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Cost-optimal implementation of energy storage systems to mitigate congestion and increase self-consumption in future Dutch low-voltage networks

A master's thesis for Energy Science

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Abstract

Using preliminary versions of Advanced Scenario Management – Phase 2 (ASM-2) hourly supply and demand profiles on neighborhood scale for three 2030 energy transition scenarios, this study answers the research question *"to what extent can energy storage systems (ESSs) serve as a cost-optimal mitigation option to address congestion and increase self-consumption in 2030?"*. As ASM-2 profiles are on neighborhood scale, ESSs are evaluated on neighborhood scale as well, and only congestion in distribution transformers is taken into account. In addition to ESSs, PV-curtailment and grid reinforcement are assessed as additional mitigation options. To determine implementation and control strategies for the three mitigation options taken into account, an optimization study was performed using Mixed Linear Integer Programming in Gurobi (Python), for three different perspectives of ownership and managing ESSs: a collective of prosumers, distribution system operators and a combination of these. Results show that for the prosumer perspective it is likely that ESSs will serve as a cost-optimal mitigation option to increase self-consumption by 2030. For the DSO perspective, it is highly unlikely that ESSs will serve as a cost-optimal mitigation option to address congestion. However in the combined perspective, the potential for self-consumption increase provides reasonable possibilities to mitigate congestion 'along the way'. The actual applicability of ESSs is however heavily dependent on ESS price developments and the further advancement of rooftop-PV. While this is taken into account in this study, it is recommended that further research adopts a monitoring approach with regard to these parameters. As DSOs are currently not explicitly allowed to own and operate ESSs, and prosumers are not allowed to own ESSs collectively on neighborhood scale, changes in laws and regulations would be needed to facilitate this. Lastly, because of (run)time constraints, the geographical scope for this study was restricted to neighborhoods in the Province of Utrecht. However, using the optimization script written for this study, a full scale version will be published as part of the ASM-2 results.

Preface

This study is carried out as part of the project Advanced Scenario Management – Phase 2, which is set up by Utrecht University, Geodan and TNO and supported by Rijksdienst voor Ondernemend Nederland. The ASM-2 project aims to provide insight in changes that will occur in the Dutch electricity grid because of the electrification of heating and transport towards 2030 and 2050. The optimization script produced during this study will in turn help to provide insight in the need and potential for flexibility in the Dutch electricity grid. The official ASM-2 results will be portrayed geographically and made publicly available towards the end of 2020.

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List of abbreviations

ASM-2	Advanced Scenario Management – Phase 2
BAU	Business-as-usual
COP	Coefficient of performance
DOD	Depth of discharge
DSO	Distribution System Operator
EAA	Equivalent Annual Annuity
EAC	Equivalent Annual Costs
EOL	End-of-life
ESS	Energy storage system
EV	Electric vehicle
HP	Heat pump
Lead-acid	Lead-acid battery
Li-ion	Lithium-ion battery
MILP	Mixed Integer Linear Programming
NaS	Sodium-sulfur high temperature battery
NPV	Net present value
NRMSE	Normalized root mean square error
O&M	Operation and maintenance
PV	Photovoltaics
SOC	State of charge
St. dev	Standard deviation
VRFB	Vanadium redox flow battery

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1. Introduction

Over the last few decades there has been an increase in the generation of renewable energy to address issues like climate change (Edenhofer et al., 2011), poor air quality (Buonocore et al., 2016) and the electrification of remote areas (Kuang et al., 2016). Due to the nature of most renewable energy sources, like wind turbines and photovoltaics (PV), this has in turn resulted in electricity generation that is more decentralized and intermittent (Yaqoot, Diwan & Kandpal, 2016). In the Netherlands, the percentage of renewables in the electricity mix was 13.8% in 2017 (Eurostat, 2018), remaining low enough to not cause any major concerns yet. However, both national and international targets for renewable energy generation anticipate a further increase towards 2030 (van der Ree, Honig, Uijt de Haag, Kelfkens & Ven, 2019) and 2050 (Afman & Rooijers, 2017). If not addressed timely, this will have several consequences for both generation and use of electricity, especially with regard to increasing deployment of rooftop-PV in low-voltage networks. Some of the major issues that come with decentralized and intermittent generation are peaks exceeding grid capacity (congestion), low self-consumption due to a (short-term) mismatch between supply and demand, and voltage and frequency instability (reduced power quality) (Lott & Kim, 2014; Teller et al., 2017). In addition, with the rise of electric vehicles (EVs) and heat pumps (HPs), an increase in electricity demand for transport and space heating can be expected. Both mostly draw electricity from low-voltage networks in the evening, especially in residential areas. Often coinciding with a drop in generation through rooftop-PV, this further intensifies congestion and low self-consumption (Lott & Kim, 2014; Teller et al., 2017).

Multiple (costly) mitigation options can be thought of, some with more limitations than others. For example, conventionally increasing grid capacity to deal with congestion might bring unnecessary costs if large peaks do not occur frequently. Otherwise, curtailment of renewable electricity (i.e. purposely discarding electricity if grid capacity is exceeded by a (short-term) surplus) can be a relatively low-cost and therefore attractive solution (ECN, 2017), but also seems objectionable as it perpetuates the need for fossil fuels in the electricity mix. While these and other mitigation options can be useful (supplementary) options (Luthander, Widén, Munkhammar, & Lingfors, 2016; Sevilla et al., 2018; Maier, Nemec-Begluk & Gawlik, 2019), a solution that can both mitigate congestion and support the advance of renewable electricity can be found in energy storage systems (ESSs) (Lott & Kim, 2014; Teller et al., 2017). ESSs can be used to increase flexibility and stability across many compartments of the energy system, including generation, transmission, distribution and end-user services. Specific functions of ESSs that are beneficial for low-voltage networks are (inter and intraday) demand shifting and peak reduction to mitigate congestion and increase self-consumption, and frequency and voltage regulation to maintain power quality (Lott & Kim, 2014; Teller et al., 2017). As ESSs often come with high investment costs, it is important to determine their optimal configuration in terms of technology, location, size, control strategy, and relation to other mitigation options (Sufyan, Rahim, Aman, Tan & Raihan, 2019). While there is already a substantial amount of research on how to optimize ESSs in this respect (Yang, Bremner, Menictas & Kay, 2018; Sufyan et al., 2019), actual optimization studies are rare, especially on a larger geographical scale. For the Netherlands specifically, an optimization study regarding congestion mitigation has been performed by Distribution System Operators (DSOs), but insights for specific regions are not publicly available because of confidentiality and privacy reasons. While general results showed little prospects for purely mitigating congestion through ESSs, the potential for increasing self-consumption and a combination of ESS functions was not thoroughly assessed (ECN, 2017).

Since 2017 a research group consisting of Utrecht University, independent research organizations and commercial parties has been trying to obtain a better understanding of the effects that increased renewable generation, in combination with more EVs and HPs, will have on the Dutch electricity grid. The project, called 'Advanced Scenario Management – Phase 2' (ASM-2), aims to do so by generating annual electricity demand profiles (hourly resolution) for every neighborhood in the Netherlands for the present day, and 2030 and 2050 energy transition scenarios. More so, renewable electricity supply profiles are generated for the same years and scenarios. By combining the two, a residual demand profile arises that can give insight in hourly congestion and supply-demand matching issues on neighborhood level (RVO, 2016). The next step in the project is to examine options to mitigate these issues, as soon as the hourly profiles are finished.

Based on preliminary versions of ASM-2 supply and demand profiles, this research provides a first insight in the potential of ESSs to mitigate congestion and increase self-consumption in future Dutch low-voltage networks on neighborhood level. Assuming perfect forecast, cost-optimal combinations of ESSs, PV-curtailment and grid reinforcement are obtained through Mixed Integer Linear Programming (MILP) in Gurobi (Python). This process is performed for three (economic) perspectives for owning and managing ESSs: neighborhood collective of prosumers (i.e. end-consumers with PV-systems), DSOs, and a combination of the two. To lay the groundwork for this optimization process, important technical and financial parameters for mitigation options (in particular for ESSs) are mapped through literature study and the evaluation of (inter)national policy documents. Considering that ASM-2 profiles are on neighborhood scale, it is assumed that one low-voltage network is present per neighborhood. Moreover, while congestion can in reality occur in various components within low-voltage grids, congestion is only assessed on distribution transformer level. Consequently, at maximum one ESS per neighborhood is implemented. Because the ASM-2 profiles are still preliminary, only supply and demand profiles for 2030 are assessed and demand for EVs is not taken into account. Finally, because of (run)time constraints the geographical scope is restricted to the Province of Utrecht. However, using the optimization script that was constructed during this study, a renewed and full country-scale version of the results in this study will be portrayed geographically as part of the final ASM-2 results.

Considering the ASM-2 supply and demand profiles for its 2030 energy transition scenarios and different perspectives for owning and managing ESSs, the following research question was formed:

> *"To what extent can ESSs serve as a cost-optimal mitigation option to address congestion and increase self-consumption in 2030?"*

In addition to ESSs, PV-curtailment and grid reinforcement are taken into account as other mitigation options. Optimization concerning the deployment and control strategies of these options is carried out conform the principle of perfect forecast.

In section 2 of this report, theoretical background is discussed with regard to the ASM-2 project, Dutch low-voltage networks, PV-curtailment and ESSs. In section 3, assumptions and methods of analysis are discussed with regard to the ESS technology used, perspectives of ownership examined, and the optimization model created for this study. In section 4, the results of this study are reported for different ASM-2 scenarios and perspectives of ownership. In section 5, conclusions are drawn from these results. Finally in section 6, limitations of this report and recommendations for future research are discussed.

2. Theoretical background

This section intends to further elaborate on the scope of this study and introduce some key concepts and definitions. In particular, this section includes relevant background information on the ASM-2 project and the hourly supply and demand profiles used. Moreover, the geographical scope for assessing Dutch low-voltage networks is further discussed, and the definitions for congestion and self-consumption are specified in this light. In addition, the concept of PV-curtailment is explained. Furthermore, incentives for owning and managing ESSs are introduced, as well as relevant policy. Finally, ESS placement and important technical and financial parameters are discussed.

2.1. ASM-2

This study is carried out as part of the ASM-2 project, supported by Rijksdienst voor Ondernemend Nederland (RVO, 2016). Since its start in 2017 multiple organizations have contributed, the most prominent and still remaining contributors are Utrecht University, TNO, and Geodan. The main goal of the project is to analyze the effects that an increase in renewable electricity generation, EVs and HPs have on the Dutch electricity grid, specifically examining congestion and supply-demand matching issues, provide a first insight in possible mitigation measures, and make this information accessible in a geographical interface.

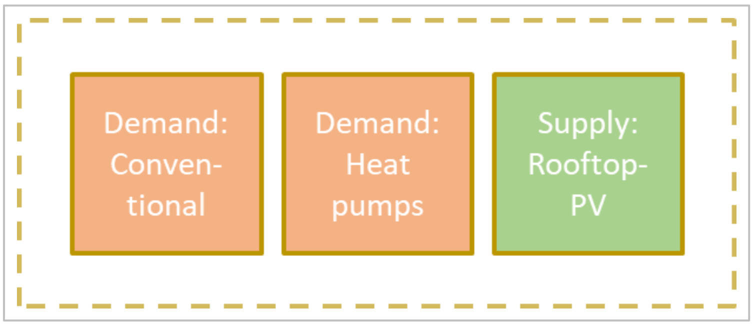
2.1.1. Supply and demand profiles

To assess the effects of an increase in intermittent renewables, HPs and EVs on low-voltage networks, part of the ASM-2 project involves generating supply and demand profiles for Dutch neighborhoods. These profiles are produced with a resolution of one hour for every hour of the year. The following four profiles are produced, for both residences and utilities:

- Supply: rooftop-PV electricity (2017 data and predictions)
- Demand: conventional electricity (2017 data)
- Demand: heating and cooling electricity via HPs (predictions)
- Demand: transport electricity via charging of EVs (predictions)

At the time of writing this thesis, demand profiles for EVs could not be finished and were not used. Moreover, only profiles for neighborhoods in the Province of Utrecht were assessed, because of (run)time constraints. A diagrammatic representation of the low-voltage supply and demand profiles used in this study can be seen in figure 1. A brief description of the basic methodology used for constructing these (preliminary) profiles will follow. Note that this comprises preliminary versions and unpublished work from within the ASM-2 project.

Figure 1: ASM-2 supply and demand profiles used in this study



Note. Profiles are created separately for residences and utilities, but summed before being examined as one low-voltage network.

Supply profile: rooftop-PV

By combining building footprints from the Dutch Land Registry (PDOK, 2018) and a high-density LiDAR height point cloud (PDOK, 2015), roof surface polygons characterized by a certain slope and aspect are identified for all buildings in the Netherlands. Hour-by-hour measurements of global horizontal irradiation (KNMI, 2018) are converted to solar resource profiles for each of these roof surfaces by subsequently applying the Erbs diffuse fraction (Erbs, Klein & Duffie, 1982) and Perez transposition (Perez, Ineichen, Seals, Michalsky & Stewawrt, 1990) models. Afterwards, solar elevation angle dependent performance ratios (Moraitis, Kausika, Nortier & van Sark, 2018) and an assumed panel efficiency of 20% are applied to obtain PV-potential profiles.

For the present situation, the installed roof PV-capacity per neighborhood is deducted from three datasets on currently registered PV-systems (CBS, 2019a*;* CBS, 2019b; RVO, 2019). For the future situation, a scenario specific national roof PV-capacity is distributed over neighborhoods proportional to the total yearly PV-potential on their roof surfaces. For both the present situation and future scenarios, the neighborhood capacity is sub-distributed over slope-aspect-positions by applying the same distribution ratios found in a large dataset of registered Dutch PV-systems.

Finally, the capacities per slope-aspect-position are multiplied by corresponding normalized versions of the earlier produced PV-potential profiles to obtain hour-by-hour rooftop-PV supply profiles for each neighborhood.

Demand profile: conventional (residential)

Measured residential electricity demand profiles (Liander, 2019) are normalized and binned into one of three household types (one person, multiple persons without children, or nuclear family). To ensure that the dataset reflects conventional demand, profiles indicating the presence of either a heat pump or PV-system are filtered out.

For each neighborhood, the number of households per type, as well as their current average yearly electricity demand is publicly available (CBS, 2019c). For each household, the corresponding average demand is multiplied with a normalized demand profile randomly selected from the relevant household type bin. By summing the produced household profiles, a single residential conventional demand profile is obtained for each neighborhood. For now, future scenario profiles are assumed to be identical to the present situation profiles.

Demand profile: conventional (utility)

Measured yearly electricity demands on municipality level for 20 Chamber of Commerce segments (CBS, 2019d) are distributed among neighborhoods proportional to their relevant building floor spaces as found in the Dutch Land Registry (PDOK, 2018). Segments for which the majority of the buildings will most likely be connected to a mid or high instead of a low voltage grid, are disregarded.

The remaining segment values are then multiplied by corresponding measured and normalized electricity demand profiles (Liander, 2019). Finally, the resulting segment demand profiles are summed to produce a single utility conventional demand profile for each neighborhood. Similar to residential conventional demand, future scenario profiles are assumed to be identical to the present situation profiles.

Demand profile: HPs (residential)

Using maps on building types (PDOK, 2018), scenario specific modeled energy labels (van ‘t Rein, 2018), neighborhood demography (CBS, 2019c) and real estates (PDOK, 2018), each neighborhood is assigned a residential floor space per home type. Here, each home type is a combination of a building type (detached, semidetached, terraced corner, terraced between, or apartment), an isolation level (low, medium, or high) and a household type (one senior, one adult, two seniors, two adults, multiple adults, one adult with children, or nuclear family). These floor spaces are multiplied by corresponding normalized residential space heating profiles (Ecofys, 2015), then summed, to obtain a single residential space heating demand profile per neighborhood.

Scenario specific national numbers of air-source, ground-source and hybrid HPs are distributed over neighborhoods in a way that national heat transition costs (PBL, 2019a) are kept to a minimum. Here, neighborhoods are either entirely equipped with one of the three types of HPs, or not at all. For the ones that are equipped with HPs, the earlier produced space heating demand profiles are multiplied with an assumed average HP intensity (air-source: 0.33, ground-source: 0.22, hybrid: 0.13 J/J) to produce neighborhood HP electricity demand profiles.

Demand profile: HPs (utility)

Small consumer yearly gas demands per postal code (Liander, 2018) are aggregated to neighborhood level and reduced by residential gas demands (CBS, 2019c) to acquire a yearly gas demand for small utility buildings per neighborhood. These are multiplied with normalized average gas use profiles (NEDU, 2018) to produce neighborhood gas use profiles, which are in turn converted to heat demand profiles assuming an average gas boiler efficiency of 90% and a gas energy density of 9.77 kWh/m3.

It is assumed that utility buildings within a neighborhood make use of the same scenario specific heating technology as was assigned to its residential buildings in the previous section. Again, for neighborhoods equipped with HPs, utility HP electricity demand profiles are generated by multiplying their heating demand profiles by the same HP intensities as mentioned above.

2.1.2. Energy transition scenarios

The ASM-2 supply and demand profiles are generated for three different moments in time: present day, 2030 and 2050. The present day serves as a single reference point. For 2030 and 2050 multiple energy transition scenarios are explored, based on national policy documents and predictions by independent research organizations (PBL, 2019b; Rijksoverheid, 2019). There are three scenarios, called ‘Local’, ‘Regional’ and ‘National’. For 2030, these scenarios differentiate in the amount and the geographical scale on which renewable electricity is generated. For 2050, the scenarios also differentiate on the distribution of different heating strategies throughout neighborhoods. At the time of writing this thesis, supply and demand profiles for 2050 could however not be finished and were not used. Actual values used for 2030 scenarios are depicted in table 1.

Table 1: Values used for 2030 energy transition scenarios

Scenario	Local	Regional	National
Total residential rooftop-PV peak power (GWp)	13.7	10.5	8.1
Total utility rooftop-PV peak power (GWp)	15.4	11.2	7.3
Share of households with air-source HPs	5.8%		
Share of households with ground-source HPs	2.8%		
Share of households with hybrid HPs	5.0%		

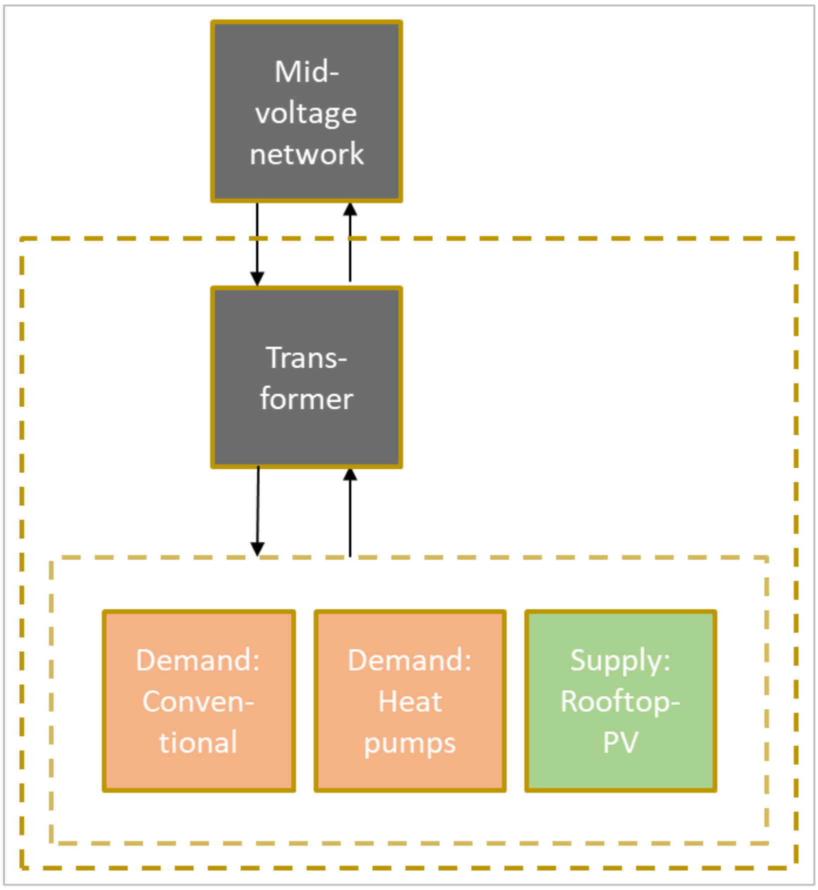
2.2. Dutch low-voltage networks

To gain basic understanding of Dutch low-voltage networks and further define the assessment of ‘congestion’ and ‘self-consumption’, some preliminary research was performed on the characteristics of low-voltage networks, mainly through literature study.

2.2.1. Geographical scale

The geographical scale of low-voltage networks is dependent on the amount and geographical density of connections attached to a single distribution transformer (where mid-voltage networks are connected to low-voltage networks). As a rule of thumb, the scale of low-voltage networks is in the range of 40-50 connections in rural areas to 200-250 in residential areas (Alliander, 2015; Phase to Phase, 2019). Moreover, publicly available location data on network components (Liander, 2020) show that neighborhoods often contain more than one distribution transformer, and that low-voltage networks do not necessarily stick to neighborhood borders. While it is acknowledged that the scale of low-voltage networks often does not correspond with neighborhood borders, this study assumes that every neighborhood consists of a single low-voltage network (with one allocated distribution transformer) as ASM-2 supply and demand profiles are produced on neighborhood scale and due to data availability. A diagrammatic representation of distribution transformers in low-voltage networks as assessed in this study can be seen in figure 2.

Figure 2: The basic low-voltage network as assessed in this study



Note. The outer dashed-line symbolizes the low-voltage network, whereas the inner dashed-line symbolizes the summed value of supply and demand profiles.

2.2.2. Congestion

Congestion in low-voltage networks occurs when the capacity (rated power) of one or more network components is exceeded and thermal limits are reached, either by peaks in demand or surpluses from intermittent renewables. This can result in severe voltage problems, and reduced lifetime and in the worst case collapse of network components (ECN, 2017; Godina, Rodrigues, Matias & Catalão, 2015). Typically, Dutch low-voltage networks contain three main components where congestion might take place: distribution transformers (where voltage is lowered from mid-voltage (10-25 kV) to 400 V), low-voltage distribution boxes (to distribute and optionally further lower voltage from 400 to 230 V), and low-voltage cables (for transport) (ECN, 2017; Phase to Phase, 2020)

As ASM-2 supply and demand profiles are generated on neighborhood scale, this study focuses on congestion at distribution transformer level. Thermal limits for distribution transformers are reached (and congestion occurs) when rated power is exceeded for prolonged periods of time. For short periods of time however it is possible for a transformer to operate above its rated power (up to 110%) while thermal limits are not reached (ECN, 2017). Distribution transformers can be subject to upward congestion (PV-surpluses and/or electricity discharged from ESSs to the mid-voltage network) and downward congestion ((residual) electricity demand for direct consumption and/or charging of ESSs).

2.2.3. Self-consumption

Short term (inter and intraday) supply-demand matching issues are likely to occur more frequently in future low-voltage networks, mainly due to increasing deployment of rooftop-PV. A parameter that can quantitatively define supply-demand matching in this regard is 'self-consumption'. It is used to express the extent to which energy produced within certain system boundaries is used within those same system boundaries. In this study the parameter self-consumption is defined as 'the percentage of electricity produced through rooftop-PV within a low-voltage network, used within that same low-voltage network'.

2.3. PV-curtailment

PV-curtailment as a means of dealing with congestion involves purposely discarding electricity if grid capacity is exceeded by a (short-term) PV-surplus. This process often takes place at the inverter of PV-systems. On first sight this seems objectionable as it perpetuates the need for fossil fuels. However, in recent years it has received more recognition as in some cases grid capacity has in fact limited the deployment of new PV-systems (Tennet, 2019). Because the highest capacity exceeding peaks are often scarce throughout the year, curtailment electricity losses (and costs) for these peaks are relatively low in comparison to grid reinforcement. Following this same principle, PV-curtailment has shown to work complementary to ESSs: by decreasing the ESS capacity required for congestion mitigation, its capacity is used more efficient (Zerrahn, Schill & Kemfert, 2018). Curtailment of renewable electricity in the Netherlands is currently limited to DSO pilot projects or producer initiatives, but in other European countries it is actively implemented (Furusawa, Brunekreeft & Hattori, 2019; Kies, Schyscka & von Bremen, 2016).

2.4. Incentives for owning and managing ESSs

Consistent with the scope of the ASM-2 project, ESS functions that this study examines are demand-shifting and peak-shaving with the aim to mitigate congestion and/or increase self-consumption. Preliminary research showed that the advancement of rooftop-PV in low-voltage networks also causes phase imbalance and power quality issues (Brinkel et al., 2020). While ESSs can actually be helpful in preserving power quality (Teller et al., 2017), this is outside of the scope of this study. Considering the ESS functions taken into account, three incentives for owning and managing ESS are commonly reported:

- Reducing costs for electricity by prosumers
- Reducing costs for congestion mitigation by DSOs
- Combination of incentives: multifunctional storage

For each of these incentives, basic principles and relevant policy are described below.

2.4.1. Reducing costs for electricity by prosumers

Dutch electricity prices for end consumers for the biggest part consist out of taxes. These taxes are planned to be increased significantly towards 2030. Moreover, net metering (Dutch: salderingsregeling) is planned to be completely phased out from 2023 to 2031, disallowing owners of PV-systems to subtract a surplus in generated electricity from their demand from the grid. Instead, PV-owners can sell a surplus of electricity against feed-in tariffs, which are lower than the electricity price (Energiekaart, 2016). These developments can serve as a stimulus for collective ownership of ESSs by prosumers. However, current laws and regulations only specifically allow end-users in the Netherlands to store electricity 'behind-the-meter', i.e. within the boundaries of a single residence (RVO, 2014).

2.4.2. Reducing costs for congestion mitigation by DSOs

The conventional method for DSOs to mitigate congestion in distribution transformers is to increase their capacity, which can come with high costs. ESSs can also mitigate congestion through demand-shifting and peak-shaving. Current Dutch laws and regulations however prohibit DSOs from commercially participating on the energy market, with the exception of compensating for any electricity losses on their part (Netbeheerder Nederland, 2018). As storing electricity likely involves buying and selling electricity to some extent, this is also not allowed. However, real time balancing of the electricity grid is a function already allocated to DSOs, meaning short time storage is already happening in practice. There is a good possibility that regulations will be altered in the future, as ultimately cost-optimal congestion mitigation also leads to cheaper electricity prices for end-consumers (RVO, 2014).

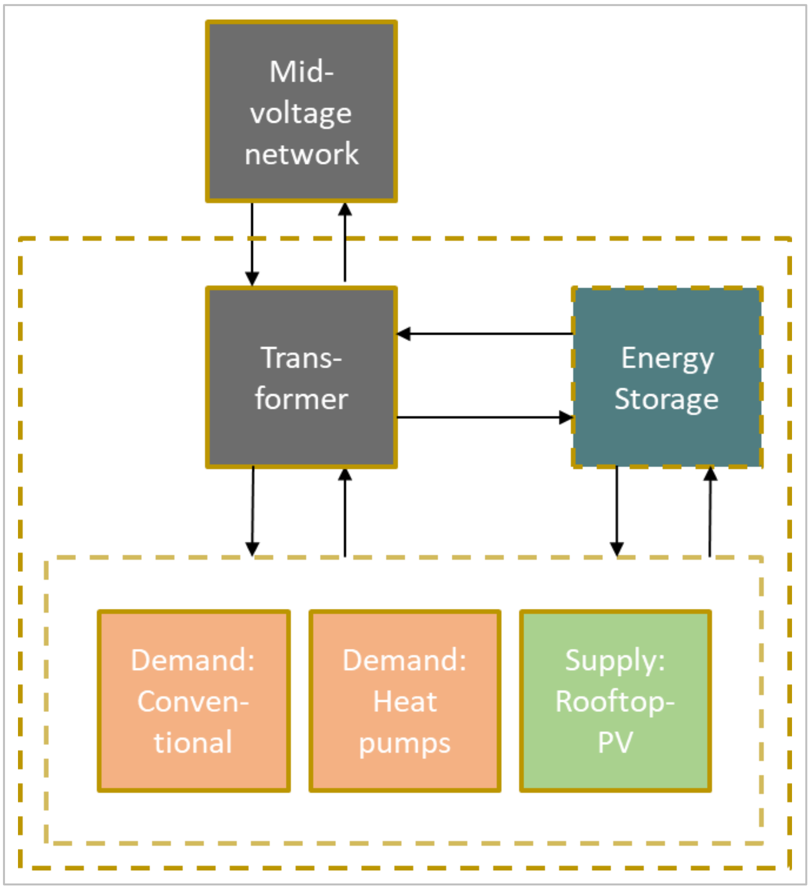
2.4.3. Combination of incentives: multifunctional storage

As ESSs can fulfill several functions, it is likely that ESSs will actually be multifunctional in some low-voltage networks (e.g. mitigating congestion, increasing self-consumption, and preserving power quality). In this regard it is expected that an independent (commercial) third party, also referred to as an aggregator, will own and manage ESSs to make as much profit as possible by buying and selling electricity at different prices (Energiekaart, 2017). However, Dutch policy is focused on maintaining an equal electricity price for every private end-user, and the purely commercial aggregator business case is likely to interfere with that aim. Moreover, electricity market prices are not necessarily driven by congestion, and a commercial perspective based on real-time pricing or price forecasting is proven to have a negative effect on power quality, making it a less favorable option in that sense (Faessler, Schuler, Preißinger & Kepplinger, 2017).

2.5. ESS placement

This study examines supply and demand profiles on neighborhood scale. Consequently it also focuses solely on ESSs on neighborhood scale. Because of the focus on congestion in distribution transformers, the scope of this study is restricted to the placement of at maximum one ESS per neighborhood, directly ‘after’ its distribution transformer (on the low-voltage side). ESSs on this scale are commonly referred to as ‘community storage’ or ‘storage on utility scale’. A diagrammatic representation of ESS placement within low-voltage networks as assessed in this study can be seen in figure 3.

Figure 3: ESS placement within low-voltage networks as assessed in this study



Note. The outer dashed-line symbolizes the low-voltage network, whereas the inner dashed-line symbolizes the summed value of supply and demand profiles.

2.6. ESS technical and financial parameters

The assessment of ESSs in this study is subject to several technical and financial parameters that require some elaboration. This section discusses some of these parameters.

Inverter efficiency

Before electricity can be stored in ESSs placed in low-voltage networks, it is converted from alternating current (AC) to direct current (DC) via an inverter. The reverse process occurs before electricity is returned to the grid. Inverter efficiencies are often defined as 'one-way' efficiencies, and should be accounted for twice in the storage process (Hesse et al., 2017).

'Round-trip' efficiency

Next to inverter efficiency, ESSs can be subject to technology specific efficiencies, often dependent on battery chemistry. It describes the ability of a technology to convert DC electricity to chemical energy and vice versa, and is often defined as 'round-trip' efficiency (not to be mistaken for 'system round-trip efficiency', which includes inverter efficiency). As it describes the combined efficiency of charging and discharging, its square root should be applied when assessing one of these processes (IRENA, 2017; Mongird et al., 2019).

Self-discharge

Self-discharge refers to the process of discharge taking place without purposely discharging the ESS. However as no electricity is discharged to the grid in this process, it actually results in electricity loss (Hesse et al., 2017).

Depth of discharge and state of charge

Depth of discharge indicates the percentage of ESS capacity that is uncharged. Often it is used to describe a maximum ‘allowable’ depth of discharge, as some technologies deteriorate substantially faster beyond this level. The inverse of DOD is the state of charge (SOC), which refers to the percentage of ESS capacity (or absolute value) that is charged (IRENA, 2017).

Degradation and end-of-life

Specifically for battery technologies, degradation usually takes place in the form of capacity-fade, which means that no longer the full originally installed capacity can be used. The end-of-life (EOL) criterion for batteries is traditionally set at 20% capacity-fade (or 80% of original capacity remaining), however various studies show potential for longer life (after 20% capacity fade) of certain battery technologies, and use of second-hand batteries (Casals, García & Canal, 2019; JRC, 2018).

Shelf and cycle-life

Specifically for battery technologies, lifetime is dependent on two factors, namely shelf-life and cycle-life (Schmidt, Melchior, Hawkes & Staffell, 2019; Schram, Lampropoulus & van Sark, 2018). Shelf-life describes the time ESSs can be used before EOL is reached, independent of use intensity. It is often specified in years. Cycle-life on the other hand describes the amount of cycles ESSs can endure before EOL is reached. It is often specified in amount of full range cycles (i.e. from maximum DOD to 100% SOC and back). However, cycle-life is often higher for non-full range cycles than for full range cycles (Masaud & El-Saadany, 2019).

3. Methodology

This section discusses the methodology leading up to multiple results, as well as important assumptions and the model used for optimization. First, assumptions with regard to the ESS technology adopted in this study are discussed, along with values (and respective sources) assumed for important parameters. Second, methods for initial assessment of 2017 and 2030 supply and demand profiles are discussed. Third, the process of determining cost-optimal combinations of mitigation options is discussed for three different perspectives of ownership, namely collective ownership by prosumers, DSOs, and a combination of these. Fourth, actual mathematical equations that form the optimization model are discussed at once for all perspectives. Finally, analysis of model outputs is discussed.

3.1. ESS technology

Specifically with a focus on demand-shifting and peak-shaving, rated power for utility scale storage is usually within the range of 100 kW to 50 MW (IRENA, 2017). Various ESS technologies operate within this range, the majority being battery technologies. Predictions on future applicability of technologies are largely based on learning rates and expected global capacity growth, resulting in divergence between sources and general uncertainty regarding technical and financial parameters. However, four battery technologies in particular are often mentioned as promising for post-2030 application (IRENA, 2017; Jülch, 2016; Masaud & El-Saadany, 2019; Schram et al., 2018):

- Vanadium redox flow battery (VRFB)
- Sodium-sulfur high temperature battery (NaS)
- Lead-acid battery (Lead-acid)
- Lithium-ion battery (Li-ion)[1]

3.1.1. Technology selection

Selection of ESS technologies for actual application is case-specific, but considering the level of detail this study aims to provide a case-specific selection process is deemed out of scope. Instead, on the basis of technology exclusive characteristics, Li-ion is deemed the most appropriate ESS technology for the optimization model in this study. Below some technology exclusive characteristics and successive assumptions are highlighted to substantiate the selection of Li-ion.

VRFB

VRFB has shown great potential in terms of lifetime (both shelf and cycle-life) and maximum DOD (100%) (Mongird et al., 2019). While investment costs are still relatively high, a fast decline is expected towards 2030. Its main limitation however is energy density: VRFB installations require a lot of space for relatively little storage capacity (IRENA, 2017). As this study examines ESSs in low-voltage networks and therefore also in residential areas, VRFB is deemed not a suitable technology.

[1] While Li-ion actually covers a collection of sub-technologies, all with slightly different features, this study considers the branch as a whole.

NaS

NaS performs relatively well on most important technical parameters (DOD, lifetime, energy density). While investment costs are still relatively high, a fast decline is expected towards 2030 (IRENA, 2017). However its high operating temperatures lead to safety concerns and relatively high operation costs (Akinyele, Belikov & Levron, 2017; IRENA, 2017). As there is no indication for these shortcomings to dissolve in the nearby future, NaS is not deemed an appropriate technology for use in this study.

Lead-acid

Lead-acid has traditionally been the go-to technology for a variety of ESS functions, with high technology readiness and very low investment costs compared to other technologies (IRENA, 2017; JRC, 2018). However, its limited maximum DOD (50%) and short shelf and cycle-life largely cancel out this financial advantage. Moreover, Lead-acid is susceptible to abrupt failure after the EOL criterion (20% capacity-fade) is reached, while other technologies have shown reliable operation well after this point. Furthermore, Lead-acid is nearing 'the end' of its technological learning curve, with a high total global capacity already installed compared to other technologies (IRENA, 2017).

Li-ion

Li-ion performs relatively well in terms of maximum DOD (80-85%), round-trip efficiency and shelf-life. While its cycle-life can be a limiting factor in certain applications, improvements in this respect are predicted towards 2030 (IRENA, 2017; Schmidt et al, 2019). Furthermore, the advancement of Li-ion in EVs in recent years have caused its global capacity to increase, and investment costs to decrease heavily (Cole & Frazier, 2019; JRC, 2018, IRENA, 2019). In fact, Li-ion has surpassed Lead-acid as the fastest growing battery technology (IRENA, 2019). It is assumed that this trend will continue as the demand for EVs continues to rise and investment costs continue to decrease. Hence, the ESS technology further utilized in this study is Li-ion.

3.1.2. Technical and financial parameters

This section shows values chosen for technical and financial parameters related to ESSs (table 2). Moreover, values and assumptions for some specific parameters are discussed in detail.

ESS investment costs and c-rate

When assessing ESS investment costs, it is important to make a distinction between costs for 'battery-packs' and stationary storage systems. While the first is mostly relevant for application in EV's, the latter also include costs related to construction and procurement, battery balance and safety management, and the AC-DC inverter (JRC, 2018; Schmidt et al., 2019). Moreover, investment costs are heavily dependent on the ESS's c-rate (JRC, 2018). For utility scale stationary storage, a c-rate of 0.25 is deemed appropriate and hence assumed for this study

(JRC, 2018; Letcher, 2020, p. 270) (and rated power is assumed constant for every SOC). ESS investment prices are adopted accordingly. Multiple extensive reports have been published that predict future ESS investment costs. However, values from one specific report are used in this study as it cites multiple other sources, uses a broad definition of stationary storage systems, focuses on Li-ion specifically and has been published relatively recently (JRC, 2018).

Battery degradation and operation and maintenance (O&M) costs

As mentioned in section 3.1.1., cycle-life is a limiting factor for Li-ion in certain applications. While extensive studies have been done on control strategies that limit battery degradation, this is outside the scope of this study. Moreover, it is assumed that at maximum one full-range (and probably smaller) charge cycle occurs per day (due to the intermittent nature of rooftop-PV profiles) and that by 2030 technological improvements have achieved a cycle-life that is high enough to facilitate this intensity of use. Shelf-life is hence the only determinant factor for ESS lifetime in this study. While capacity-fade occurs because of degradation, it is assumed that yearly O&M will counteract this effect as constraints are set to make sure SOC stays within acceptable bounds (Cole & Frazier, 2019). Prices for ESS O&M are adopted accordingly.

Table 2: Values for (2030) technical and financial parameters related to ESSs

Symbol	**Description**	**Value**	**Unit**	**Source**
η_{inv}	Inverter efficiency	97	%	Hesse et al., 2017
$\eta_{dc,dc}$	'Round-trip' efficiency (dc-to-dc)	96	%	IRENA, 2017
c-rate	Power-to-energy-ratio	0.25	Factor	IRENA, 2017
L_{ESS}	Lifetime (shelf) of ESS	18	Year	IRENA, 2017
$disch_{self}$	Hourly self-discharge	0.9995	Factor	Hesse et al., 2017
$SOC_{max,\%}$	Maximum state of charge in %	100	%	IRENA, 2017
$SOC_{min,\%}$	Minimum state of charge in % (inverse of maximum DOD)	15	%	IRENA, 2017
p_{ESS} (ref)	ESS price for investment (reference)	284	€/kWh	JRC, 2018
p_{ESS} (low)	ESS price for investment (low)	175	€/kWh	JRC, 2018
p_{ESS} (high)	ESS price for investment (high)	406	€/kWh	JRC, 2018
$p_{ESS,vom}$	ESS price for variable O&M (based on total electricity throughput)	0.00025	€/kWh	Cole & Frazier, 2019; Mongird et al., 2018
$p_{ESS,fom}$	ESS price for fixed O&M (based on rated power)	7.50	€/kW per year	Cole & Frazier, 2019; Mongird et al., 2019

3.2. Assessment of unmitigated supply and demand profiles

To find primary anomalies in input data and to create a reference point for the assessment of cost-optimal mitigation options, 2017 and 2030 (all scenarios) supply and demand profiles are combined and basic descriptive statistics are gathered.

3.2.1. Residual demand profiles

Because ASM-2 profiles are on neighborhood scale, the individual distribution of rooftop-PV systems and electricity demand are outside the scope of this study, as are losses within low-voltage networks. As a result, perfect electricity exchange is assumed within low-voltage networks over the course of one hour. Moreover, PV-inverter losses are already accounted for in the ASM-2 supply profiles. Hence, residual demand profiles are created by simply subtracting hourly supply values (rooftop-PV profiles) from hourly demand values (conventional and HP profiles).

3.2.2. Direct self-consumption and initial congestion

The most important descriptive statistics that are gathered are direct self-consumption and initial congestion. Direct self-consumption is defined as PV-generated electricity that is directly used (i.e. within the low-voltage network within one hour and without any mitigation applied). Mean percentage and standard deviation (st. dev.) are given, as are histograms to show distribution across all neighborhoods. Initial congestion is defined as congestion that takes place without any mitigation applied. The amount of neighborhoods were initial (upward and downward) congestion takes place is specified, as is mean hours of (upward and downward) congestion.

3.2.3. Grid capacities

As of March 2020 Dutch DSOs have collectively published aggregated transformer capacities for (almost) every Dutch neighborhood (Liander, 2020). Following the assumed geographical scope for low-voltage networks (neighborhood scale) this study assumes low-voltage network capacity to be equal to the aggregated transformer capacities published by DSOs. Using a rule of thumb, ‘missing’ neighborhood capacities in this dataset are assumed to be 200% in comparison to the highest peak load in the respective ASM-2 conventional (present-day) demand profiles (CE Delft, 2017). Moreover, while transformers can operate above their rated power for short periods of time, this is not taken into account as it is thought not to improve accuracy when compared to the hourly and neighborhood scale of the available data. Furthermore, aggregated transformer capacities are published in apparent power (kVA), but are considered equal to real power (kW) as perfect power quality and phase balance is assumed. Finally, no transformer losses are taken into account.

3.3. Cost-optimal mitigation options (1): prosumer perspective

Considering the incentive of owning and managing ESSs to reduce electricity costs, this section discusses cost-optimal application of ESSs from the perspective of a neighborhood collective of prosumers (hereafter: prosumer perspective). PV-curtailment and grid reinforcement are not applied in the prosumer perspective as the sole incentive is to increase self-consumption, not to mitigate congestion.

3.3.1. Electricity prices

This study assumes that regulations will change and takes into account the possibility where residents within a single neighborhood can collectively own and manage ESSs. In such a situation, it might be possible for residents to act as energy traders on the electricity market. However, as commercial incentives for energy trading have shown to have negative effects regarding congestion management and self-consumption, it is assumed that regular low-voltage prosumer electricity prices are enforced. As of March 2020, it has been determined by law that feed-in tariffs for PV-generated electricity must be at least 80% of the electricity price without taxes. For 2030, prices are based on predictions by independent research organization TNO (PBL, 2019b). Values used are 0.216 €/kWh and 0.0761 €/kWh with and without taxes respectively. The feed-in tariff hence effectively becomes 0.0610 €/kWh. Originally obtained in $€_{2019}$, above values are converted to $€_{2017}$ using average annual inflation rates (Webster, 2020). For the sake of simplicity, it is assumed that net-metering is completely disbanded by 2030.

3.3.2. ESS control strategy

In general, the optimization process makes use of the principle of perfect forecast. This implicates that both application and control strategy of mitigation options are based on 100% accurate predictions on hourly electricity supply and demand. The control strategy for the prosumer perspective is to minimize costs for electricity by increasing self-consumption. This 'increased self-consumption' is hereafter defined as 'optimized self-consumption' which, besides direct self-consumption, also includes PV-generated electricity that is discharged from ESSs (after it was stored first). In a real-life situation (i.e. without perfect forecast), it is not clear in advance when a surplus of PV-generated electricity will be at hand. To be sure of economic benefits, ESSs will usually charge as soon as a surplus occurs (Struth et al., 2013). Conversely in a situation with perfect forecast, ESSs will charge as late as possible before discharging as this minimizes losses through self-discharge. Both situations can facilitate an increase in self-consumption, as can be seen in figure 4 and 5. Both figures also show that any congestion issues are not automatically addressed with this control strategy. Then again, mitigating congestion is not part of the prosumer incentive to own ESSs.

Figure 4: Storage during a day with PV-surplus in the prosumer perspective (without forecast)

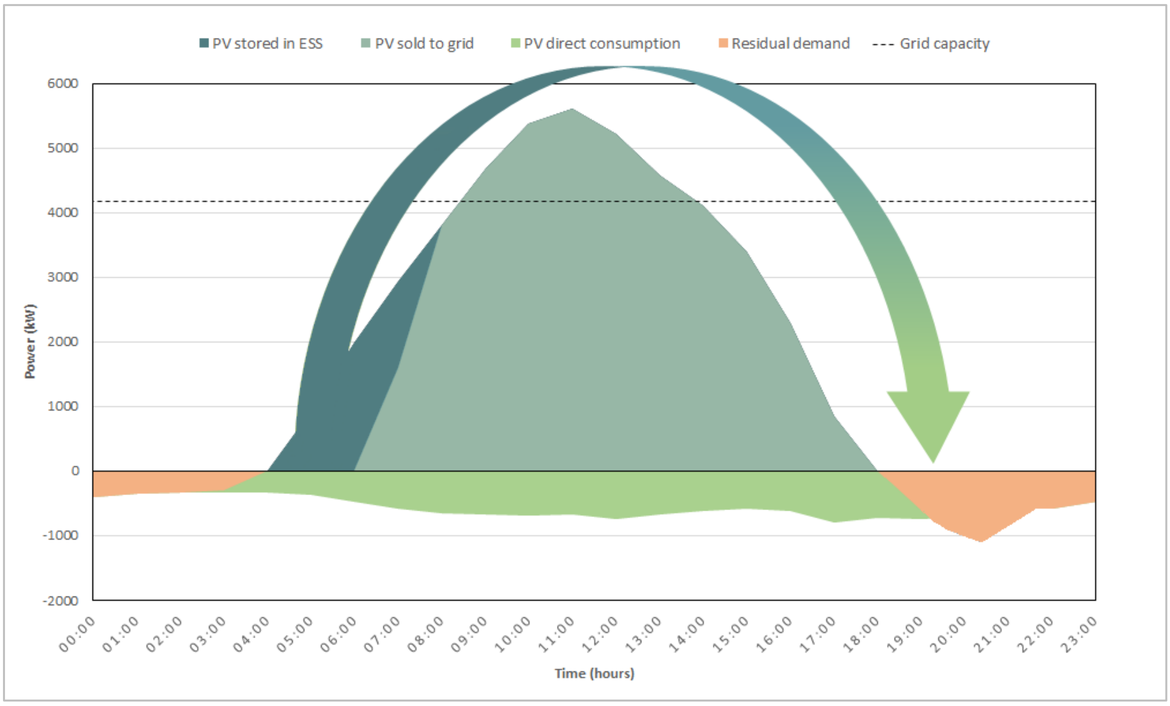
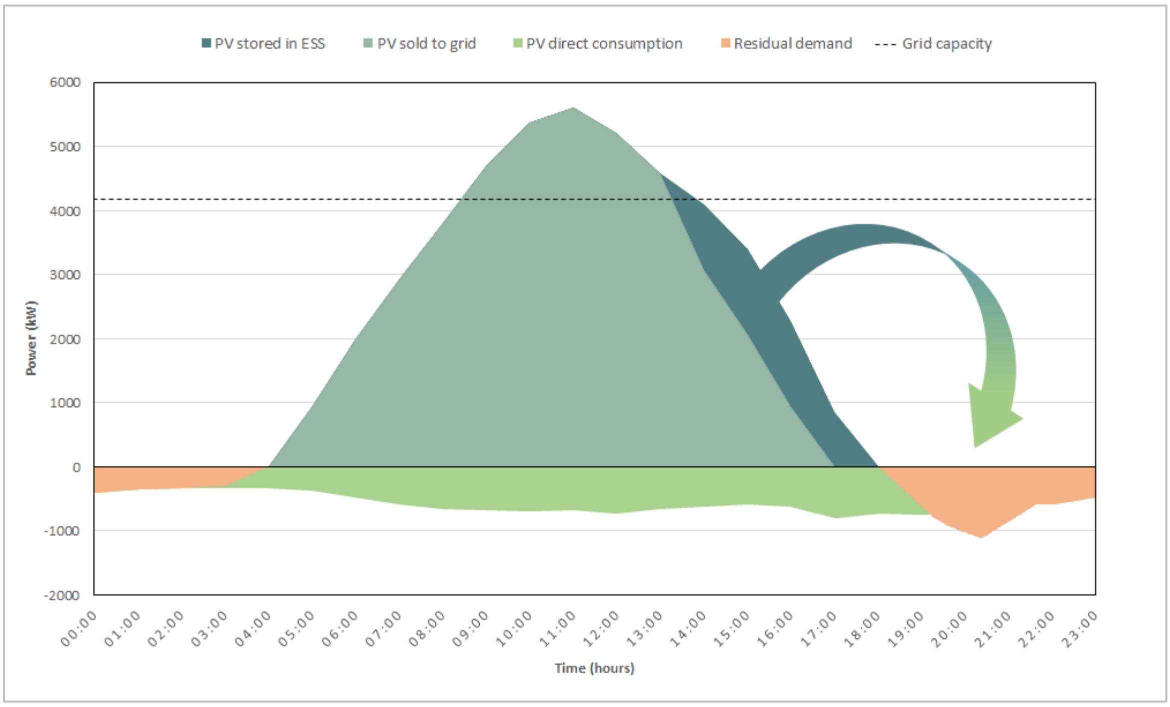


Figure 5: Storage during a day with PV-surplus in the prosumer perspective (perfect forecast)



3.4. Cost-optimal mitigation options (2): DSO perspective

As ESSs can serve as an alternative option to mitigate congestion (as opposed to the conventional grid reinforcement), the perspective of DSOs owning and managing ESSs is taken into account in this study. As additional mitigation options, PV-curtailment and grid reinforcement are assessed. Grid capacities are considered as discussed in section 3.2.3..

3.4.1. ESS control strategy

In general, the optimization process makes use of the principle of perfect forecast. This implicates that both application and control strategy of mitigation options are based on 100% accurate predictions on hourly electricity supply and demand. The control strategy for the DSO perspective is to minimize costs for congestion mitigation by reducing grid reinforcement. ESSs might be charged with PV-generated electricity, but this is only necessary in the case of a grid capacity exceeding PV-surplus. In other cases, grid-bought electricity might also be charged as increasing self-consumption is not part of the DSO incentive to own ESSs.

3.4.2. PV-curtailment

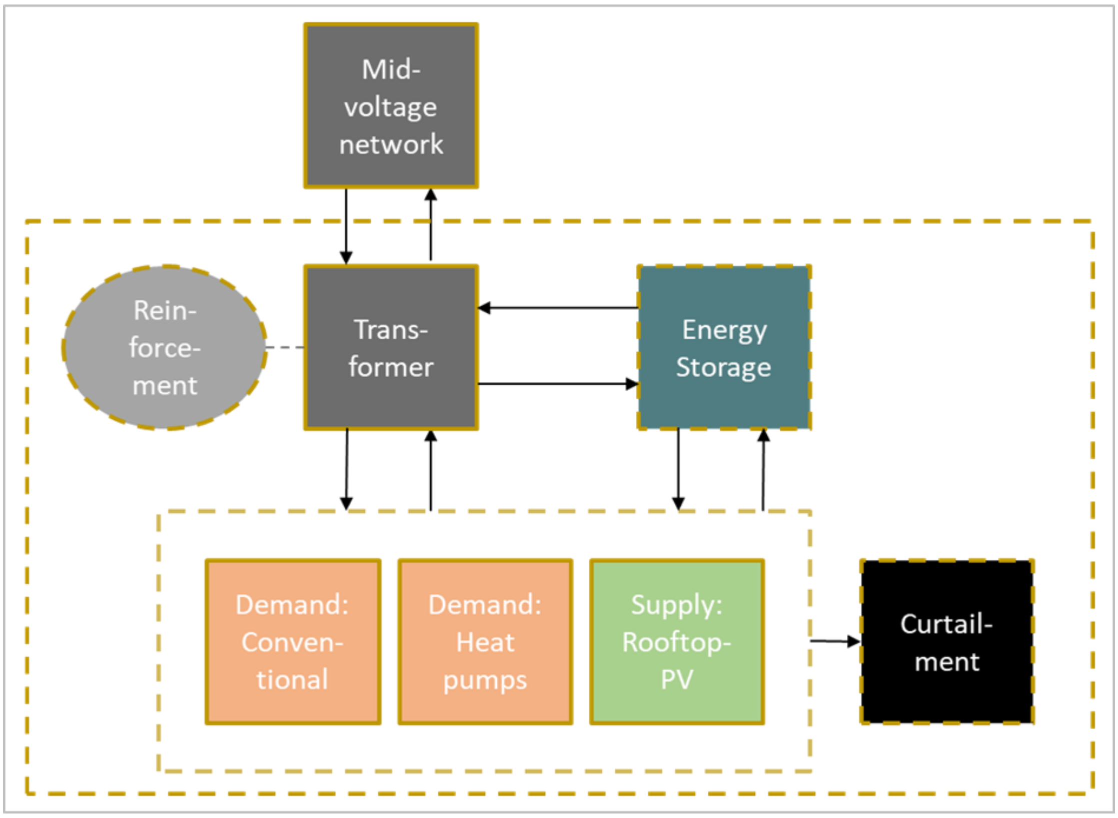
In addition to ESSs, PV-curtailment is applied to take care of the largest but scarce PV-surplus peaks. Since 2013, regulations in Germany allow and facilitate curtailment of renewable electricity, however with certain restrictions. For new PV-systems, consumers have the choice for power-based curtailment or energy-based curtailment. Power-based curtailment involves installing inverters with 70% power of the installed peak power, which is a clear in advance indicator, but can result in curtailment when there is no congestion. On the other hand, energy-based curtailment allows DSOs to 'smart curtail', with no restrictions on reduced power but to a maximum of 3% of all PV-generated electricity. As the latter requires full reimbursement of curtailed electricity, this is often also a satisfactory option for prosumers (Furusawa et al., 2019; Kies et al., 2016)

Dutch DSOs are vocal about implementing curtailment in future years to save reinforcement costs (ECN, 2017). This study assumes that policy regarding curtailment will be similar to German regulations. Consequently this study assumes that curtailment will be allowed up to a maximum of 3% of all PV-generated electricity, set as a constraint that is evaluated independently on neighborhood scale. For the sake of simplicity, it is assumed that PV-curtailment does not require investment costs. A diagrammatic representation of PV-curtailment as mitigation option within low-voltage networks can be seen in figure 6.

3.4.3. Grid reinforcement

Reinforcement of transformer capacity can be performed with two different techniques. First, (old) transformers can simply be replaced with new transformers with a higher rated power, preferably after the old transformer has completed its full lifecycle. Alternatively, a new transformer can be 'added' at a strategical position in a low-voltage network, effectively splitting the network between these transformers. The lifetime of distribution transformers (further referenced as L_{grid}) is estimated at 60 years (Elia, 2019). Because of scarcity in publicly available data on actual transformer age and geographical boundaries of actual low-voltage networks, this study does not take into account 'logical' moments for replacement or strategic placement of transformers. Considering uncertainties and the level of detail that come with these assumptions, it is chosen to not set a minimum for reinforcement in terms of rated power. However, as ASM-2 supply and demand data is provided in kW rounded to whole numbers, minimal grid reinforcement is effectively 1 kW. In regard to prices for distribution transformer reinforcement/placement, a range of 20.000 to 70.000 €/MW was found in literature and policy documents (Ecofys, 2014; Enexis, 2020). As multiple sources opt for a price in the range of 35.000 €/MW (Dekker, 2016; Ecofys, 2014), this value (35 €/kW) was adopted as constant price for both transformer reinforcement and replacement (further referenced as p_{grid}). A diagrammatic representation of grid-curtailment as a mitigation option within low-voltage networks can be seen in figure 6.

Figure 6: All mitigation options within low-voltage networks as assessed in this study



Note. The outer dashed-line symbolizes the low-voltage network, whereas the inner dashed-line symbolizes the summed value of supply and demand profiles.

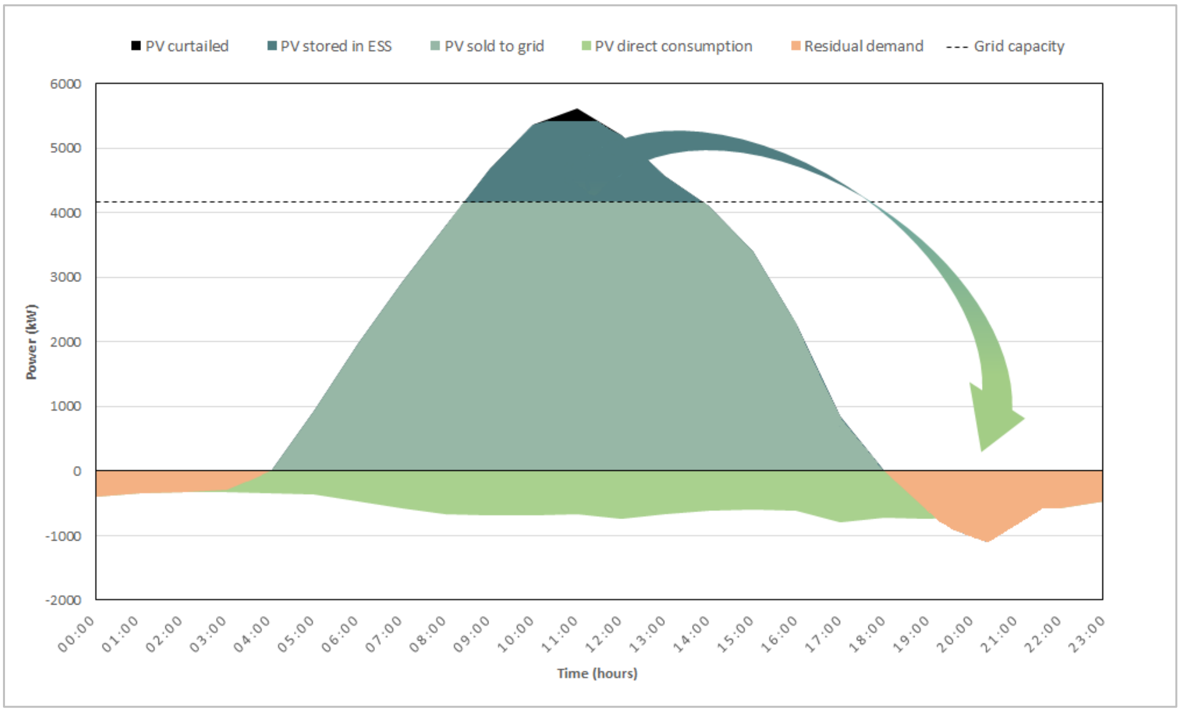
3.5. Cost-optimal mitigation options (3): combined perspective

As explained in section 2.4.3., multifunctional application of ESSs is deemed promising and often interpreted as a commercial service provided by a third party (or aggregator). However, market prices are often not based on congestion levels, and commercial incentives for energy trading have shown to cause negative effects on power quality. Considering these limitations, the ‘combined perspective’ has been created for this study. In this perspective mitigating congestion and increasing self-consumption are both incentives for owning and managing ESSs, but standard 'prosumer prices' for buying and selling electricity are imposed (as discussed in section 3.3.1.). As additional mitigation options, PV-curtailment and grid reinforcement are assessed. Grid capacities are considered as discussed in section 3.3.2..

3.5.1. ESS control strategy

In general, the optimization process makes use of the principle of perfect forecast. This implicates that both application and control strategy of mitigation options are based on 100% accurate predictions on hourly electricity supply and demand. The control strategy in the combined perspective is to minimize costs both for congestion mitigation (DSO oriented) and electricity (prosumer oriented) by reducing grid reinforcement and increasing self-consumption. With perfect forecast, charging PV-surpluses that exceed grid capacity get highest priority (Struth et al,. 2013), as is demonstrated in figure 7. Secondary, charging is performed as late as possible before discharging to minimize self-discharge losses. In addition to ESSs, PV-curtailment is applied to take care of the largest but scarce PV-surplus peaks.

Figure 7: Storage and curtailment during a day with PV-surplus in the combined perspective (perfect forecast)



3.5.2. PV-curtailment

PV-curtailment is considered in the same way as in the DSO perspective and hence discussed in section 3.4.2..

3.5.3. Grid reinforcement

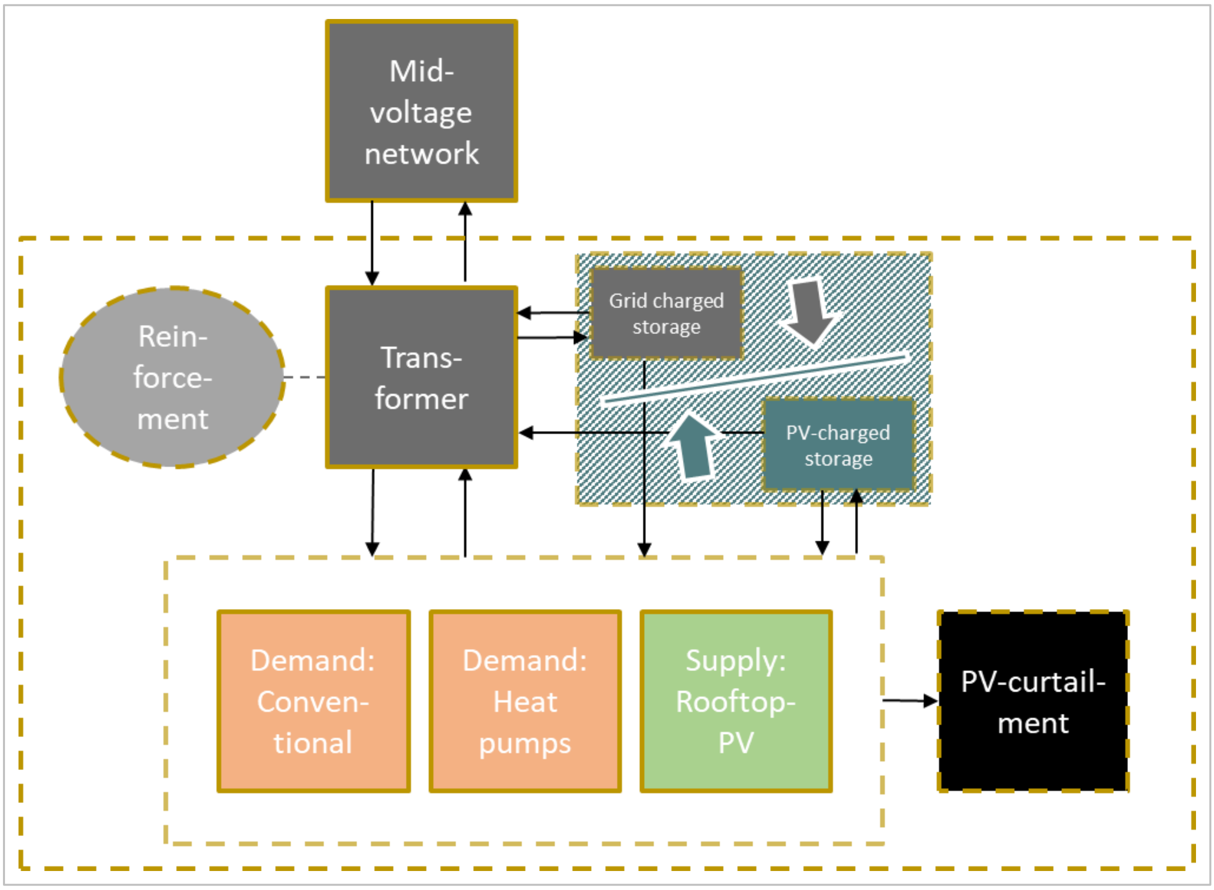
Grid reinforcement is considered in the same way as in the DSO perspective and hence discussed in section 3.4.3..

3.6. Optimization model: Mixed Integer Linear Programming

To obtain cost-optimal mitigation options for all perspectives, optimization was carried out with Mixed Integer Linear Programming (MILP). MILP allows for one or more variables to have integer values (whole numbers), which enables the possibility to adopt binary decision variables in the model. For this particular model decision variables are needed to determine the mode of operation for ESSs, as will be explained in the following sections. The optimization script was written for Python, using the MILP dedicated module Gurobi (Gurobi, 2019).

While the model in general follows the principles of system compartments and electricity flows as depicted in figure 6, some alterations had to be made to determine levels of optimized self-consumption. With one large energy storage compartment it is not possible to keep track of the amount of PV-generated electricity that flows through the ESS, as it also possible to charge grid-bought electricity. Hence, two interchangeable virtual compartments were created inside the system, where either PV-generated or grid-bought electricity is charged, with corresponding additional electricity flows. A diagrammatic representation of these two compartments implemented in the ESS can be seen in figure 8.

Figure 8: System boundaries and virtual compartments for energy storage



Note. The outer dashed-line symbolizes the low-voltage network, whereas the inner dashed-line symbolizes the summed value of supply and demand profiles.

3.6.1. Model variables

Variables are created in Gurobi to model electricity flows, and capacities and mode of operation of mitigation options. All variables are continuous variables, with the exception of variables for ESS mode of operation which are binary decision variables. The majority of these variables are created for each hour of the year, which is notated and further referenced as time periods t in set T (equation 1). This results in the creation of over 100.000 variables per neighborhood for each optimization process.

$$T = \{t_1, t_{2,} \dots, t_{8760}\} \quad (1)$$

, with T as yearly set "T" and t as time periods (hours).

Decision variables

All mitigation options examined can possibly co-exist in one neighborhood. Decision variables are hence only necessary to determine mode operation, which is relevant only for ESS. Two binary decision variables are made for charging and discharging mode (table 3). The constraints applied to these variables will also allow for 'idle' ESS mode, as will become clear in section 3.2.3..

Continuous variables

Continuous variables in Gurobi can take on any value between 0 and ∞ by default (including float numbers), as is usual in mathematical programming (Gurobi, 2020). In this study, continuous variables are used to model the capacity of ESS and transformer reinforcement, and electricity flows (both basic and related to ESS and PV-curtailment), as can be seen in table 3.

Table 3: Model variables and descriptions

Name/symbol	Description	Type	Quantity
ch_{bin}	Decides if ESS is in charging mode (1) or not (0)	Binary decision	$\forall\, t \in T$
$disch_{bin}$	Decides if ESS is in discharging mode (1) or not (0)	Binary decision	$\forall\, t \in T$
$grid_{cap,reinf}$	Added transformer capacity (power) in kW	Continuous	single
cap_{ESS}	Installed capacity of the ESS in kWh	Continuous	single
SOC_{tot}	Total absolute SOC of the ESS in kWh	Continuous	$\forall\, t \in T$
SOC_{pv}	Absolute SOC allocated to PV-generated electricity in kWh	Continuous	$\forall\, t \in T$
SOC_{grid}	Absolute SOC allocated to grid-bought electricity in kWh	Continuous	$\forall\, t \in T$
pv_{curt}	PV-generated electricity directly curtailed by the DSO in kWh	Continuous	$\forall\, t \in T$
pv_{grid}	PV-generated electricity directly sold to the grid (and not curtailed!) in kWh	Continuous	$\forall\, t \in T$
$grid_{dem}$	Grid-bought electricity directly used for electricity demand in kWh	Continuous	$\forall\, t \in T$
pv_{ch}	PV-generated electricity charged into the ESS in kWh	Continuous	$\forall\, t \in T$
$grid_{ch}$	Grid-bought generated electricity charged into the ESS in kWh	Continuous	$\forall\, t \in T$
$disch_{pv,dem}$	PV-generated electricity discharged from the ESS and used for electricity demand in kWh	Continuous	$\forall\, t \in T$
$disch_{pv.grid}$	PV-generated electricity discharged from the ESS and sold to the grid in kWh	Continuous	$\forall\, t \in T$
$disch_{grid,dem}$	Grid-bought electricity discharged from the ESS and used for electricity demand in kWh	Continuous	$\forall\, t \in T$
$disch_{grid,grid}$	Grid-bought electricity discharged from the ESS and sold to the grid in kWh	Continuous	$\forall\, t \in T$

3.6.2. Model objective: EAA maximization

This section includes some equations that describe the optimization model used in this research, specifically the model objective. The main goal of the optimization is to decide which (combination of) investment(s) is cost-optimal regarding three mitigation options, namely grid reinforcement, ESS and PV-curtailment. Generally in capital budgeting, to determine whether an investment is profitable, the 'Net Present Value' (NPV) is calculated. In addition to totaling the initial investment and annual cash flows, it corrects for the time-value of money by taking in to account an annual discount rate for annual cash flows (Blok & Nieuwlaar, 2016). However, this method is unpractical when comparing investments with different lifetimes, as is the case with grid reinforcement and ESSs. In this situation, the Equivalent Annual Annuity (EAA) approach can be adopted. The EAA for an investment is calculated by dividing the NPV with an 'annuity factor' that is subject to the investment lifetime (Shim, Siegel & Dauber, 2008). The EAA thereby converts both initial investment and discounted cash flows to a single annuity, i.e. a constant annual cash flow that is independent of investment lifetime. As a result, using the EAA allows for all three mitigation options to be optimized in a single mathematical equation. Moreover, as all annual cash flows in this study are annuities by definition, as they are based on a single year of supply and demand profiles and thus constant. The annuity factor is hence only applied to initial investments.

Typically it is argued that one should only advance on investments with a positive EAA (thereby indicating profitability). In this case however, the business-as-usual (BAU) cases for the DSO and combined perspective involve a negative EAA, as grid reinforcements do not provide annual benefits. Hence a situation arises where a negative EAA can still be beneficial compared to the BAU case- it just needs to be as high as possible. Alternatively, when benefits are not per definition not included in an objective function, a negative EAA can be written as a positive EAC (Equivalent Annual Costs).

The EAA method presumes that investments can and will be renewed indefinitely and that investment costs and cash flows will stay constant forever, which is of course not realistic. However, this study also assumes that inter(national) energy transition targets, regulations and subsidies will ensure that the demand for low-voltage network flexibility will continuously increase towards 2050. Vice versa, costs for ESSs are expected to continuously decrease. Hence the EAA method is considered appropriate for providing insight in the general profitability of ESSs.

Main functions: EAAs

For the three perspectives of ESS ownership that are taken into account in this study, the respective EAA objective functions are expressed in equations 2, 3 and 4, and broken down further in equations 5-13. ESS technology specific parameters, chosen values, and respective sources are used as discussed in table 2 (section 3.1.). Electricity prices are used as discussed in section 3.3.1.. Values with respect to grid reinforcement are discussed in section 3.4.3..)

$$EAA_{prosumer} \ = \ B_{el,costs,sav} - C_{ESS} - \frac{I_{ESS}}{\propto_{ESS}} \qquad (2)$$

, with $EAA_{prosumer}$ as the EAA for the prosumer perspective of ownership, $B_{el,costs,sav}$ as annual benefits associated with saved electricity costs, C_{ESS} as annual costs associated with ESS O&M, I_{ESS} as the initial investment for the ESS, and $\propto_{ESS}$ as the annuity factor related to ESS investments. $\propto_{ESS}$ is broken down further in equation 4, $B_{el,costs,sav}$ is broken down further in equations 6, 7, and 8, C_{ESS} is broken down in equation 10, and I_{ESS} is broken down further in equation 12.

$$EAA_{DSO} \ = -C_{el,loss} - C_{ESS} - \frac{I_{ESS}}{\propto_{ESS}} - C_{curtailment} - \frac{I_{grid,reinforced}}{\propto_{grid}} \qquad (3)$$

, with EAA_{DSO} as the EAA for the DSO perspective of ownership, $C_{el,loss}$ as annual costs associated with electricity losses in the storage process, $C_{curtailment}$ as annual costs associated with PV-curtailment, $I_{grid,reinforced}$ as the investment for grid reinforcement in the optimized case and $\propto_{grid}$ as the annuity factor related to grid reinforcement investments. $\propto_{grid}$ is broken down further in equation 5, $C_{curtailment}$ is broken down further in equation 11. $I_{grid,reinforced}$ is broken down further in equation 13.

$$EAA_{combined} \ = \ B_{el,costs,sav} - C_{ESS} - \frac{I_{ESS}}{\propto_{ESS}} - \frac{I_{grid,reinforced}}{\propto_{grid}} \qquad (4)$$

, with $EAA_{combined}$ as the EAA for the combined perspective of ownership.

Annuity factor and discount rate

As explained earlier in this section, the annuity factor is used to calculate the EAA for discounted cash flows and initial investments. Only the latter is the case here, as all annual cash flows in this study are considered annuities by definition. The annuity factor is subject to investment lifetime. Hence, two different annuity factors are used in this study, one for ESS investment and one for grid reinforcement investment. Moreover, the annuity factor is subject to the discount rate. The discount rate for this study is assumed to be constant at 7%, which is considered middle ground between sources in the field of renewable energy and Dutch DSO statements regarding long term investments (Alliander, 2019; Schmidt et al., 2019).

$$\propto = \frac{(1+r)^{L} - 1}{r \cdot (1+r)^{L}} \qquad (5)$$

, with r as the discount rate and L as the investment lifetime, in this case for either ESS (L_{ESS}) or grid reinforcement (L_{grid}).

Annual benefits: saved electricity costs (prosumer)

For prosumers, the only benefit involves saved electricity costs, which originates in storing and self-consuming PV-generated electricity in an ESS. Any costs related to electricity losses originating in the storage process are automatically accounted for through parameters for efficiency and self-discharge in the $C_{el,costs}$ function (equation 8) and ESS balance constraints (section 3.8.3). In the combined perspective, the costs for these losses are in reality shared between DSO and prosumer. However as this has very little, if any, influence on the total EAA, no distinction is made in this regard for the sake of simplicity.

$$B_{el,costs,sav} = C_{el,costs,bau} - C_{el,costs} \tag{6}$$

, with $C_{el,costs,bau}$ as the annual costs of electricity for prosumers in the BAU case, and $C_{el,costs}$ as the annual costs of electricity in the optimized case. Both are further broken down in equations 7 and 8 respectively.

$$C_{el,costs,bau} = E_{el,bought,bau} \cdot p_{el,buy} - E_{el,sold,bau} \cdot p_{el,sell} \tag{7}$$

, with $E_{el,bought,bau}$ and $E_{el,sold,bau}$ as amount of electricity bought and sold in the BAU case in kWh, and $p_{el,buy}$ and $p_{el,sell}$ as the price for buying and selling electricity from/to the grid in €/kWh.

$$C_{el,costs} = \sum_{t \in T} (grid_{dem}[t] + grid_{ch}[t]) \cdot p_{el,buy} - \big(pv_{grid}[t] + \big(disch_{pv,grid}[t] + disch_{grid,grid}[t]\big) \cdot \eta_{inv} \cdot \sqrt{\eta_{dc,dc}}\big) \cdot p_{el,sell} \tag{8}$$

Annual costs (1): electricity losses through storage process (DSO)

In the prosumer and combined perspective, costs related to electricity losses in the storage process are automatically accounted for through parameters for efficiency and self-discharge in the $C_{el,costs}$ function (equation 8) and ESS balance constraints (section 3.8.3). In the DSO perspective however, buying and selling electricity for financial gain is by law not part of DSO activities and thus $B_{el,costs,sav}$ (and $C_{el,costs}$) are not included in the objective function. As noted in section 2.4.2., it is however still the obligation of DSOs to make up for any electricity losses caused by their activities. In the case of storage processes, involving either PV-generated electricity or grid-bought electricity, it is assumed that all losses are compensated for by buying electricity for the regular buying price (including taxes). The resulting costs are described by $C_{el,loss}$ in equation 9 and added to the DSO objective function.

$$C_{el,loss} = \sum_{t \in T} \big(pv_{ch}[t] + grid_{ch}[t] - (disch_{pv,dem}[t] + disch_{pv,grid}[t] + disch_{grid,dem}[t] + disch_{grid,grid}) \cdot \eta_{inv} \cdot \sqrt{\eta_{dc,dc}}\big) \cdot p_{el,buy} \tag{9}$$

Annual costs (2): fixed and variable O&M for ESS (prosumer and DSO)

$$C_{ESS} = C_{ESS,vom} + C_{ESS,fom} = \sum_{t \in T} (grid_{ch}[t] + pv_{ch}[t]) \cdot p_{ESS,vom} + c\text{-}rate \cdot cap_{ESS} \cdot p_{ESS,fom} \tag{10}$$

, with $C_{ESS,fom}$, $C_{ESS,vom}$ as respectively the fixed and variable operation and maintenance (O&M) costs associated with ESS.

Annual costs (3): curtailment reimbursement (DSO)

As explained in section 3.4.2., it is assumed that DSOs need to fully reimburse prosumers for any PV-generated electricity that is curtailed. This results in annual costs for the DSO. As the exact same amount weighs as a benefit to prosumers, the costs cancel themselves out in the combined perspective (and thus are not present in the $EAA_{combined}$ equation).

$$C_{curtailment} = \sum_{t \in T} pv_{curtailment}[t] \cdot p_{el,sell} \tag{11}$$

Investments: ESS (prosumer and DSO) and grid reinforcement (DSO)

$$I_{ESS} = cap_{ESS} \cdot p_{ESS} \tag{12}$$

$$I_{grid,reinforced} = grid_{cap,reinf} \cdot p_{grid} \tag{13}$$

3.6.3. Model constraints

This section demonstrates model constraints set up to either define relationships between variables or set minimum/maximum values for variables. The constraints are set up for decision variables and continuous variables, and mostly for every time period in T.

Decision variable constraints (ESS mode of operation)

The decision variables decide whether the ESS is in (dis)charging or idle mode. However, these modes can only be operational one a time. To facilitate this, first a constraint is set to ensure that the sum of binary variables ch_{bin} and $disch_{bin}$ is lower or equal to 1 for every time period in T (equation 14). In addition, conditional constraints are set to make sure no (dis)charging takes place if one of these variables is equal to 0 (equations 15 and 16).

$$ch_{bin}[t] + disch_{bin}[t] \leq 1 \qquad (\forall\, t \in T) \tag{14}$$

$$ch_{bin}[t] = 0 \rightarrow ch_{pv}[t] + ch_{grid}[t] = 0 \qquad (\forall\, t \in T) \tag{15}$$

$$ch_{bin}[t] = 0 \rightarrow disch_{pv,dem}[t] + disch_{pv,grid}[t] + disch_{grid,dem}[t] + disch_{grid,grid}[t] = 0 \qquad (\forall\, t \in T) \tag{16}$$

Energy balance constraints: residual demand

As this study assumes that electricity exchange with a low-voltage network is 100% efficient between all network components, the residual demand equals neighborhood demand minus neighborhood PV-supply for time period in T. Therefore, the basic electricity balance constraint is set up using the residual demand (equation 17).

$$dem_{res}[t] = grid_{dem}[t] + (disch_{pv,dem}[t] + disch_{grid,dem}[t]) \cdot \eta_{inv} \cdot \sqrt{\eta_{dc,dc}} - pv_{grid}[t] - pv_{ch}[t] - pv_{curt}[t] \qquad (\forall\, t \in T) \tag{17}$$

, with dem_{res} as residual demand in kWh.

As all variables in Gurobi can only take on positive values, equation 17 is true for both positive (more demand) and negative (more PV-supply) residual demand. In addition, two other constraints are set up to ensure that in each of these situations only the appropriate variables are assigned with a value higher than 0.

$$dem_{res}[t] \geq 0 \rightarrow pv_{grid}[t] + pv_{ch}[t] + pv_{curt}[t] = 0 \qquad (\forall\, t \in T) \tag{18}$$

$$dem_{res}[t] \leq 0 \rightarrow grid_{dem}[t] + disch_{pv,dem}[t] + disch_{grid,dem}[t] = 0 \qquad (\forall\, t \in T) \tag{19}$$

ESS (1): capacity constraints

Several constraints related to ESS performance parameters have been set. First, maximum and minimum values are set for the absolute SOC, based on ESS capacity and performance related maximum DOD (equations 20 and 21). Moreover, a constraint is set to ensure that maximum ESS (dis)charging power is not exceeded, based on c-rate and ESS capacity (equation 22 and 23).

$$SOC_{tot}[t] \leq SOC_{max,\%} \cdot cap_{ESS} \qquad (\forall\, t \in T) \tag{20}$$

$$SOC_{tot}[t] \geq SOC_{min,\%} \cdot cap_{ESS} \qquad (\forall\, t \in T) \tag{21}$$

$$(pv_{ch}[t] + grid_{ch}[t]) \cdot \eta_{inv} \cdot \sqrt{\eta_{dc,dc}} \leq c\text{-}rate \cdot cap_{ESS} \qquad (\forall\, t \in T) \tag{22}$$

$$disch_{pv,dem}[t] + disch_{pv,grid}[t] + disch_{grid,dem}[t] + disch_{grid,grid}[t] \leq c\text{-}rate \cdot cap_{ESS} \qquad (\forall\, t \in T) \tag{23}$$

ESS (2): energy balance constraints

In addition to ESS performance constraints, ESS energy balance constraints are set. As explained in section 3.6., the modeled ESS has two virtual compartments: one for PV-generated electricity and one for grid-bought electricity. First a constraint is set to create the two compartments (equation 24). In addition, constraints are set for the respective energy balances of these compartments (equations 25 and 26). Finally, constraints are set for the

SOC start-value. As one year of supply and demand profiles are assessed (but is recurrently accounted for over the ESS lifetime), it is deemed most accurate to assume a start value that is equal to SOC_{min} (equation 27). Moreover, it is assumed that at start of operation the ESS is pre-charged (i.e. not charged with PV-generated electricity) (equation 28).

$$SOC_{tot}[t] = SOC_{pv}[t] + SOC_{grid}[t] \qquad (\forall\, t \in T) \tag{24}$$

$$SOC_{pv}[t+1] = SOC_{pv}[t] \cdot disch_{self} + pv_{ch}[t] \cdot \eta_{inv} \cdot \sqrt{\eta_{dc,dc}} - disch_{pv,dem}[t] - disch_{pv,grid}[t] \qquad (\forall\, t \in T) \tag{25}$$

$$SOC_{grid}[t+1] = SOC_{grid}[t] \cdot disch_{self} + grid_{ch}[t] \cdot \eta_{inv} \cdot \sqrt{\eta_{dc,dc}} - disch_{grid,dem}[t] - disch_{grid,grid}[t] \qquad (\forall\, t \in T) \tag{26}$$

$$SOC_{tot}[1] = SOC_{min,\%} \cdot cap_{ESS} \tag{27}$$

$$SOC_{grid}[1] = SOC_{min,\%} \cdot cap_{ESS} \tag{28}$$

Grid capacity constraints (DSO and combined only)

For the DSO and combined perspective, two constraints are set that obligate electricity flows to stay below (possibly reinforced) transformer capacity, thereby dealing with both upward congestion (PV to grid and discharged to grid) and downward congestion (grid to demand and grid charged) (equation 29 and 30).

$$pv_{grid}[t] + \left(disch_{pv,grid}[t] + disch_{grid,grid}[t]\right) \cdot \eta_{inv} \cdot \sqrt{\eta_{dc,dc}} \leq grid_{cap} + grid_{cap,reinf} \qquad (\forall\, t \in T) \tag{29}$$

$$grid_{dem}[t] + grid_{ch}[t] \leq grid_{cap} + grid_{cap,reinf} \qquad (\forall\, t \in T) \tag{30}$$

Curtailment constraints

For the prosumer perspective it is assumed that no curtailment takes place, so a constraint is to keep the variable's value at 0 (equation 31a). For the DSO and combined perspective, a constraint is set to keep total curtailment below or equal to 3% of total PV-generated electricity (equation 31b).

$$pv_{curtailment}[t] = 0 \qquad (\forall\, t \in T) \tag{31a}$$

$$\sum_{t \in T} pv_{curtail}[t] = 3\% \cdot \sum_{t \in T} pv[t] \tag{31b}$$

, with pv as all PV-generated electricity in kWh.

3.6.4. Analysis of model output

To analyze model outputs, a csv-file containing neighborhood specific values and indicators is created with Python after optimization is completed, and further analysis is performed using Microsoft Excel. For each perspective of ownership examined, the most important indicators are reported as descriptive statistics in the results section of this report, and some are further examined through bivariate analysis. A short overview of the assessed indicators is given below for each perspective examined. However as a general annotation, it should first be noted that as grid reinforcement in this study effectively has a minimum value of 1 kW (see section 3.4.3), it is deemed appropriate to only take into account ESSs with a capacity of 1 kWh and higher. Moreover, for the DSO and combined perspective, only neighborhoods with initial congestion are taken into account. Values are reported for every energy transition scenario, except where noted.

Prosumer perspective

Reported descriptive statistics for the prosumer perspective are:

- Amount and share (%) of neighborhoods with ESSs installed
- Direct self-consumption of neighborhoods with ESS installed (mean % and st. dev.)
- Optimized self-consumption of neighborhoods with ESS installed (mean % and st. dev.)
- Increase in self-consumption of neighborhoods with ESS installed (%-point)
- Normalized ESS capacity (ESS capacity installed divided by PV-peak power installed) (mean kWh/kWp)
- Amount of neighborhoods with congestion and were ESSs are installed
- Decrease in congestion after ESS implementation (mean % of hours)

In addition, histograms are produced that portray the distribution of implemented ESSs over different levels of both direct and optimized self-consumption. Moreover, scatter plots are generated to show the relationship between normalized ESS capacity and levels of direct self-consumption.

DSO perspective

Reported descriptive statistics for the DSO perspective are:

- Amount and share (%) of neighborhoods with ESSs installed
- Amount and share (%) of neighborhoods with PV-curtailment applied
- Percentage of total PV-generated electricity curtailed (mean % and st. dev.)
- Amount and share (%) of neighborhoods with grid reinforcement applied
- Reinforcement costs saved compared to BAU costs in (mean % and st. dev.)

Combined perspective

Reported descriptive statistics for the combined perspective are all values mentioned in the prosumer and DSO perspectives. In addition, a direct comparison with both the prosumer and DSO perspective is made for 6 neighborhoods for the local scenario. Four indicators are compared: normalized ESS capacity, increased self-consumption, percentage of total PV-generated electricity curtailed, and reinforcement costs saved. Moreover, a load-duration curve is produced showing how the combined perspective operates over the course of a whole year.

Sensitivity analysis

Finally, as prices regarding ESS investment costs vary greatly throughout literature, a concise sensitivity analysis is performed for the local scenario using the lowest and highest value obtained from literature. Outputs entail the amount and share (%) of neighborhoods with ESSs installed, mean normalized ESS capacity, mean increase in self-consumption, and mean % reinforcement costs saved. As this is considered essential for answering the research question, the outcome is included in the results section and subsequently referred to in the conclusion (as opposed to discussion).

4. Results

4.1. Assessment of unmitigated supply and demand profiles

For 2017 supply and demand profiles, basic descriptive statistics are gathered to find primary anomalies in input data. For 2030 supply and demand profiles, basic descriptive statistics are gathered to serve as a reference point for assessment of cost-optimal mitigation options. Statistics are presented for each energy transition scenario and mainly focus on direct self-consumption and initial congestion. An overview can be found in table 4.

4.1.1. 2017 supply and demand profiles

First assessment of 2017 supply and demand profiles shows that for 19 out the 891 neighborhoods, total electricity demand is 0. Moreover, congestion occurs in 81 neighborhoods (all downward congestion). This is deemed not realistic and thus a total of 100 neighborhoods are not taken into account for further assessment.

For the remaining 791 neighborhoods, the mean direct self-consumption is 95.7%, with a standard deviation of 7.9%. For 28 (3.5%) neighborhoods, direct self-consumption is 0% as no rooftop-PV is installed. For 703 neighborhoods (88.9%), direct self-consumption is 100%. A histogram depicting the distribution of direct self-consumption of all neighborhoods in 2017 (present-day) can be seen in figure 9.

4.1.2. 2030 supply and demand profiles

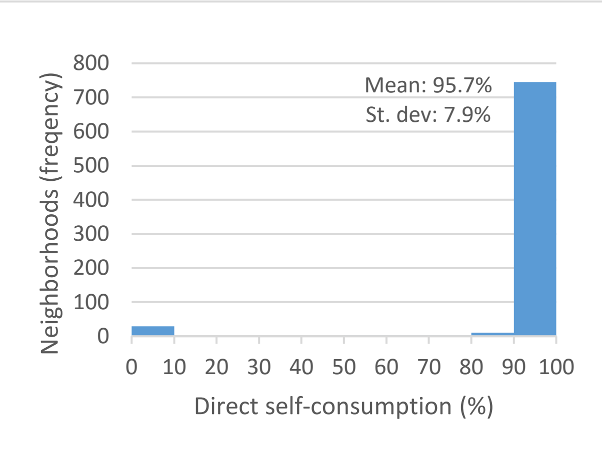
Concerning 2030 supply and demand profiles for 791 neighborhoods, congestion values for upward congestion differ greatly from downward congestion. Upward congestion occurs in 7, 4 and 1 neighborhood(s) in the local, regional and national scenarios respectively, whereas downward congestion occurs in 319 neighborhoods in all scenarios.

Concerning direct self-consumption, 2030 mean values are 80.5%, 87.7% and 93.3% for the local, regional and national scenarios respectively, showing an inverse relationship with the total rooftop-PV installed. Histograms depicting the distribution of direct self-consumption of all neighborhoods can be seen in figure 10, 11 and 12 for each scenario respectively.

Table 4: Initial congestion and direct self-consumption (2017 and 2030) (n=791)

Year/energy transition scenario	2017	2030 Local	2030 Regional	2030 National
Direct self-consumption (mean % (st. dev.))	95.7% (7.9%)	80.5% (19.4%)	87.8% (17.2%)	93.3% (13.8%)
Neighborhoods with congestion (amount (%))	0 (0.0%)	323 (40.8%)	322 (40.7%)	320 (40.5%)
Neighborhoods with initial upward congestion (amount (%))	0 (0.0%)	7 (0.9%)	4 (0.5%)	1 (0.1%)
Hours of initial upward congestion (mean)	0	698	627	615
Neighborhoods with initial downward congestion (amount (%))	0 (0.0%)	319 (40.3%)	319 (40.3%)	319 (40.3%)
Hours of initial downward congestion (mean)	0	424	434	445

Figure 9 and 10: Distribution of direct self-consumption of all neighborhoods in 2017 (left) and 2030 local scenario (right) (n=791)



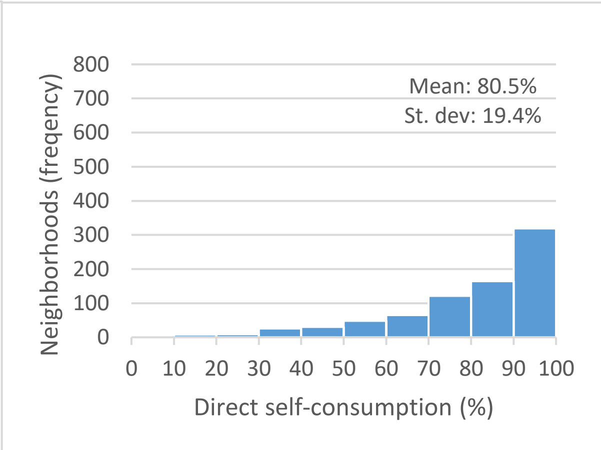
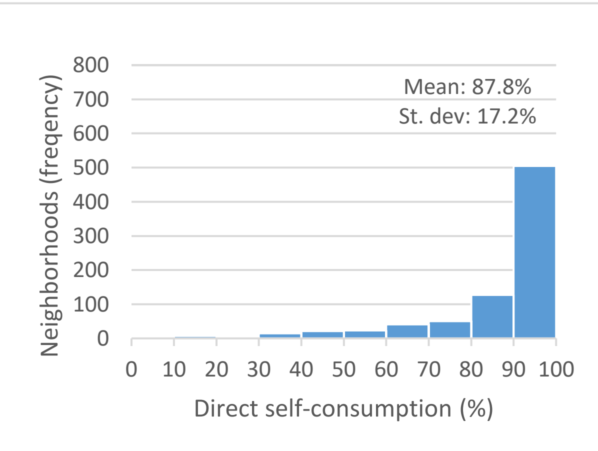
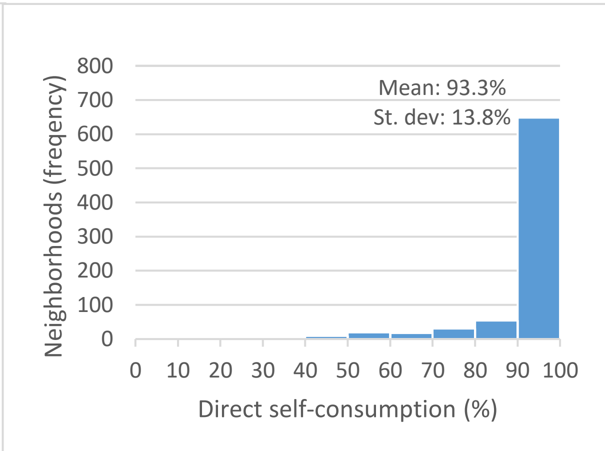


Figure 11 and 12: Distribution of direct self-consumption of all neighborhoods for 2030 regional scenario (left) and 2030 national scenario (right) (n=791)





4.2. Cost-optimal mitigation options (1): prosumer perspective

Basic descriptive statistics were gathered on cost-optimal mitigation options for the prosumer perspective. These statistics are presented for each energy transition scenario and mainly focus on the intensity of ESS implementation and consequential improvements with regard to self-consumption and congestion. An overview can be found in table 5.

In the local, regional and national scenario, ESSs were installed in 75, 44 and 28 neighborhoods respectively. The mean direct self-consumption for these neighborhoods is 36.8%, 37.1% and 40.1% for the three scenarios respectively, again showing an inverse relationship with total rooftop-PV installed. Mean optimized self-consumption shows an increase of 6.8%, 6.6% an 5.6% for the three scenarios, implicating a higher increase for lower direct self-consumption values. Histograms depicting the distribution of direct and optimized self-consumption of neighborhoods with ESSs can be seen in figure 12-17 for all scenarios.

Out of the 7, 4 and 1 neighborhoods with initial upward congestion, ESSs were installed in 5, 3, and 1 neighborhood(s) for the local, regional and national scenarios respectively. Out of the 319 neighborhoods with initial downward congestion, ESSs were installed in 2, 1 and 0 neighborhood(s) in the local, regional and national scenario respectively. In none of the scenarios congestion is fully mitigated, but a decrease in (% of) hours of congestion is seen for upward congestion: 7.35%, 5.84%, 4.15% in the local, regional and national scenario respectively.

Table 5: Descriptive statistics for optimized 2030 prosumer perspective (n=791)

Energy transition scenario	Local	Regional	National
Neighborhoods with ESS installed (amount (%))	75 (9.5%)	44 (5.6%)	28 (3.5%)
Direct self-consumption of neighborhoods with ESS installed (mean % (st. dev.))	36.8% (12.2%)	37.1% (12.0%)	40.1% (12.5%)
Optimized self-consumption of neighborhoods with ESS installed (mean % (st. dev.))	43.6% (10.2%)	43.7% (10.7%)	45.7% (9.6%)
Increase in self-consumption of neighborhoods with ESS installed (mean %-point)	6.8%	6.6%	5.6%
Normalized ESS capacity (mean kWh/kWp)	0.23	0.22	0.19
Neighborhoods with ESS installed and upward congestion (initial and residual) (amount)	5	3	1
Decrease of upward congestion (mean % of hours)	7.35%	5.84%	4.15%
Neighborhoods with ESS installed and downward congestion (initial and residual) (amount)	2	1	0
Decrease of downward congestion (mean % of hours)	-1.19%	0%	N.A.

Figure 12 and 13: Distribution of direct (left) and optimized (right) self-consumption of neighborhoods with ESSs for 2030, local scenario, prosumer perspective (n=75)

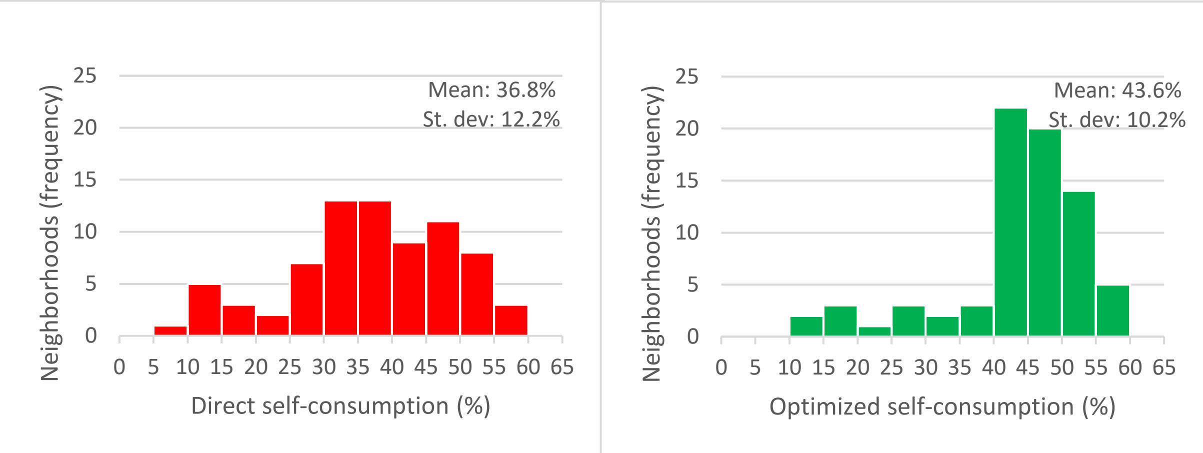


Figure 14 and 15: Distribution of direct (left) and optimized (right) self-consumption of neighborhoods with ESSs in 2030, regional scenario, prosumer perspective (n=44)

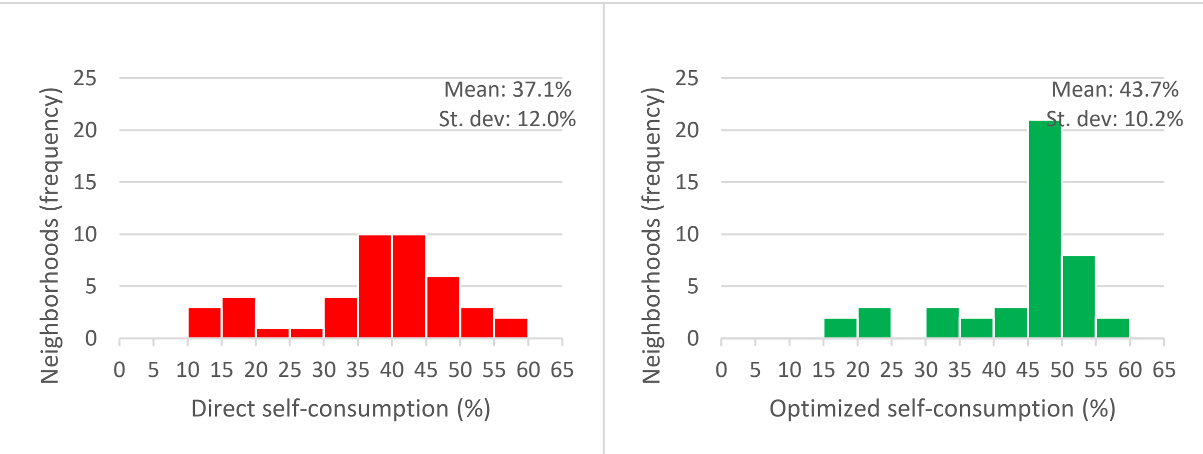
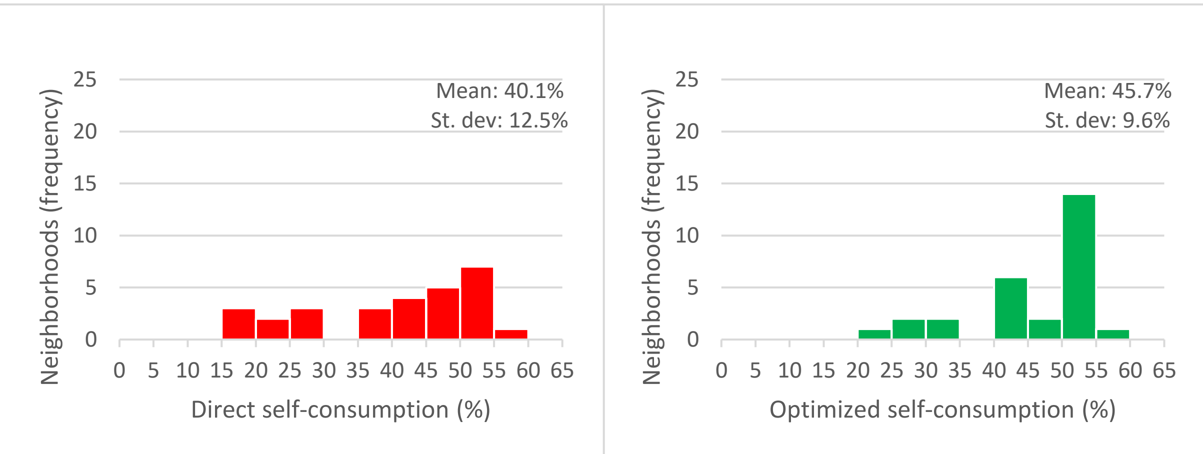


Figure 16 and 17: Distribution of direct (left) and optimized (right) self-consumption of neighborhoods with ESSs for 2030, national scenario, prosumer perspective (n=28)



To better illustrate the increase in self-consumption for different levels of direct self-consumption, scatter-plots were generated for each scenario showing normalized ESS capacity (i.e. divided by PV-peak power installed) on the y-axis, and the percentage of direct self-consumption on the x-axis (figure 18 – 20). It shows that normalized ESS capacity follows a polynomial pattern and has a peak between 27% and 28% self-consumption in each scenario. After this result was generated, the mean increase in optimized self-consumption for neighborhoods with a direct self-consumption between 25% and 35% was calculated as 11,5% for the local scenario (n=20), almost double in comparison to the mean increase of all neighborhoods with ESS installed.

Figure 18: ESS capacity/PV-peak power vs. direct self-consumption in 2030, local scenario, prosumer perspective (n=75)

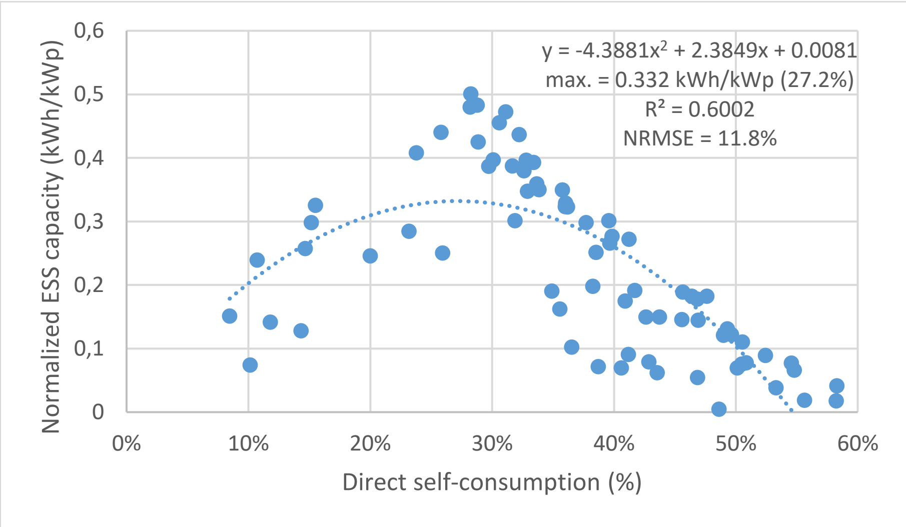


Figure 19: ESS capacity/PV-peak power vs. direct self-consumption in 2030, regional scenario, prosumer perspective (n=44)

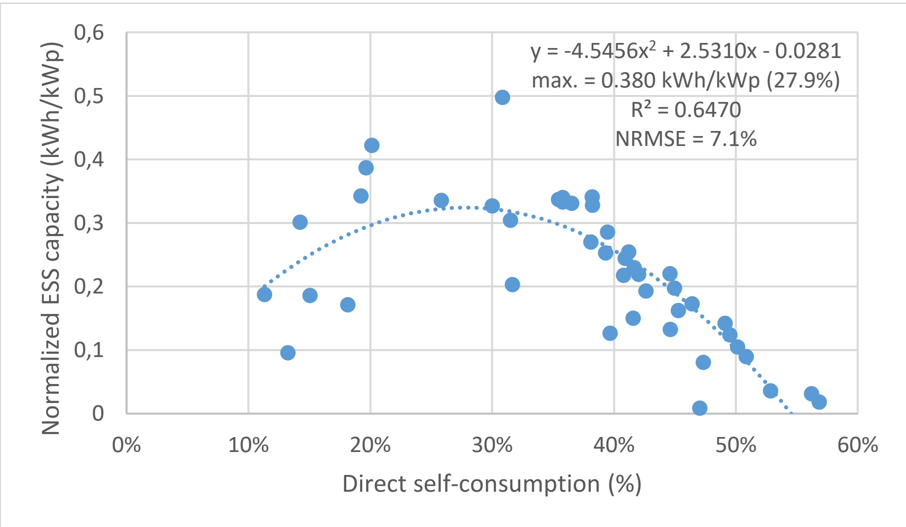
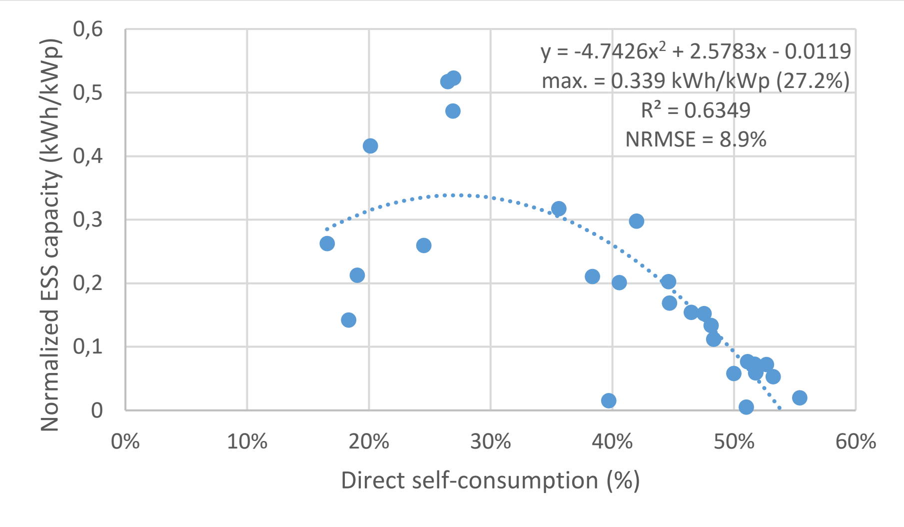


Figure 20: ESS capacity/PV-peak power vs. direct self-consumption in 2030, national scenario, prosumer perspective (n=28)



4.3. Cost-optimal mitigation options (2): DSO perspective

For neighborhoods where initial congestion occurs (see section 4.1), basic descriptive statistics were gathered on cost-optimal mitigation options for the DSO perspective. These statistics are presented for each energy transition scenario and mainly focus on the intensity of ESSs implementation, PV-curtailment, and grid reinforcement. An overview can be found in table 6.

Table 6: Descriptive statistics for optimized 2030 DSO perspective

Energy transition scenario	Local (n=323)	Regional (n=322)	National (n=320)
Neighborhoods with ESS installed (amount (%))	0 (0%)	0 (0%)	0 (0%)
Neighborhoods with PV-curtailment applied (amount (%))	4 (1.2%)	3 (0.9%)	1 (0.3%)
Percentage of total PV-generated electricity curtailed (mean (st. dev.))	0.06% (0.03%)	0.08% (0.01%)	0.07% (N.A.)
Neighborhoods with grid reinforcement applied (amount (%))	322 (99.7%)	322 (100%)	320 (100%)
Percentage of BAU reinforcement costs saved in neighborhoods with PV-curtailment (mean (st. dev.))	38.2% (41.5%)	34.2% (24.5%)	29.5% (N.A.)

No ESSs were implemented in any of the scenarios in the DSO perspective. PV-curtailment was applied in 4, 3, and 1 neighborhood in the local, regional and national scenario respectively. With the exception of one neighborhood in the local scenario, grid reinforcement was applied for all neighborhoods to mitigate (residual) congestion. In one neighborhood in the local scenario (where no grid reinforcement is applied), PV-curtailment fully mitigates congestion. On average, grid reinforcement costs are reduced by 38.2% when PV-curtailment is implemented, although this value is subject to a very high standard deviation (41.5%).

4.4. Cost-optimal mitigation options (3): combined perspective

For neighborhoods where initial congestion occurs (see section 4.1), basic descriptive statistics were gathered on cost-optimal mitigation options for the combined perspective. These statistics are presented for each energy transition scenario and mainly focus on the intensity of ESSs implementation, PV-curtailment, and grid reinforcement. An overview can be found in table 7. However, it should be noted that significance of some values is questionable as they apply to a small amount of neighborhoods. To better illustrate how the combined perspective operates, a direct comparison with both the prosumer and DSO perspective is made for 6 neighborhoods where ESSs are implemented in the local scenario (table 8). Specifically, four indicators are compared: normalized ESS capacity (prosumers), increased self-consumption (prosumers), PV-curtailment (DSO), and reinforcement costs saved (DSO).

Table 7: Descriptive statistics for optimized 2030 combined perspective

Energy transition scenario	Local (n=323)	Regional (n=322)	National (n=320)
Neighborhoods with ESS installed (amount (%))	6 (1.9%)	4 (1.2%)	1 (0.3%)
Direct self-consumption of neighborhoods with ESS installed (mean % (st. dev.))	33.8% (16.7%)	32.0% (17.7%)	16.6% (N.A.)
Optimized self-consumption of neighborhoods with ESS installed (mean % (st. dev.))	40.3% (14.8%)	38.5% (15.5%)	25.7% (N.A.)
Increase in self-consumption of neighborhoods with ESS installed (mean %-point)	6.5%	6.5%	9.1%
Normalized ESS capacity (mean kWh/kWp)	0.22	0.16	0.13
Neighborhoods with ESS installed and initial upward congestion (amount)	4	3	1
Neighborhoods with ESS installed and initial downward congestion (amount)	3	1	0
Neighborhoods with PV-curtailment applied (amount (%))	3 (0.9%)	3 (0.9%)	1 (0.3%)
Percentage of total PV-generated electricity curtailed (mean (st. dev.))	0.06% (0.03%)	0.04% (0.03%)	0.05% (N.A.)
Neighborhoods with grid reinforcement applied (amount (%))	322 (99.7%)	321 (99.7%)	320 (100%)
Percentage of BAU reinforcement costs saved in neighborhoods with PV-curtailment (mean (st. dev.))	39.1% (35.0%)	51% (42.7%)	73.7% (N.A.)

Table 8: Comparison of neighborhood statistics for the combined perspective and the prosumer and DSO perspective (local scenario) (n=6)

Neighborhood	*Prosumer perspective*		*DSO perspective*		*Combined perspective*			
	Normalized ESS capacity (kWh/kWp)	Increased self-consumption (%-point)	PV-curtailment (% of total PV)	Reinforce-ment costs saved (%)	Normalized ESS capacity (kWh/kWp)	Increased self-consumption (%-point)	PV-curtailment (% of total PV)	Reinforce-ment costs saved (%)
BU03212064	0.246	7.88%	0.073%	16.15%	0.248	7.92%	0.063%	38.66%
BU03420705	0.437	12.44%	0.004%	100.00%	0.437	12.44%	0.000%	100.00%
BU06320501	0.062	1.67%	0.000%	0.00%	0.096	2.58%	0.000%	33.28%
BU06320604	0.152	5.51%	0.068%	12.69%	0.154	5.58%	0.063%	24.32%
BU07070603	0.150	4.20%	0.000%	0.00%	0.191	5.29%	0.000%	8.32%
BU07360108	0.397	11.31%	0.081%	23.82%	0.408	11.59%	0.068%	68.96%

Across all indicators, the combined perspective behaves differently from the prosumer and/or DSO perspective. With regard to the prosumer perspective, higher normalized ESS capacity and increased self-consumption can be noted in 5 out of 6 neighborhoods. With regard to the DSO perspective, lower percentages of PV-curtailment can be observed in all appropriate neighborhoods. Moreover, reinforcement costs are lower in 5 out of 6 neighborhoods- in the one neighborhood left over (BU03420705) PV-curtailment is fully mitigated congestion but is completely substituted by energy storage. To illustrate how mitigation options in the combined perspective operate over the course of a whole year, a load-duration curve has been produced for neighborhood BU07360108 and is included in Appendix A (figure A1).

4.6. Sensitivity analysis

To get insight in the effect that ESS investment costs have on the implementation of ESSs, a sensitivity analysis was performed on the local scenario for every perspective examined. Because of (run)time constraints, only the lowest and highest prices found in literature were examined. Using the highest price, no ESSs were installed in any of the perspectives. Moreover, even using the lowest price, no ESSs were installed in the DSO perspective. An overview of the results using the lowest price for the prosumer and combined perspectives can be found in table 9.

In the prosumer and combined perspective, ESSs were installed in 437 and 91 neighborhoods respectively, indicating a large difference with the reference ESS price. It also implies that in the combined perspective, purely downward congestion is mitigated in the majority of the neighborhoods. Using the lowest ESS price, ESS capacity is on average more than 7 times bigger in the prosumer perspective and more than 4 times bigger in the combined perspective. The mean increase in self-consumption is 10.4% and 7.1% for the prosumer and combined perspective respectively. In the combined perspective, reinforcement costs are reduced by 48.1% on average in comparison to BAU costs.

Table 9: Sensitivity analysis: descriptive statistics for optimized 2030 prosumer and combined perspectives using lowest ESS price for investment (local scenario)

Perspective	Prosumer (n=791)	Combined (n=323)
Neighborhoods with ESS installed (amount (%))	437 (55.2%)	91 (28.2%)
Increase in self-consumption of neighborhoods with ESS installed (mean %-point)	10.4%	7.1%
Normalized ESS capacity (mean kWh/kWp)	1.56	0.95
Percentage of BAU reinforcement costs saved in neighborhoods with PV-curtailment (mean (st. dev.))	N.A.	48.1% (37.1%)

5. Discussion

This section discusses the reliability of the results obtained in this study. First, general limitations are conversed, mainly related to the methodology of this study. Secondly, as preliminary versions of ASM-2 supply and demand profiles are used, limitations of input data are discussed.

5.1. General limitations

2030 supply and profiles

As this study only assesses supply and demand profiles for 2030, optimization with regard to the implementation of mitigation options that span several years is inherently not very accurate. This study should however not be seen as an optimization study for actual implementation, but as a first insight to demonstrate economic and technical viability of ESSs on neighborhood scale.

Perfect forecast

Perfect forecast allows for ESS control strategies to perform optimally. Especially for the combined perspective, where ESSs are used to mitigate congestion and must charge at the right moment, some reservations need to be made. As congestion mitigation has priority in the combined perspective, the ESS cannot charge before the peak PV-surplus has passed. In a real-life situation some mistakes are inevitable in real life in this regard, and thus by assuming perfect forecast this leads to an overestimation of self-consumption and ESS profitability. Moreover, it might lead to an underestimation of PV-curtailment as this never has to be used as an 'emergency option', but only in the smallest, pre-calculated amounts.

Hourly resolution and perfect electricity exchange

As this study assesses hourly supply and demand profiles, some peaks in either supply or demand cannot be monitored. This inherently 'smoothens' the electricity profile and reduces the 'visibility' of congestion, and thus possibly incites an underestimation of PV-curtailment or ESSs implemented. Moreover, perfect electricity exchange was assumed within neighborhoods for a time resolution of one hour, but in reality rooftop-PV systems and electricity demand are not evenly distributed throughout a neighborhood, nor throughout time. Inevitably, some losses will occur in the process of exchanging electricity with other connections, and some electricity exchange cannot take place at all because of the actual (smaller) size of low-voltage networks. As a result, it is possible that in reality hourly PV-surpluses are higher and direct self-consumption levels are lower. Considering the relatively low amount of neighborhoods with low direct self-consumption, this could lead to a underestimation of the amount of ESSs installed.

5.2. Limitations of input data

At the time of writing this thesis, several ASM-2 supply and demand profiles are still in their preliminary versions and are subject to some limitations. While most of these limitations will be addressed in the final result of the ASM-2 project, this section discusses the most important limitations for the profiles (not) used in this study.

Demand: EVs (not included)

The most obvious input data limitation is the absence of profiles regarding electricity demand for EVs. Especially in residential areas EVs are often charged during evenings, possibly leading to higher peaks in demand. However, EV batteries are also likely to contribute to the flexibility of low-voltage networks through 'smart charging' initiatives.

Supply: rooftop-PV

Rooftop-PV supply profiles used in this study assume that all PV-systems are attached to the low-voltage grid, while in reality large producers (with connections higher than 160 kVA (Liander, 2014)) are connected directly to the mid-voltage network. This might lead to an overestimation of total electricity supply and thus in some cases overestimation of congestion and (capacities of) ESSs installed. Moreover, PV-systems in future scenarios are assumed to be placed at orientations and angles corresponding to currently installed systems. As the space available for rooftop-PV decreases with higher capacities installed, this might lead to an overestimation of optimally placed PV-systems, which might in turn lead to an overestimation of electricity supply.

Demand: conventional

The assumption that conventional demand will stay constant in comparison to present-day data might lead to an underestimation for future years, when more electrical appliances are likely to contribute to conventional demand. However it is also likely that appliances will be more efficient, possibly canceling out this underestimation (Allouhi et al., 2015). Another limitation is that public services like street lighting are not taken into account, which might lead to a smaller peak-demand during evenings. This effect is however considered relatively small.

Specifically for utility profiles, some data on remote connections is not available due to privacy reasons, possibly causing underestimation of electricity use in certain areas. On the other hand, also because of privacy reasons, some data on large consumers might be clustered with small consumers. This might lead to a possible overestimation of electricity use in certain areas, as in reality large consumers (with connections higher than 160 kVA (Liander, 2014)) are connected directly to the mid-voltage network. Hence it is a possible explanation for downward congestion seen in some neighborhoods in 2017.

Demand: HPs

Residence heat demand profiles for HPs are based on a constant coefficient of performance (COP), which means that outside temperatures are not taken into account. This might lead to under or overestimation of electricity use in colder or warmer days. Moreover, the input data is based on national policy 'advice' regarding heating strategies on local level, which at this point does not seem to take into account legacy of heating strategies already in place. Specifically for utility profiles, underlying gas-use profiles are not based on utility type. This leads to general inaccuracy of hourly profiles when for example night-time operation or periodical peaks in demand are not specifically accounted for.

6. Conclusion

Following all the results provided, the research question for this study was answered:

"To what extent can ESSs serve as a cost-optimal mitigation option to address congestion and increase self-consumption in 2030?"

Considering that the results of this study are based on preliminary ASM-2 supply and demand profiles for a restricted geographical scope, and that optimization is carried out using perfect forecast, this study finds that ESSs are likely to serve as a cost-optimal mitigation option in Dutch low-voltage networks by 2030 for the objective of increasing self-consumption, however under certain circumstances. Optimization results for the prosumer perspective and all ASM-2 energy transition scenarios show that for direct self-consumption levels up to ± 55% ESSs can be profitable on neighborhood scale. Moreover, optimal direct self-consumption levels were obtained as between 27-28% for all scenarios, with normalized ESS capacity peaking around these levels. Out of the 791 neighborhoods taken into consideration, ESSs were installed in 75, 44, and 28 neighborhoods in the local, regional and national scenario respectively. Self-consumption was increased on average by 6.8%, 6.6% and 5.8% for each scenario respectively. Actual applicability of ESSs will be very dependent on ESS price developments as sensitivity analysis performed for the local scenario shows a large variation in the number of ESSs installed: 437 for the lowest and 0 for the highest prices found in literature.

Moreover, this study finds that purely to address congestion in distribution transformers, ESSs are not likely to serve as a cost-optimal mitigation option in Dutch low-voltage networks by 2030. Optimization results for the DSO perspective show that, even for the lowest ESS price found in literature, no ESSs were installed in any of the energy transition scenarios. PV-curtailment is applied only in 4, 3 and 1 neighborhood(s) in the local, regional and national scenarios, mainly because upward congestion does not occur very often.

Finally, in combination with the incentive to reduce electricity costs for prosumers, ESSs might actually be used as a cost-optimal mitigation option to (partly) mitigate congestion in Dutch low-voltage networks by 2030. Optimization for the combined perspective showed that only 6, 4 and 1 ESS(s) were installed in the local, regional and national scenario respectively, primarily mitigation upward congestion and saving 46% of reinforcement costs (compared to BAU costs) on average. Self-consumption increase is also boosted in comparison to the prosumer perspective, but often little and never more than 1 %-point. PV-curtailment is applied only in 3, 3 and 1 neighborhood(s) in the local, regional and national scenario respectively, mainly because upward congestion does not occur very often. For one neighborhood, PV-curtailment was completely substituted by an ESS. Overall it can be noted that the combined perspective in most cases provides better results for both parties involved, while costs are shared. Sensitivity analysis for the local scenario showed that for the lowest ESS price found in literature 91 ESSs were installed, thereby also mitigating downward congestion and saving 48.1% of reinforcement costs (compared to BAU costs) on average. Dissimilarly no ESSs were installed for the highest ESS price found in literature, again underlining the importance of future development of ESS prices.

7. Recommendations

After completion of this study, supplementary research will soon follow as part of the final ASM-2 results. Large differences will be optimization on full geographical scale (i.e. for all neighborhoods in the Netherlands), and improvements with regard to input data. In addition, this section provides some other recommendations for further research.

First, it is recommended to incorporate supply and demand profiles for multiple years as this will give a more realistic insight in optimal ESS capacity and optimal moment in time for ESS deployment. Moreover, other types and combinations of ESSs that were out of scope for this study might also be researched in depth, for example VRFBs for business parks with lots of free space, or aggregated home-batteries controlled from a central unit. Furthermore, as actual applicability of ESSs is very case-specific, it is recommended to perform research that takes into account actual geographical boundaries of low-voltage networks, and capacity and age data of individual network components. Practicality of this type of research is however very dependent on data availability, which is currently restricted to DSO use because of privacy reasons.

In earlier studies DSOs have claimed to see little to no potential for ESSs in low-voltage networks for the sole function of mitigating congestion (ECN, 2017). While this study acknowledges this, it is recommended to assess actual possibilities to employ ESSs in a multifunctional setting as this will likely bring to light the full potential of ESSs for congestion mitigation. However for realistic predictions regarding ESS performance in such a setting, perfect forecast should be avoided. In addition, Dutch policy does not allow DSOs to explicitly engage in the practice of energy storage, and prosumers are not allowed to store energy outside of their own residence. As this limits the possibilities for (multifunctional) storage on neighborhood scale, amendments of laws and regulations are desirable in this regard.

Lastly, predictions on future ESS investment prices have been adjusted to lower values multiple times in recent years. As profitability of ESSs is heavily dependent on developments regarding ESS investment prices, it is recommended to adopt a monitoring approach in this regard and periodically assess the potential of ESSs to become cost-optimal in the future.

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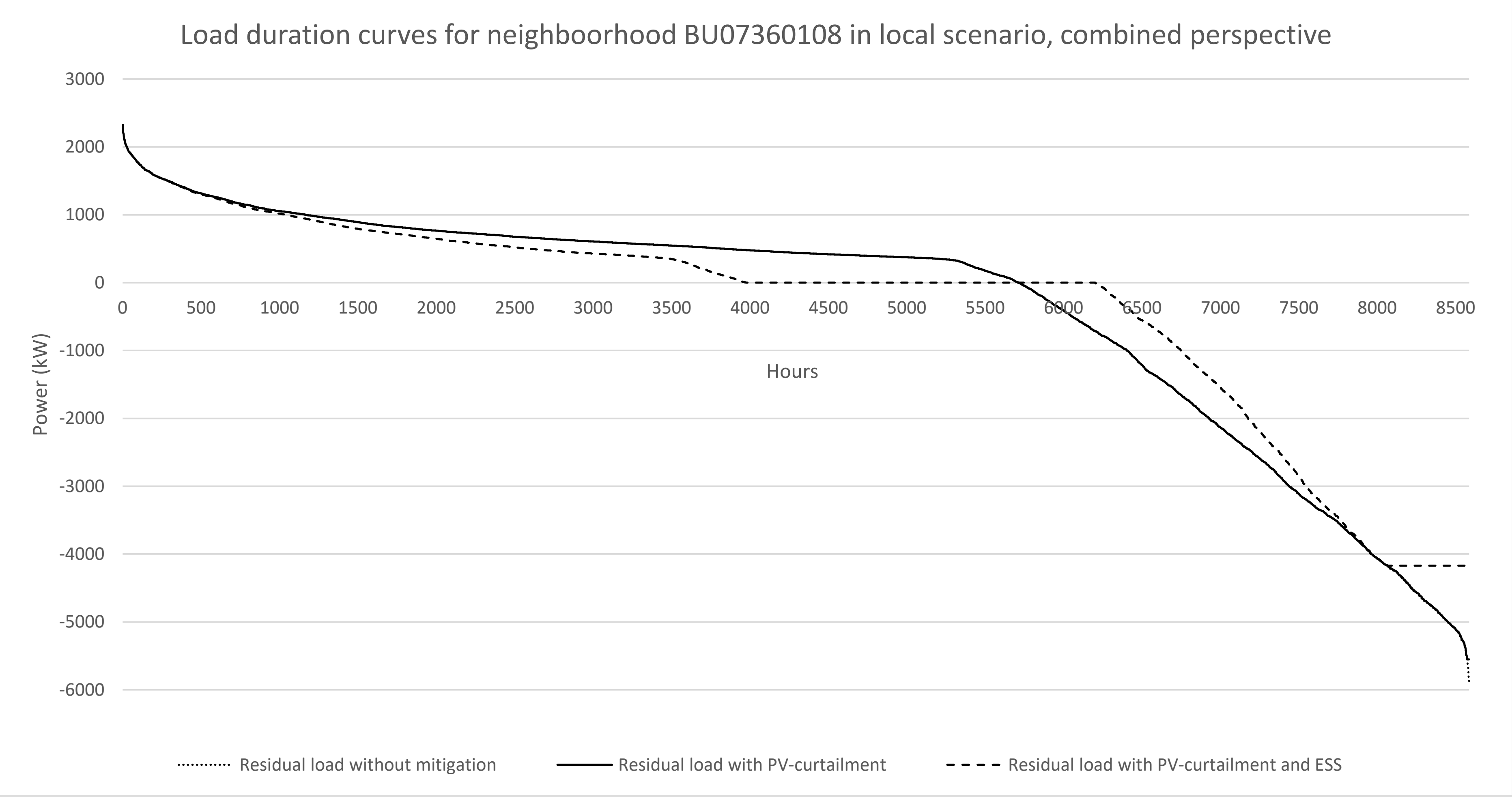
Appendix A

Figure A1: Load duration curves for neighborhood BU07360108 in local scenario, combined perspective



Note. Negative power represents PV-surplus or electricity discharged to the mid-voltage network. Positive power represents electricity demand. Reinforced grid capacity equals 4172 kVA (both for positive and negative power), while currently installed grid capacity is 3400 kVA.