 as described in the project proposal | 25 |
| 6.2 Software in the Loop (applied to the electromobility grid impact analysis) | 26 |
| 6.2.1 Business idea behind the Software in the Loop laboratory | 26 |

Table of Figures

| | |
|--|----|
| Figure 1-1 The Liander electricity network in Buiksloterham, the pilot site in Amsterdam. (PDOK, 2023), location: Buiksloterham (Noord and Zuid). | 6 |
| Figure 2-1 Comparing electric, hybrid and alternative carbon-free fuel solutions towards 2050 for different modes of transport. (DNV, 2023) | 7 |
| Figure 2-2, Energy demand for different energy carriers and the consequence if they would be electrified, considering the energy efficiencies for heat pumps and EV's (DNV GL, 2020), (data Eurostat 2020). | 8 |
| Figure 2-3, Residual load duration curve of a system with an installed capacity of both wind and solar equal to max demand (i.e. with a peak demand is 100 GW, the installed variable renewable capacity would be 200 GW (100 GW wind and 100 GW solar) (DNV GL, 2018). | 9 |
| Figure 2-4, Daily variations in electricity demand for a week in May Germany in 2022, and the potential impact of V2G with the current EV fleet on reducing the mismatch between renewable supply and demand (DNV, 2023). | 10 |
| Figure 3-1 Kerber network used in the simulation study | 15 |
| Figure 3-2 A Schematic representation of the simulation with a focus on the EV simulation module | 17 |
| Figure 3-3 Performance comparison of different charging strategies in different scenarios: a) Scenario 1: 50% EV ownership and 4 EVs per public charger, b) Scenario 2: 100% EV ownership and 4 EVs per public charger, c) Scenario 3: 50% EV ownership and 9 EVs per public charger | 19 |
| Figure 3-4 Normalized distribution of voltage at first and last nodes off all the feeders for the three charging strategies across all scenarios. | 21 |
| Figure 3-5 Price signal and power-flow measured at 400kVA transformer during V2G strategy for all the scenarios for a period of 5 days. | 22 |

Abbreviations and Acronyms

| Acronym | Description |
|---------|----------------------------------|
| EU | European Union |
| EV | (Battery) Electric Vehicle |
| HP | Heat Pump |
| kJ | Kilo Joule |
| kW | Kilo Watt [kJ/s] |
| kWh | Kilo Watt hour [3600 kJ] |
| PED | Positive Energy District |
| PV | Photo-Voltaic (solar) |
| VRES | Variable Renewable Energy Source |

1. Introduction

1.1 Electromobility-grid interaction

This report is the result of Atelier subtask 4.7.1 ‘Electromobility-grid interaction’, which is a subtask of task 4.7 ‘Electromobility’ within work package 4—the Amsterdam pilot—of the EU HORIZON 2020 project Atelier.

All preparatory and supervisory related to e-mobility in the Amsterdam pilot are concentrated in Task 4.7. This includes, among others, smart charging and facilitating inductive charging infrastructure at parking garages. All non-technical aspects related to e-mobility are explored in work package 3. This includes the social aspects of smart charging and adaptation strategies.

The results of subtask 4.7.1 are summarized in this report and consist of an overview of the impact of e-mobility on the electricity system in general and more specifically the impact on the load of the public electricity infrastructure in and around a PED (Positive Energy District).

The topology of the grid in and around the pilot site is publicly available (see Figure 1-1). However, this information does not have the required level of detail that is necessary to assess the potential impact of the electric vehicle charging behaviour on the network. The required level of detail was not readily available as the local grid operator, Liander, was not part of the consortium. To make the results of this assessment verifiable, as well as applicable beyond the scope of the pilot site, a decision was made to use a standard open source and well-defined electricity network.

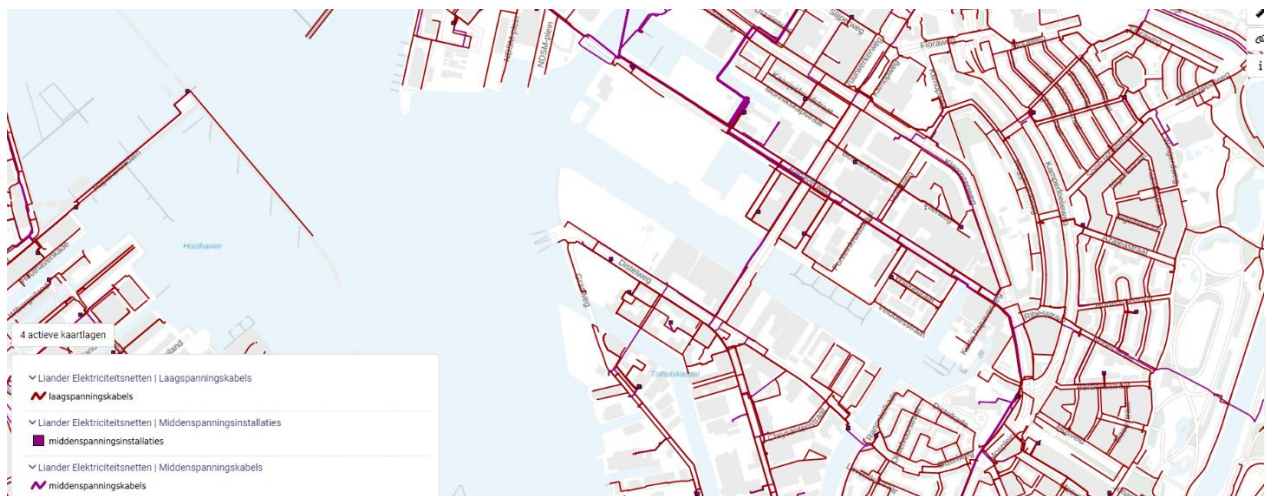


Figure 1-1 The Liander electricity network in Buiksloterham, the pilot site in Amsterdam. (PDOK, 2023), location: Buiksloterham (Noord and Zuid).

Within the Amsterdam PED we explored the possibility to test the functionality of the EMS designed by Spectral in the DNV Software-in-the-Loop lab and validate its services to the grid operator. The EMS is designed for optimizing the electricity demand and supply within the PED, among others the charging of electric vehicles. The EMS can mitigate the risks to the integrity of the network as a service to the grid operator, such as capacity pooling/ group transport contract; participating in congestion management (selling flexibility to the DSO); or making part of the required capacity ‘non-firm’ (allowing the DSO to curtail demand and/or generation under specific conditions). Unfortunately the implementation of the EMS within the simulated environment of the SIL lab was not planned and could not be implemented due to lack of resources.

2. The impact of e-mobility on the electricity system

2.1 Decarbonising energy use through electrification

Electrification of road transport using renewable electricity is one of the most viable pathways to decarbonize the bulk of road transport as is indicated in Figure 2-1. Annual sales of electric vehicles are growing rapidly. In 2021 they were three times as large as in 2018, resulting in 16.5 million cars on the road in 2021 worldwide. China, followed by Europe are clearly leading with sales in the US picking up (International Energy Agency, 2021)

Electrifying heavy and long-distance road transport still poses a challenge, and alternative fuels, such as hydrogen or synthetic fuels might emerge as dominant in this niche, but at the same 'hard to abate' niche is becoming smaller because of technical developments such as cheaper and higher capacity batteries, fast charging technologies and even battery swapping. So, while a minor part of road transport might be using other means, the main bulk of road transport will be decarbonized using electrification.

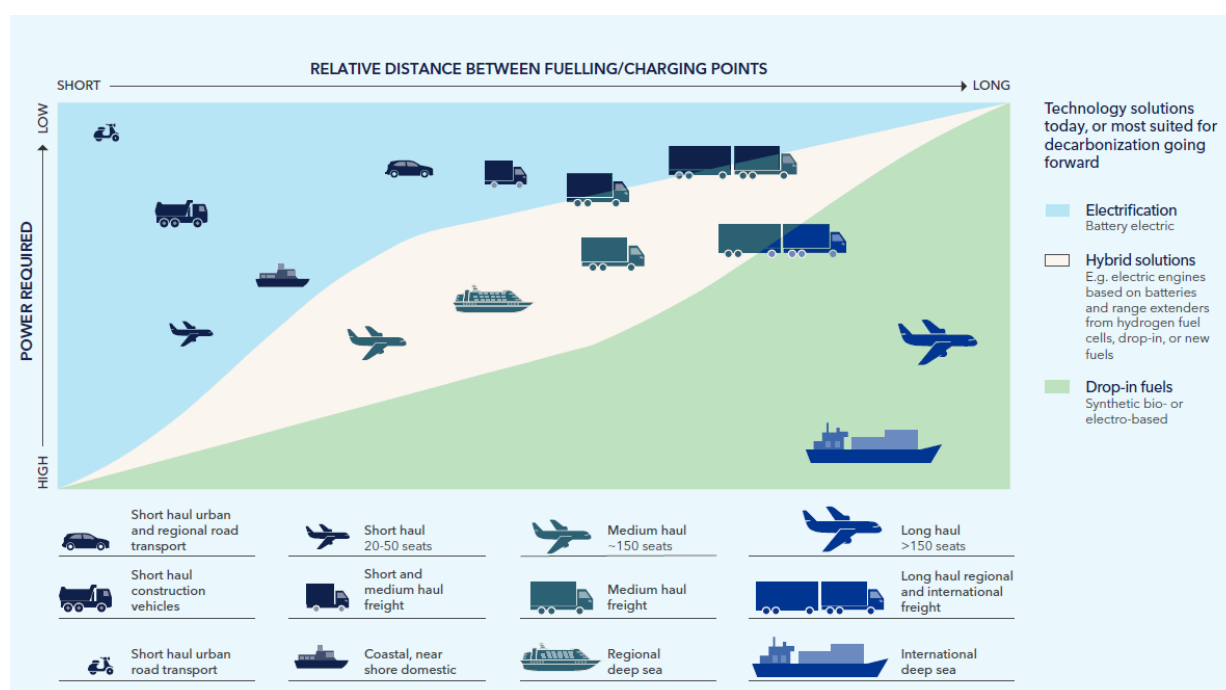


Figure 2-1 Comparing electric, hybrid and alternative carbon-free fuel solutions towards 2050 for different modes of transport. (DNV, 2023)

From the electricity systems point of view this means a major increase of electricity demand. Other sectors, such as residential heating and industry also look at electrification to decarbonize.

Currently electricity supply takes care of about 20% of total energy use in Europe, so the electricity sector is facing a major challenge if it is to supply the larger part of the remaining 80% of total energy use. This while at the same time the electricity sector is going through a major transformation itself, switching from fossil dispatchable generation to (predominately) variable renewable electricity generation.

Luckily, electricity can be used or converted to other forms of energy with a remarkably high efficiency. All ‘inefficiencies’ have been filtered out while generating electricity from less easy to convert primary energy sources (such as wind, solar and heat from burning fuels). This means that the electricity system at large does not need to grow 5 times as big to be able to electrify energy demand, but only about 3 times (not considering autonomous growth). This is still a major challenge though, especially because electricity supply from variable renewables is depending on the weather and it is extremely expensive and unpractical to store electricity in the quantities required to match this to the demand at all times.

Figure 2-2 shows the EU member states’ monthly final energy demand by per energy carrier for 4 years, clearly indicating the seasonal variation in gas demand (and a little in electricity demand) due to heating. It also shows the increase in demand for electricity if these sectors would be fully electrified, taking into account for example the relative efficiencies of electric motors compared to internal combustion engines, and the coefficient of performance of heat pumps (DNV GL, 2020).

The graph shows that the size of the power system needs to approximately triple in size to fully decarbonize all major sectors, including industry, which is very challenging, but not unfeasible. This indicative assessment assumes sufficient storage and flexibility in the electricity demand and generation to smooth out the main intra-monthly deviations (daily and weekly), so that there are no significant daily and weekly spikes that are not shown in this monthly averaged graph. Note, this still leaves a significant seasonal variation in electricity demand, which becomes even more challenging considering that (in Europe), solar electricity is mainly produced in summer.

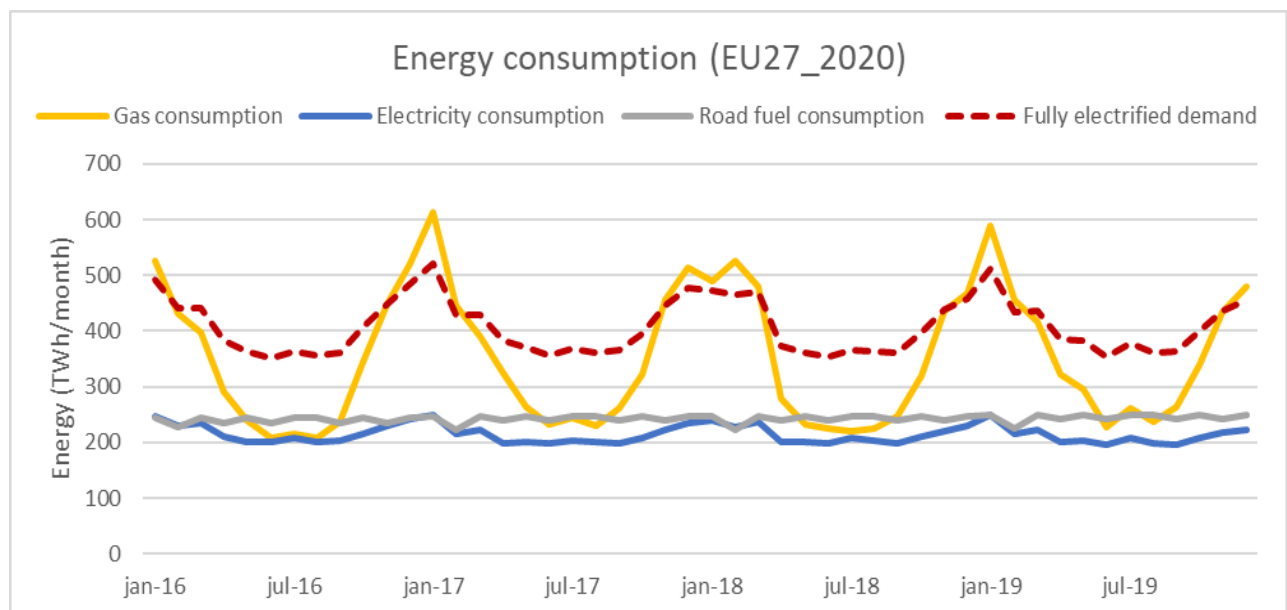


Figure 2-2, Energy demand for different energy carriers and the consequence if they would be electrified, considering the energy efficiencies for heat pumps and EV’s (DNV GL, 2020), (data Eurostat 2020).

2.2 Generation of variable renewable energy

Decarbonizing by electrification assumes a shift from fossil to renewable electricity generation. In the Netherlands—the location of the Amsterdam PED—this means predominately wind and solar energy, which are variable renewable energy sources (VRES). Electricity generation thus

becomes highly dependent on weather conditions and will be highly variable. This makes that the capacity factor—the annual energy yield in kWh per installed kW capacity compared to if that kW would be produced continuously—of VRES is lower than that of other generation, implying that more capacity needs to be installed to generate an equal amount of energy.

For example, in the Netherlands 1 kW capacity of PV panels will generate about 800 to 1000 kWh of energy per year, as opposed to 8760 kWh if it could generate 24/7 the whole year around. This means that PV in the Netherlands has a capacity factor of about 10%. For onshore wind the capacity factor is about 30% and for offshore wind it is currently around 50%.

Figure 2-3 shows how electricity demand will be satisfied in a system consisting of a total installed variable generation capacity of 200% of demand (Half of this is solar PV and the other half onshore + offshore wind); and sorted on the amount of dispatchable generation that is still needed to satisfy the residual demand, creating the so-called residual load duration curve. This residual load duration curve represents a system that is comparable with a system that meets the decarbonisation ambitions of the Netherlands in 2030. It shows that with 2 times the capacity of renewables compared to demand, there is still a large need for dispatchable generation (left side). It also shows that there will be a significant amount of time when there is over supply of variable renewable generation. Note, the demand in this figure does not include the electrification of the sectors mentioned in the previous graphs.

The discrepancy between electricity demand and the supply of variable renewable generation can be partly mitigated by interconnections with neighbouring countries (although this is limited because weather patterns tend to be similar in neighbouring countries), partly with tweaking flexible demand to available supply, and partly with (battery) storage. Smart charging Electric Vehicles may play an important part in adjusting the demand to the variable generation, and—using vehicle to grid—can also supply electricity at times when there is insufficient renewable generation, basically functioning as grid connected storage, which is the topic of the next section.

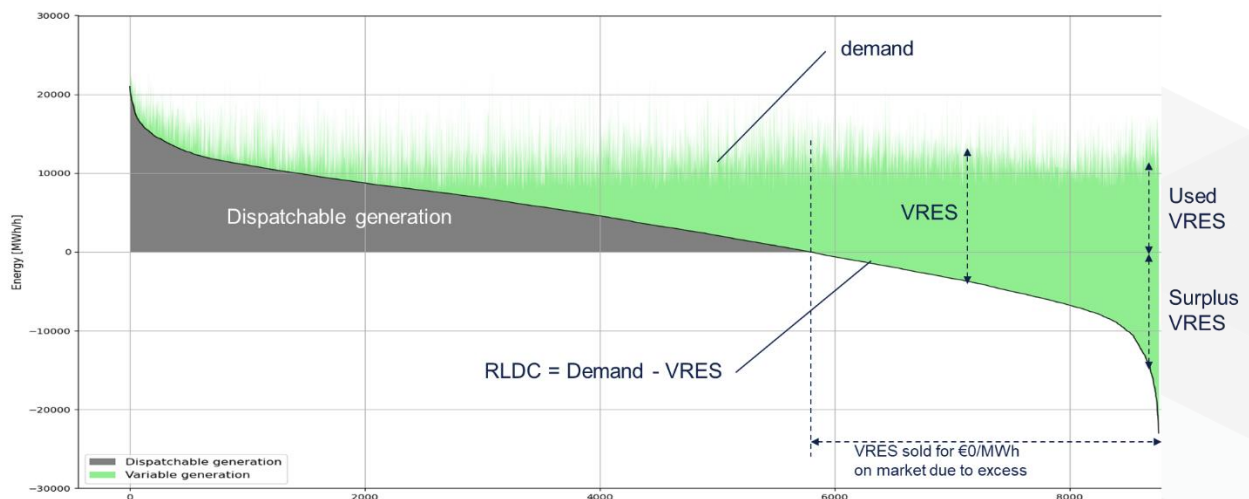


Figure 2-3, Residual load duration curve of a system with an installed capacity of both wind and solar equal to max demand (i.e. with a peak demand is 100 GW, the installed variable renewable capacity would be 200 GW (100 GW wind and 100 GW solar) (DNV GL, 2018).

2.3 Impact of electric mobility on the energy balance

As mentioned in the previous chapter, variable renewable generation does not follow electricity demand. Instead, demand will need to follow generation much more than is the case now. So much more demand response is needed. Besides demand response energy storage is needed as an intermediary between generation and demand. Charging electric vehicles can play a significant role as demand response. With vehicle-to-grid (V2G) and vehicle-to-Building (V2B) technologies, the batteries of electric vehicles can be used like regular grid connected or house connected batteries, significantly boosting the storage capacity the vehicle batteries can offer to the electricity system. With smart charging the flexibility is (on average) limited to replenishing the energy that has been used for the last trip. With V2G or V2B, the whole capacity of the battery can be used for flexibility, except the capacity that is reserved for the next trip (which still offers the same charging flexibility as vehicles without V2G).

Figure 2-4 shows the variations of electricity demand and renewable generation in Germany for a week in May 2022. As explained in the previous paragraph, the overall demand that cannot be satisfied by renewable generation is called residual load. The figure shows the effect on the residual load if the approximately 2 million EV's that are currently driving in Germany (4% of the total fleet) were to offer, on average, 20 kWh of storage capacity to the electricity system through smart charging and V2G. This is the equivalent of a capacity of grid connected batteries of between 20 GWh and 40 GWh (accounting for a safety margin to avoid battery degradation). There are many challenges to access this potential, such as current EVs are not designed for Vehicle to Grid functionality, and consumers' willingness to participate, but the graph does show that such a volume already would have a significant impact on the electricity system, allowing for a better integration of variable renewable electricity generation, especially solar.

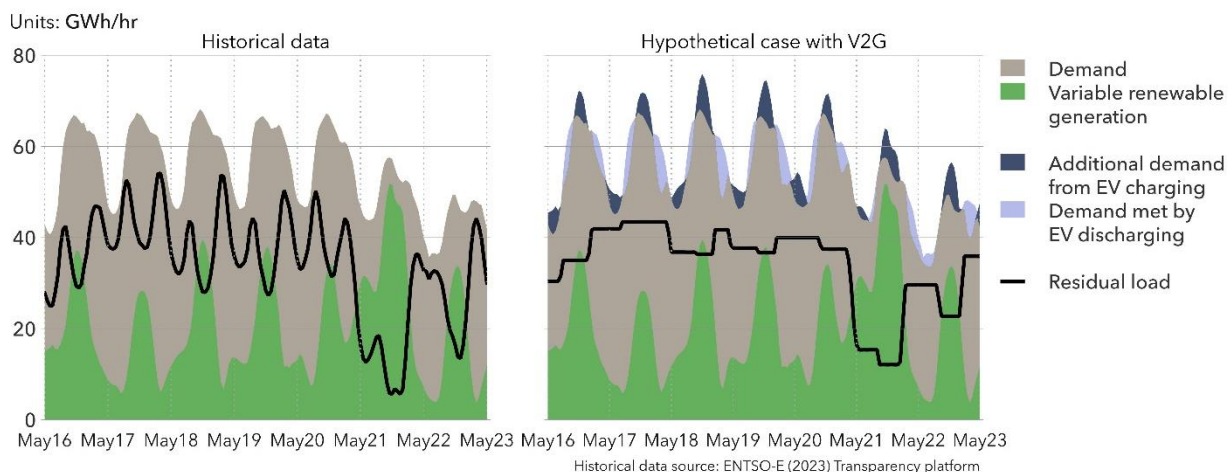


Figure 2-4, Daily variations in electricity demand for a week in May Germany in 2022, and the potential impact of V2G with the current EV fleet on reducing the mismatch between renewable supply and demand (DNV, 2023).

2.4 Integration in the electricity network

Figure 2-4 clearly shows the solar electricity generation peaks each day (the daily green peaks). It shows that the batteries of the EVs—that are connected to the grid—will charge during the day to absorb this energy. They can discharge when residual demand (and thus the electricity prices) is at its peak, reducing residual demand.

So, while Figure 2-4 shows that peaks in residual demand are reduced (the black line) to allow for better use of renewable generation, it also shows that the absolute demand peak is increasing, because EV charging is synchronized by the electricity generation of solar energy (The dark blue additional demand in the figure).

The effect on the network can be positive if this electricity is generated locally near EVs. Charging these EVs will reduce the need to transport the solar energy out of the area. However, if the solar electricity is generated further away from the vehicles needing it, the network might require significant reinforcements to accommodate the resulting power flows.

Thus, the benefits electric vehicles have on the infrastructure is highly determined by location and proximity of variable generation and EV charging/discharging locations, and the number of EV's and especially charging stations in a neighbourhood. This will be further examined in chapter 3.

For a positive energy district, this means that the required electricity needed for transport should be generated as close to the district as possible, preferable within the district itself. If this is the case, the vehicles can help in balancing the local system and limit the required electricity exchange with the districts surrounding and help limit the impact on the power grid. If not, an—on average—positive energy district will require a significant enforcement of the grid to facilitate the increased and fluctuating electricity flows between the district and its surrounding.

2.5 Private vs public charging

An important consideration, especially in urban areas, is the (lack of) opportunities for private charging. Not many residents have the opportunity to charge their car using the same electricity grid connection as their house/apartment, thus they rely on (semi-)public charging locations. EV drivers with a private and suitable grid connection can reduce their energy bill through incentives from the grid operator that reflect the available grid capacity. The primary concern of EV drivers, who have to rely on public or semi-public charging locations (e.g. charging stations dedicated to residents, but not sharing the same meter) might be access to a charging spot. Smart charging and V2G, which requires a stable connection to the grid, will be of secondary concern.

How to ensure, then, that other vehicles occupy the scarce charging capacity in an urban district for as short a time as possible? Tesla, for example, levies 'idle' fees that apply when a car is fully charged and left at a busy supercharger location; the fee is waived if the car is moved within 5 minutes of reaching full charge. Many other solutions are being explored, such as chargers that make smart use of scarce shared network capacity, with insights gained from real world use of public charge points.

3. The impact of smart charging on the local grid

Propelled by advancements in battery technology, lower costs and helpful economic and environmental policies, recent years have seen a substantial increase in the share of EVs in the mobility sector. With a strong motivation towards de-carbonizing the mobility sector and reducing the greenhouse emissions, many countries plan to phase out the traditional fossil fuel based personal vehicles in coming decades. In Europe, till 2021, the share of EVs among new bought cars had risen to 9% with Norway, Sweden and the Netherlands leading with about 75%, 38% and 30% respectively (International Energy Agency, 2021). While having great potential to help de-carbonize the mobility sector, integration of large number of EVs into the electricity grid will cause issues like over-loading of assets, increased system losses and under voltage problems.

To fulfil their high energy demands, EVs consume a very high amount of power when connected to the grid. A single-phase AC charger can have a power rating up to 7 kW while a three-phase one can deliver up to 22 kW of electrical power to the EVs. Most of the EU member states have between 5 to 10 EVs per public charger. On the other hand, countries like the Netherlands which is a more mature EV market has about 4 EVs per charger. Proliferation of such chargers across distribution grid accompanied with variable charging times could cause under voltage and overloading problems across the grid. With increasing EV adoption rate, assessment of the impact of EV charging on the grid has become critical to devise mitigation actions. It can also give insights for planning investments to prepare the grids to accommodate the ever-increasing EV load.

This chapter presents results from a co-simulation-based study to assess the interaction of electric vehicles (EVs) with the residential electricity distribution grid. The impact of this interaction on the grid as well as on the EV charging objectives is studied. The impact of EV charging strategies on the grid is measured in terms of deterioration of the quality of the grid voltage and overloading of the grid assets. The performance of the charging strategies from EV owner's perspective is studied using metrics such as delay in charging and average cost of charging. The charging behaviour of the EVs has been incorporated using models based on empirical data collected from public chargers in the Netherlands. A modern residential grid with high adoption of renewable resources is simulated.

The remainder of this chapter is arranged as follows: Section 3.1 discusses the methodology used in the study. Section 3.2 presents the results and conclusions are drawn in chapter 4.

3.1 Methodology

A co-simulation-based approach is utilized to simulate the models of the grid and its constituting elements such as house-hold loads, solar PV and EVs by separate synchronized simulators. The use of a co-simulation platform makes it possible to utilize dedicated simulators for different processes. Another advantage of co-simulation is that an interactive eco-system can be created with possible exchange of information between simulators using different inputs and protocols. In addition, the simulation can also be carried out in real-time where external controllers can also be integrated to manage the simulated devices. In this work we use the Mosaik platform which provides a flexible smart-grid scenario development and co-simulation framework (OFFIS, 2022).

The EV behaviour model used for the simulations is based on the data collected by Amsterdam University of Applied Sciences (AUAS). This database consists of 4.9 million charging sessions from the public charging points in the Netherlands. The processing and categorization of the measured data into clusters of different kinds of charging sessions is done and presented by the authors of (Helmus, Lees, & Hoed, 2020). To describe in brief, a two-step clustering approach was used where firstly, clusters of different types of charging sessions were identified. Thereafter a portfolio of different charging sessions per EV user was found. Charging sessions were clustered into 13 different types using a Gaussian Mixture Model. These clusters are based on the properties of charging sessions such as charging time (day or night), charging duration (short, medium and long) and hours between sessions. Each cluster has multiple instances of similar charging sessions where each charging session is defined by three properties: Arrival time, Connection time and Time between sessions.

Arrival time is the time an EV arrives in the simulated network. Depending on the availability of the charger, the EV might still have to wait to connect and start charging. Connection time the time an EV is connected to the charger. This time is used to calculate the departure time. Time between sessions is the time an EV will be away from a charger in the simulated network. This time is used to calculate the next arrival time. The EV user portfolio defines the probability distribution of different types of charge sessions for a given EV user, thus defining different kinds of EV users. Nine such portfolios were found based on the charging sessions of 27000 users.

The data received from AUAS contain three types of information about the EV charging behaviour:

- The thirteen clusters of different charging types,
- the nine clusters of user portfolio types and
- a probability distribution of required energy per session as a percentage of the battery capacity.

In this work, all the EVs are assumed to have a capacity of 100kWh. This capacity is on a higher side and is chosen to simulate future scenario. For an EV used in this model, at first a cluster is picked in which the particular EV user belongs. After that, within that cluster, a portfolio of charging sessions is selected. Using the portfolio of different types of charging sessions, attributes of the future charging sessions are created. It is here to be noted that, the results presented in this chapter use the EV behaviour models based on the database. However, the simulation can still be performed on user created synthetic EV user behaviour. For example, different charging session types can be created to model public, residential or workplace charging events. Each type of charging session can be assigned a probability distribution for arrival time, connection time and time between sessions. Each user then can be assigned a hypothetical portfolio of these charging session types.

The charging of the EVs is divided into two phases; constant current and constant voltage phase. During the constant current phase, a constant maximum power is transferred from the chargers to the EVs. In this work, all the EVs are able to charge with 22kW chargers. In the second phase of charging, when status of charge (SoC) is greater than 75%, the current and the power transfer decrease exponentially such that:

$$I(t) = I_0 e^{-\alpha t},$$

where, I_0 is the current during constant current phase, t is the SoC and α is the acceptance rate. In this study, the acceptance rate after 0.75 SoC is taken to be -0.1.

3.1.1 EV Charging Strategies

Three different types of charging strategies are used in this analysis. The base case (EV-basic) has no strategy where the EVs start to charge as soon as they are connected to the charger and charge as fast as possible. The EVs depart if they have sufficient energy (given by the desired SoC). The second charging strategy (EV-smart) is where the EVs after connecting to the charger receive a 'perfect' price forecast. It is called perfect because this is taken from the actual price of electricity at the moment of the charging session. So, there are no errors considered in the price forecast. Based on the price forecast, total energy needed and the departure time, the EVs schedule their charging instances by solving an optimization problem such that the cost of charging is minimized. The objective is to charge the EVs with the desired energy in a given period of time (connection time). In the third and the final strategy (EV-v2g), the EVs are also capable of delivering power back into the grid. The EVs then pick the charge and discharge time slots within the departure time to minimize the cost of charging. The connection time is the difference between the arrival and the departure time. For all of the EV-strategies, if the connection time is so small that the charging by the desired amount of energy is not possible, then the original departure time is postponed by a minimum time duration which allows the EVs to charge by choosing all the time-slots.

3.1.2 Grid

Pandapower (an open source power system analysis tool with validated network components) is used to build the network and perform the power-flow calculations (Pandapower, 2022). A modified version of a suburban-type Kerber network (which comes predefined in Pandapower) is used in the simulations. More information about the network can be found on Pandapower's webpage. The layout of the network is shown in Figure 3-1. There are 145 houses whose loads were replaced by household profile data provided by NEDU (association which represents all the different stakeholders in the energy sector in the Netherlands) for the year of 2020. The normalized profile was scaled up for electricity usage by 4 and 5-person households. The maximum total household load in the network at any given time during the day is about 170 kW. The used Pandapower network model has a very big transformer of 630 kVA. To avoid the redundancy of capacity, the nominal power rating of the transformer in the model is modified from 630 to 400 kVA. Other different power ratings of commonly used distribution transformers such as 200kVA can also be used. Each of the households also hosts a roof-top PV installation of 3 kW capacity. Due to the losses in the power inverters and the cables, the power actually delivered to the electricity grid is lower than the power produced by the PV modules. Hence the efficiency of the simulated PV system is considered to be 87%. The generated PV power is based on irradiance data for the city of Utrecht (coordinates: 52.094, 5.040) (PVGIS, 2022). The electricity prices used in the simulation were the wholesale market price values of electricity at the APX energy exchange for the year 2016. Table 3-1 lists down the network, simulated components and EV charging algorithms applied in this study.

| Element | Remarks |
|---------------------|--|
| Network | 'Extreme Kerber Vorstadtnetze' with transformer rating 400 kVA. (https://pandapower.readthedocs.io/en/v2.6.0/networks/kerber.html#extreme-kerber-vorstadtnetze) |
| Household | 145 houses with a mix of 4-person (4800 kWh/year) and 5-person (5500 kWh/year) household. |
| PV system | 3 kW (87 % efficiency) |
| EV Chargers | 22 kW public chargers spread across the network. |
| Charging Strategies | EV-basic, EV-smart and EV- v2g (smart and vehicle to grid capabilities) |
| Electricity price | Wholesale prices |

Table 3-1 List of elements simulated in the co-simulation to evaluate the impact of EVs on the grid.

A number of EV chargers with a maximum rating of 22 kW are distributed uniformly along each of the feeders of the Network. In this work, only public charging facility is considered. The number of chargers depends on the simulated case to match a certain number of EVs per charger ratio. Depending upon the number of cars being simulated in a given scenario, the required number of chargers are distributed across all the feeders of the network. For example, if the number of EVs in the network is half the number of households and the ratio of EVs to charger is 4:1, then a charger is placed at every eighth node in the network.

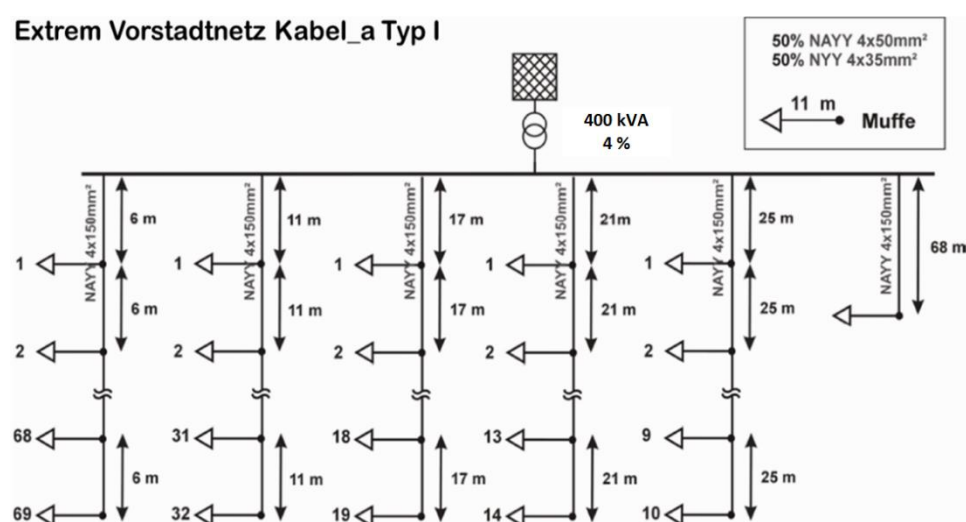


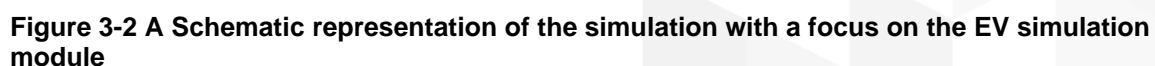
Figure 3-1 Kerber network used in the simulation study

3.1.3 Simulation

Different simulators for the grid, EVs, PVs and household loads are initiated and synchronously run using the Mosaik's ecosystem. The grid is simulated using Pandapower. The EVs are simulated using python modules which model the EV charging behaviour whereas the profiles of PVs, household loads and electricity prices are read directly from the time-series data. The exchange of data between these simulators is facilitated by Mosaik. The simulation time step is 15 minutes and at each time-step power-flow is calculated. At each time step the SoC values of the EVs connected to the charger are updated and if required, the arrival and departure events are executed. All the load and generation profiles and price data have either 15 minutes time resolution or are interpolated to have a 15-minute resolution. A total of 35 days is simulated (from January 1 to February 4). Month of January was chosen because due to higher electricity demand during the winter period, the grid is more burdened as compared to the summer months. At the beginning of the simulation, all the EVs are either connected to the chargers or are in the network waiting to be connected. In the initial part of the simulation, one by one all the EVs are charged with the desired energy and depart so that the EVs in the queue can connect. Data from the first 5 days of the simulation is discarded so that all the EVs have completed their first charge session at least once and have departed the network.

During the simulation, the EVs arrive at the network area according to the scheduled arrival time. At the time of arrival, a charging session is picked based on the selected profile of the EV user. The charging session has information about the scheduled departure time. The desired energy level before departure is calculated based on the required energy per session data which is a percentage of the battery capacity of the EV. The EVs connect to the first available charger in the list of chargers and begin the charging session.

In case all the chargers in the network are full, the EVs arriving to charge are put into a first in first out queue using a serial order. The chargers have also been given a serial number. This means that, when an EV arrives at the network, it will look at the list of chargers serially to check if they are free for connection. The chargers in the first feeder are at the front of this serial list and will be occupied more than the chargers which are at the end of the serial list. If at its original departure time, the EV has not charged to its required SoC level, then the EV is considered delayed. The three charging strategies mentioned in section 3.1.1 were used to run for all the EVs for the entire period of the simulation. A schematic representation of the simulation process focussing on the EV simulation module is presented in Figure 3-2.



To compare the simulation results from different cases, performance indicators from the perspective of the network operator and the EV users are created. From the perspective of the network operator, the impact of EVs in terms of the overloading of the transformer and under voltage at network nodes is studied. The transformer is considered overloaded if the power measured at its secondary terminal is higher than the rated capacity of the transformer. The duration of transformer overloading (in terms of percentage of total simulation steps) and maximum load of the transformer are measured. It is expected that when the EVs use cost-optimized charging schedule, the chance of transformer overloading would increase as a greater number of EVs would like to charge at the same time instances when the price is lower. The

longest feeder of 69 households faced the most severe cases of low voltage, hence to account for under voltage events, voltage is measured at the end of that feeder (at node 69). Under voltage is noted when the voltage measured is lower than the 90 % of the nominal voltage of the network. The duration of under voltage (in terms of percentage of total simulation steps) is also measured. It is expected that with cost-optimized charging, bigger under voltage instances would be observed.

From the perspective of the EV owners, average cost of charging and the number of unsatisfactory charging sessions in terms of delays in departure are used as performance indicators. Average cost of charging is calculated for the whole simulation period and for all the EVs combined. The delay in departure is caused by queues in case all the chargers are occupied. Since the EVs are modelled to leave the charging station as soon as they are adequately charged, it is expected that the cars will have to wait less in the queue when they do not use any cost-optimized charging strategy (like EV-smart and EV-v2g) and the delays will be less.

3.2 Results

This section presents the simulation results for all the three charging strategies on the basis of the performance indicators. For the first scenario, we begin with a very probable (in near future) case where 50% of the households will have EVs. The ratio of cars per charger is 4:1. This serves as the base case. After analysing the results, two more scenarios are simulated. In the second scenario, the number of cars in the network are increased. The number of chargers in the network is also increased to keep the same cars per charger ratio. In the third scenario the ratio of cars per charger is increased to 9:1. To do this, the number of cars in the network is kept the same as scenario 1 while the number of chargers is decreased.

The performance measurement for the three charging strategies is presented using spider plots in Figure 3-3. In these plots, the following reference values have been set for the performance indicators: delayed departure: 100% of the time, voltage dip level: 15% dip from the rated value, voltage dip duration: 10% of the simulation time, transformer overloading duration: 10% of the simulation time, Max transformer loading: 250% of the rated capacity, average costs: 3.3 cents/kWh. Using the plots, the performance indicators of all the three charging strategies can be compared for different scenarios can be compared.

3.2.1 Scenario 1

In the first scenario, it was assumed that half of the households have an EV. So, there are 73 EVs in the network. Using the ratio of 4 EVs per charger, 18 chargers are connected to the grid spread over all the feeders. In a month time, about 1000 arrivals and departures were observed.

Figure 3-3a shows the comparison of performance indicators for the Scenario 1. It shows that the delays in departure increase when EVs use cost-optimized charging strategies (EV-smart and EV-v2g). The total duration for which the transformer is overloaded is lower when price-based, smart charging strategy (EV-smart) is applied when compared to when no price-based strategy (EV-basic) is applied. This is because in case of smart-charging, more EVs charge together in times of low-prices and hence the spread of charging times is less in comparison to the case where no charging strategy is used. More simultaneous charging also causes an increase in the maximum loading of the transformer.

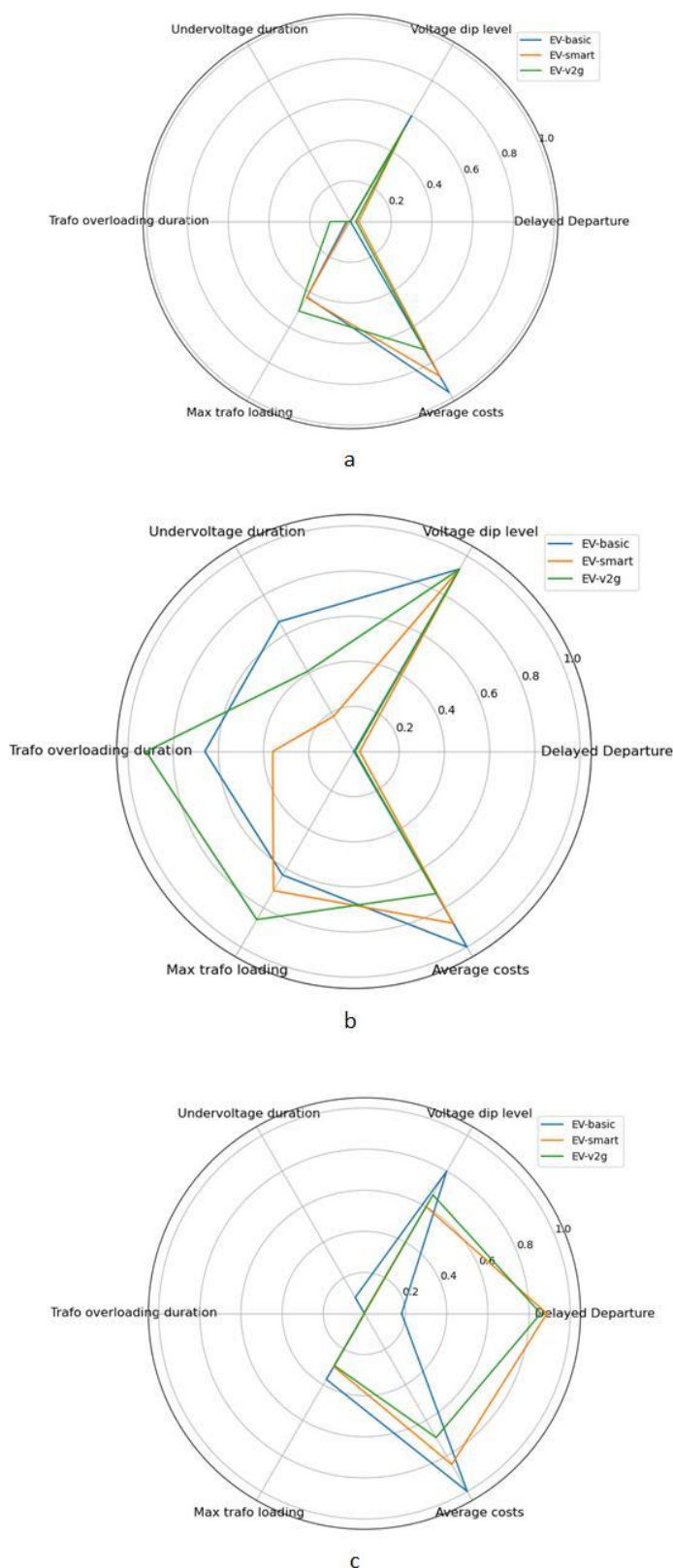


Figure 3-3 Performance comparison of different charging strategies in different scenarios:
 a) Scenario 1: 50% EV ownership and 4 EVs per public charger, b) Scenario 2: 100% EV ownership and 4 EVs per public charger, c) Scenario 3: 50% EV ownership and 9 EVs per public charger

In case of V2G strategy, the cars can discharge at high prices, again to charge at low prices. This causes the total (dis)charging time-period to be longer and results in longer periods of overloading conditions. In terms of cost, the V2G capable smart charging strategy (EV- v2g) performs better than EV-smart strategy which performs better than no price-based strategy (EV-Basic). It is to be noted that any cost associated with potential battery degradation (due to the additional charging cycle) is not accounted for in this study.

The authors were expecting a bigger dip in the voltage measured at the node 69 in the case of EV-smart and EV-v2g strategies. However, this was not observed. This could be because the cables are adequately rated and have low impedance. The minimum voltage observed for all the charging strategies is similar and no under voltage was observed for any of the charging strategy.

3.2.2 Scenario 2

In the second scenario, the number of EVs is increased such that 100% of the households in the network now have an EV. So, there are 145 EVs in total. Using the same ratio of 4 EVs per charger, 36 chargers are present in the network. Since the number of EVs and the chargers have doubled, in a month time, about 2000 arrivals and departures were observed. The performance measurement for the three charging strategies is presented in Figure 3-3b.

Observing the results for scenario 2 and comparing it for three charging strategies, it follows the same logic from the scenario 1. Since, the ratio of EVs to charger remains the same, the delays of similar magnitude are observed when compared to scenario 1. Since there are more chargers in the feeders and more EVs in the network, the power-flow is higher. The lowest voltage recorded at node 69 decreases and under voltage periods are also recorded for all the strategies. The overload and under voltage durations are lower for EV-smart strategy when compared to EV-basic strategy because in the case of EV-smart, more EVs charge simultaneously in times of low-prices making the spread of charging times less in comparison to the case where no charging strategy is used. The durations of overloading and under voltage increase again for EV-v2g strategy. The magnitude of transformer overloading increases for the EV-smart and EV- v2g strategies. The important point is that with an increase in the number of cars, the performance indicators for the grid operators have deteriorated significantly for all charging strategies. The cost of charging still remains at the same level for each strategy as it was for the scenario 1.

3.2.3 Scenario 3

In this scenario, the number of EVs is reverted to the number in scenario 1 (50% of the households in the network have an EV). The number of cars per charger is now increased from 4 to 9. So, in this scenario, only 8 chargers are distributed in the network. In a month time, about 800 arrivals and departures were observed. It is lower than about 1000 arrivals observed during the simulation of Scenario 1. This lower number of arrivals can be explained by the delay faced by EVs while waiting in the queue for an opportunity to charge due to a higher EV to charger ratio. The performance measurement for the three charging strategies is presented in Figure 3-3c.

In scenario 3, the increase of cars per charger resulted in large delays even when the EVs use the EV-basic charging strategy. This is because the waiting periods for EVs to get connected to

a charger have increased. This in turn results in an improvement in performance indicators for the network operator. For example, since in this scenario only 8 chargers are available in the network, effect of simultaneous charging of EVs on the network is reduced. This is why the maximum transformer loading across all the charging strategies is reduced and no overloading is observed. The cost of charging is the same for EV owners. However, the total energy transfer from the grid to the EVs is also much lower in this scenario.

In all the three scenarios, the lowest voltage recorded for different charging strategies is almost the same. This is because the chargers present in the first feeder (also the longest), if free, are always first in the list of chargers to which an incoming EV can connect. This means that, for all the charging strategies, the occupancy rate of the chargers present in this feeder will be high and similar, thus causing similar voltage-drop in the feeder. The reason that the lowest magnitude is observed with no charging strategy could be that in case of smart charging strategies, the EVs avoid charging simultaneously when the prices are high, which tend to coincide with high demand (power-flow) in the network. A distribution of voltage at first and last nodes off all the feeders for the three charging strategies in the three scenarios is present in Figure 3-4. The minimum voltage observed is of same magnitude for all the strategies. The only difference is the overvoltage observed in the case of EV-v2g charging. For the conducted simulations, maximum overvoltage of 1.08 p.u. was observed for the second scenario.

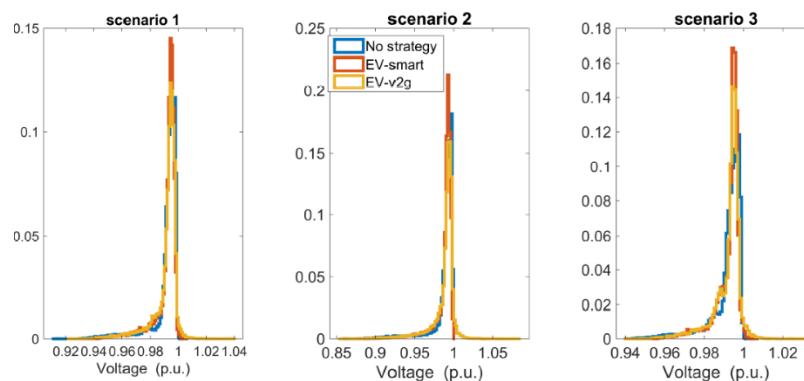


Figure 3-4 Normalized distribution of voltage at first and last nodes off all the feeders for the three charging strategies across all scenarios.

Another observation was reversal of power-flow direction in all the scenarios in case of EV-v2g strategy caused by EV discharging during periods of high price. Reverse power-flow of 48%, 127% and 43% is observed for scenarios 1, 2 and 3 respectively. Measured power at the 400 kVA transformer and electricity price during the first five days of simulation for all the scenarios is presented in Figure 3-5.

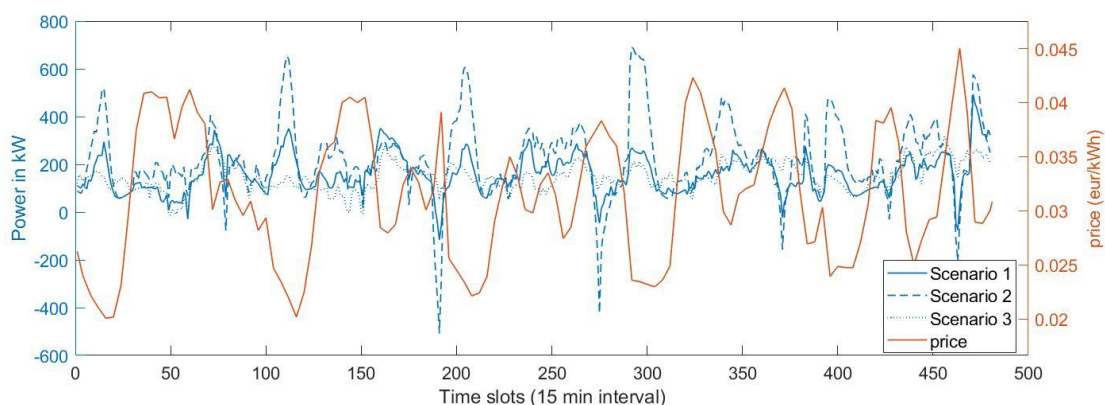


Figure 3-5 Price signal and power-flow measured at 400kVA transformer during V2G strategy for all the scenarios for a period of 5 days.

4. Conclusion and Discussion

Electric mobility is having a significant impact on the electricity system. While it is expected that electric mobility can facilitate the electricity system on a system level and can help absorbing large amounts of variable renewable power generation, the main bottleneck lies within the electricity transmission and distribution infrastructure.

This study assesses the interaction of EVs with a residential distribution grid. Using a comprehensive data-driven model which emulates EV behaviour, the effect of three different types of charging strategies on the grid and the impact of EV ownership rate is presented. It was shown that the parameters like number of EVs per charger can play a very important role in such studies. High number of EVs per charger is suitable for the network performance indicators. However, it will create a lot of delays for the EV owners. In such cases, the impact of different charging strategies on the network becomes insignificant. Also, since the amount of energy transferred in a given period is less, it will result in lower income for the network and the charging point operators and the charging point. From EV owners' perspective, lower amount of energy transfer would mean that the financial benefits of implementing an advanced charging strategy would reduce.

It was also seen that if the number of chargers and the cars increase together, then it affects the performance indicators of the network in a negative way. The maximum load of the transformers increases significantly when EVs implement smart charging strategies. To assess the impact of the V2G charging strategy, overvoltage could also be an important performance indicator. Reverse power-flow in transformer should also be assessed as in case of V2G strategy.

The results presented in this work, are from one simulation of 30-day period for each charging strategy and each scenario. This could mean that when repeated the experiments could result in slightly different numbers for the performance indicators discussed in the paper. Repetition of the simulations for a few times (for examples using the Monte Carlo approach) would help establish the variance in these results. The optimization problems in smart charging strategies were solved with a time-constraint of 30 seconds. More generous time-constraints may also affect the final numbers of the indicators to some extent.

For future work, the role of the network operator in mitigating the network problems using schemes like bandwidth tariffs could be investigated. The full potential of the co-simulation-based approach can further be utilized by integrating a third-party EV charging controller software/hardware into the system to test their performance under different scenarios.

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6. Appendices

6.1 Description of task 4.7.1 as described in the project proposal

Task 4.7.1 is a subtask of Task 4.7 Electric mobility.

Subtask 4.7.1 Electromobility-grid interaction

The energy system integration in the positive energy district involves connection of the power grid to the mobility infrastructure, that is the network of EV charging stations, and connection to the heating infrastructure like electrical heat pumps for heating and cooling that are applied in the buildings. The combination of the technologies mentioned above will have an impact on the local distribution grid in the positive energy district. This impact will be studied by simulation of the load flow with simulation tool 'PowerFactory'. Processing of production and demand profiles will be done with a dedicated tool, developed in the programming language Python.

6.2 PR36 - DNV - Software in the Loop

(applied to the electromobility grid impact analysis)

In work package 10 the exploitation strategies beyond the project are defined. One exploitation strategy is related to the results demonstrated in this report: PR36 is about the ‘Software in the loop’ laboratory of DNV. The simulation infrastructure and modelling used and developed in this subtask is set up in such a way that it can be used to test different EV-charging and control strategies, as a ‘black box’ through software in the loop and co-simulation.

This appendix gives a short introduction of this case. In the results of WP 10 the cost benefit analysis and short business plan can be found.

6.2.1 Business idea behind the Software in the Loop laboratory

Local energy management and control of electricity generation and demand are becoming essential to managing the electricity system, which is increasingly becoming dynamic because of the increase of variable renewable power generation and electrification of demand. Historically, to maintain the power balance, only large-scale generation was controlled. Now the importance of demand response and storage is increasing, not only to maintain the global balance between power supply and demand, but also to avoid congestion and voltage problems in the transportation and distribution network. The implementation of controlling large amounts of small-scale electricity generation and storage is facilitated tremendously by digitalization and automation.

The flipside of these developments is that the dependency on control to manage the power system is increasing, and thus the dependency on the software that controls the energy management systems and controllers.

As an assurance company with a strong foothold in the energy and electricity sector, DNV has the ambition to develop services that provide assurance to the application and implementation of digital energy control and energy management in the electricity system through a validation laboratory that we call “Software in the Loop (SIL) lab”. Examples of these services are:

- Control hardware in the loop, validating whether the behaviour of controllers comply to standards, regulation and (performance) claims made by the manufacturers.
- Validation of digital twins of energy control and management systems, that precisely mimic the behaviour of their physical originals, so they can be used in simulations and studies, among others.
- Validating the performance and associated risks of energy management systems, for example for smart charging of fleets of electric vehicles.

Through the Software in the Loop (SIL) lab, original equipment manufacturers (OEMs)—using control hard and software in their power electronics and energy management systems—can proof their product complies to regulation, standards, or self-made claims. Other stakeholders such as network operators will get insight in the risks of multiple and different controllers and how they interfere with each other’s behaviour, while investors can get insight in the performance and risks of the energy management systems (EMS) optimizing their combined renewable generation and battery plants under different circumstances.