When the Sun Goes Down

Solar Energy Storage in the Neighbourhood

Wouter Schram

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SOLAR ENERGY STORAGE IN THE NEIGHBORHOOD

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WHEN THE SUN GOES DOWN

SOLAR ENERGY STORAGE IN THE NEIGHBORHOOD

Als de Zon ondergaat – Opslag van Zonne-energie op Buurniveau

(met een samenvatting in het Nederlands)

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Summary

Anthropogenic global warming poses a great challenge for our society and the earth's ecosystem, and this requires decisive action. Governments around the world have agreed that efforts are required to mitigate anthropogenic climate change. As a large share of anthropogenic greenhouse gas (GHG) emissions is energy-related, modelers agree that both deep decarbonization of electricity generation and fuel switching in end-user sectors play a central role in mitigating the adverse impacts of climate change. In this context, the deployment and integration of photovoltaic (PV) systems in the power system is investigated, as well as the integration of an increasing amount of electric vehicles (EVs) resulting from a switch from vehicles with an internal combustion engine (ICE) to EVs. The economic, technical and environmental potentials of PV coupled with batteries are investigated in three settings: individual home batteries, community batteries and EV batteries.

Chapter 2 contains a determination of the GHG emission reduction potential of so-called energy communities, in which PV systems, batteries, EVs and heat pumps in eight European countries. The study uses an economic optimal configuration of these technologies as an input. Taking the full life cycle of the technologies into account, the GHG emission reductions attributed to all-electric energy communities range from 55% to 73% compared to the use of conventional technologies. It is shown that every kWp of installed PV capacity reduces the energy communities' GHG emissions by 6% to 13%, the transition from the current heat supply to heat pumps results in a GHG emission reduction of 38% to 92%, and switching from ICE vehicles to EVs saves 46% to 72% of the GHG emissions. The impact of deploying heat pumps and EVs is especially large due to the self-consumption of PV-generated electricity but is also moderated by the current power generation mix of a country. A further finding is that using stationary batteries increases the GHG emissions of the energy community, which is related to the GHG emissions associated with manufacturing of the batteries and the conversion losses during the operation of the batteries.

This last finding signifies the importance of addressing GHG emissions of batteries, also in the operational phase. Therefore, in **Chapter 3** and **Chapter**

4, it is explored how optimization techniques can result in further reductions of GHG emissions after the deployment of batteries. An important notion in this context is that GHG emissions of electricity generation are not constant, but fluctuate over time due to variations in renewable electricity generation and the economic dispatch of thermal power plants. This implies that optimal scheduling of batteries can save GHG emissions by charging at times with low carbon intensity of electricity generation and discharging at times with high carbon intensity of electricity generation. For this purpose, various marginal emission profiles are developed to be used as input in optimization.

In **Chapter 3**, the marginal emission profiles are used for the optimization of cost and emissions of a community battery. The multi-objective optimization framework that is developed allows to study the economic and environmental potential of batteries in isolation, but also provides insight in the trade-off between these potentials. It is demonstrated that GHG emissions associated with electricity consumption of a community can be reduced by 57% when the charging of a community battery is optimized. Since this would increase the cost of electricity purchase at the day-ahead market, a balanced charging schedule is also presented. Here, it is shown that compared to an uncontrolled battery, the optimized battery schedule can reduce cost and GHG emissions simultaneously, i.e. by 9.5% and 27.2%, respectively. This analysis is expanded to study smart charging and vehicle-to-grid (V2G) when deploying EVs in **Chapter 4**. It is shown that in the case of smart charging, GHG emissions can be decreased by 24% compared to uncontrolled charging, and GHG emissions can be decreased charging by 67% when applying V2G. Further, EVs' cost and emissions can be decreased simultaneously; a balanced schedule results in a cost reduction of 17.9% accompanied with a GHG emission reduction of 15.9% in case of smart charging, and a cost reduction of 13.9% accompanied with a GHG emission decrease of 50.8% in case of V2G.

The technical potential of coupling PV with batteries is determined by investigating the role that batteries can play when addressing the limited availability of PV-generated electricity in peak load hours. This becomes an increasingly important topic with the deeper penetration of variable renewable energy sources such as PV in the generation mix. Using high resolution measured power data (10 seconds), it is shown in **Chapter 5** that on the distribution system level batteries, which are optimally sized for PV self-consumption, can potentially decrease the community's peak residual load by 51%. In **Chapter 6**, the potential contribution of PV coupled with batteries to the system's resource adequacy is investigated by studying their capacity value ratio (CVR). The CVR is the expected amount of the energy output of a technology during the peak residual load, divided by the rated capacity of that technology. Even though the contribution of PV is limited without

batteries (a CVR of 1%), optimized batteries coupled with PV can have a CVR of 25% when these are charged only with PV-generated electricity, and a CVR of 47% when these are also charged from the grid, while still substantially increasing self-consumption of PV-generated electricity. Most of EV charging can be delayed to off-peak demand hours (78%), and the CVR of an EV fleet is estimated at 9%. Batteries, stationary or mobile in EVs, thus lead to a considerable increase of CVR, which is important in the context of maintaining system reliability in case of e.g. phase-out of coal-fired power plants.

In conclusion, findings show the large economic, technical and environmental potential that battery-based energy storage can have in the energy system. However, the eventual value of batteries coupled with PV is determined by the specific algorithms that are applied. Policy measures, guided by an overall vision on the energy transition, to provide appropriate incentives to steer the operations of flexible distributed resources are therefore recommended.

Samenvatting

Opwarming van de aarde door menselijke activiteit vormt een grote bedreiging voor onze samenleving en het ecosysteem van de aarde, waardoor gerichte actie vereist is. Overheden wereldwijd hebben afgesproken dat er inspanningen nodig zijn om de antropogene klimaatverandering tegen te gaan. Aangezien een groot deel van de uitstoot van antropogene broeikasgassen energiegerelateerd is, bestaat er wetenschappelijke consensus over het belang van het tegengaan van klimaatverandering in deze sector. Twee mogelijkheden hierin zijn een vergaande decarbonisatie van elektriciteitsopwekking en het veranderen van brandstofsoort bij eindgebruikers. Daarom wordt in dit proefschrift de inzet en integratie van fotonvoltaïsche zonnepanelen in het energiesysteem onderzocht, evenals de integratie van een toenemend aantal elektrische auto's als gevolg van een overstap van voertuigen met een verbrandingsmotor naar elektrische auto's. Naast hun rol in de aandrijving van elektrische auto's, kunnen batterijen een belangrijke rol spelen in de integratie van zonne-energie in het systeem door het eigenverbruik van door zonnepanelen opgewekte elektriciteit te verhogen. Daarom wordt in dit proefschrift de toegevoegde waarde van drie soorten batterijen onderzocht, te weten thuisbatterijen, buurtbatterijen en batterijen van elektrische auto's. De economische en technische toegevoegde waarde van batterijen worden uitgebreid geanalyseerd, alsmede de toegevoegde waarde op het gebied van duurzaamheid.

In **Hoofdstuk 2** wordt het potentieel van emissiereductie van zogenaamde energiegemeenschappen in acht verschillende landen vergeleken. Deze energiegemeenschappen zijn gebaseerd op een "Europees dorp". Dit is een volledig elektrische buurt met warmtepompen, elektrische auto's en een economisch geïnstalleerd vermogen aan zonnepanelen en van de buurtbatterij. Rekening houdend met de volledige levenscyclus van deze technologieën, varieert de ingeschatte emissiereductie van de energiegemeenschappen van 55% tot 73% vergeleken met buurten die conventionele technologieën gebruiken. Er wordt aangetoond dat elke kWp aan geïnstalleerd vermogen zonnepanelen leidt tot een vermindering in de broeikasgasemissies van 6% tot 13%. Daarnaast resulteert de overgang van de huidige warmtevoorziening naar warmtepompen in een vermindering

van de broeikasgasemissies van 38% tot 92%. Het overschakelen van voertuigen met verbrandingsmotoren naar elektrische auto's bespaart 46% tot 72% van de broeikasgasemissies. De impact van het gebruik van warmtepompen en elektrische auto's is vooral groot vanwege het eigenverbruik van door zonnepanelen opgewekte elektriciteit, maar wordt ook bepaald door de huidige elektriciteitsmix van een land; het installeren van zonnepanelen heeft met name veel impact in landen met een vervuilende elektriciteitsmix, terwijl overstappen naar elektrische auto's en warmtepompen vooral een grote impact heeft in landen met een elektriciteitsmix met een lage koolstofintensiteit. Een andere bevinding is dat het gebruik van stationaire batterijen de broeikasgasemissies van de energiegemeenschap verhoogt, wat wordt veroorzaakt door de broeikasgasemissies tijdens de fabricage van de batterijen en de conversieverliezen tijdens het gebruik van de batterijen.

Deze laatste bevinding geeft het belang aan van nader onderzoek naar de broeikasgasemissies van batterijen tijdens de operationele fase. Daarom wordt in **Hoofdstuk 3** en **Hoofdstuk 4** onderzocht hoe het implementeren van optimalisatietechnieken bij batterijen tot (verdere) reductie van de broeikasgasemissies kan leiden. Een belangrijk gegeven hierin is dat de broeikasgasemissies van elektriciteitsopwekking niet constant zijn, maar fluctueren in de tijd als gevolg van variaties in de opwekking van hernieuwbare elektriciteit en de verhouding van elektriciteit opgewekt door kolen- en gascentrales. Dit impliceert dat het optimaliseren van het laadproces van batterijen broeikasgasemissies kan besparen door op te laden in periodes met een lage koolstofintensiteit en te ontladen in periodes met een hoge koolstofintensiteit. Hiervoor zijn verschillende marginale emissieprofielen (dit staat ook bekend als de referentieparkmethode) ontwikkeld die als input kunnen dienen bij optimalisatie. Deze methode en haar toepassing het Nederlandse energysysteem is toegevoegd aan het proefschrift als **AppendixA**.

In **Hoofdstuk 3** worden de marginale emissieprofielen gebruikt voor het optimaliseren van kosten en emissies van een buurtbatterij. Het *multi-objective* optimalisatie-algoritme dat is ontwikkeld, maakt het mogelijk om het economische potentieel en het emissiereductiepotentieel van batterijen afzonderlijk te bestuderen, en geeft tegelijkertijd inzicht in de afweging tussen economische en duurzame doelen. Aangezien dit wordt aangetoond dat de broeikasgasemissies veroorzaakt door het elektriciteitsverbruik van een buurt met 57% kunnen worden verminderd wanneer het opladen van een buurtbatterij wordt geoptimaliseerd. Aangezien dit de kosten van de aankoop van elektriciteit op de day-aheadmarkt zou verhogen, wordt ook een gebalanceerd laadschema doorgerekend. Hier wordt aangetoond dat, in vergelijking met een batterij waarin dit optimalisatie-algoritme niet wordt toegepast, het geoptimaliseerde laden zowel de kosten als de broeikasgasemissies kan verminderen, met respectievelijk 10% en 27%. In **Hoofdstuk 4** is een soort-

gelijke analyse is uitgevoerd voor elektrische auto's, om de potentie tot kosten- en emissiereductie voor het slim laden van elektrische auto's en *vehicle-to-grid* (V2G) te bepalen. Er wordt aangetoond dat in het geval van slim laden, de uitstoot van broeikasgassen met 24% kan worden verminderd in vergelijking met ongecontroleerd laden. De uitstoot van broeikasgassen bij het toepassen van V2G kan met 67% kan worden verminderd. Bovendien kunnen de kosten en emissies van elektrische auto's tegelijkertijd worden verlaagd; een gebalanceerd schema resulteert bij slim laden in een kostenreductie van 18% vergezeld met een vermindering van de broeikasgasemissie van 16%. Bij V2G kan een kostenverlaging van 14% gepaard gaan met een emissiereductie van 51%.

Het technische potentieel van het koppelen van zonnepanelen aan batterijen wordt onderzocht door te bepalen welke rol batterijen kunnen spelen in piekuren met weinig opwek door zonnepanelen. Onderzoek naar dit potentieel wordt steeds belangrijker met de verdere penetratie van variabele hernieuwbare energiebronnen zoals zonne-energie in de elektriciteitsmix. Met behulp van gemeten elektriciteitsdata met hoge resolutie (10 seconden), wordt in **Hoofdstuk 5** eerst bepaald wat de optimale batterijgrootte is voor eigenverbruik van door zonnepanelen opgewekte elektriciteit. Simulaties laten vervolgens zien dat deze optimaal geschaalde batterijen kunnen de pieklast van de buurt vervolgens verminderen met 51%. In **Hoofdstuk 6** wordt de potentiële bijdrage van aan zonnepanelen gekoppelde batterijen aan de zogenaamde toereikendheid van energiebronnen van het energiesysteem onderzocht door hun capaciteitswaarderatio (CWR) te bestuderen. De CWR is de verwachte hoeveelheid van de energie-output van een technologie tijdens de pieklaturen gedeeld door het nominale geïnstalleerde vermogen van die technologie. Hoewel de bijdrage van zonne-energie beperkt is zonder batterijen (een CWR van 1%), kunnen geoptimaliseerde batterijen in combinatie met zonnepanelen een CWR van 25% hebben wanneer deze alleen worden opgeladen met door zonnepanelen opgewekte elektriciteit, en een CWR van 47% wanneer deze ook vanuit het net worden opgeladen. Dit terwijl ook in dit laatste geval het eigenverbruik van door zonnepanelen opgewekte elektriciteit nog steeds aanzienlijk toeneemt. Wat betreft elektrische auto's wordt aangetoond dat het grootste deel van het laden van elektrische auto's kan worden uitgesteld tot daluren (een CWR van 78%), en de CWR van een vloot elektrische auto's wordt geschat op 9%. Zowel stationaire batterijen als batterijen in elektrische auto's leiden dus tot een aanzienlijke toename van de CWR van zonnepanelen, wat belangrijk is in het kader van het handhaven van de systeembetrouwbaarheid in het geval van bijvoorbeeld de uitfasering van kolencentrales.

Resumerend, de bevindingen laten een groot economisch-, technisch- en duurzaamheidspotentieel zien van aan zonnepanelen gekoppelde batterijen. De

uiteindelijke waarde van deze batterijen wordt echter bepaald door de specifieke algoritmen die worden toegepast. Het wordt daarom geadviseerd om via beleid dat is gebaseerd op een algehele visie op de energietransitie passende stimulansen te bieden om de werking van opslagtechnologieën in de juiste richting te sturen.

Nomenclature

Acronyms

AEF	Average emission factor
AFOLU	Agriculture, forestry and other land use
aFRR	Automatic frequency restoration reserves
BESS	Battery energy storage systems
BRP	Balance responsible party
C-rate	Power to energy ratio battery
CBS	Centraal Bureau voor de Statistiek (Statistics Netherlands)
CCS	Carbon capture and storage
CES	Community energy storage
CVR	Capacity value ratio
DA	Day-ahead
DAM	Day-ahead market
DC	Direct current
DOC	Depth of cycle
DSM	Demand-side management
DSO	Distribution system operator
EF	Emission factor
ELCC	Effective load carrying capability
EMS	Energy management system
ENTSO-E	European Network of Transmission System Operators for Electricity
EU-ETS	European Union - Emission Trading System
EV	Electric vehicles
FEC	Full-equivalent cycles
FIT	Feed-in tariff
GHG	Greenhouse gas
HEF	Hourly emission factor
HEU	Heuristics
HH	Household
HP	Heat pump

ICE	Internal combustion engine
IEA	International Energy Agency
LA	Lead-acid
LCA	Life-cycle assessments
LCI	Life-cycle inventory
LDC	Load duration curve
LFP	Lithium-iron-phosphate
LiB	Lithium-ion battery
LOLE	Loss of load expectation
LOLP	Loss of load probabilities
LTO	Lithium-titanate-oxide
LV	Low voltage
MEF	Marginal emission factor
MV	Medium voltage
NCA	Nickel-cobalt-aluminum-oxide
NMC	Nickel-manganese-cobalt
OPF	Optimal power flow
PER	Perfect information algorithm
PHEV	Plugin hybrid-electric vehicles
PMU	Phasor measurement units
PV	Photovoltaic
REF	Reference case
SD	Standard deviation
Temp	Temperature
ToU	Time-of-use
TSO	Transmission system operator
V2G	Vehicle-to-grid
VRES	Variable renewable energy sources

Indices and Sets

c	Technology
f	Facility
$g \in \mathcal{G}$	Set of generation technologies
$h \in \mathcal{H}$	Household
i	Battery size
j	Country
$k \in \mathcal{K}$	Bin number in ϵ -constraint
l	Country from which electricity is imported
n	Half cycle number

$p \in \mathcal{P}$	Peak hours
$s \in \mathcal{S}$	Subsets of EV charging transactions
$t \in \mathcal{T}$	Time steps in the assessment period
y	Year in NPV calculation

Symbols

δ	Cycle depth	[%]
ϵ	Epsilon constraint	
η	Conversion efficiency	[%]
η_{ch}	Charging efficiency	[%]
η_{disch}	Discharging efficiency	[%]
ϕ	Battery's coefficient	[kWh ⁻¹]
B	Benefits of storage	[€/year]
c	Day-ahead market electricity price	[€/MWh]
C_{total}	Total costs	[€]
C_{battdeg}	Battery degradation costs	[€]
C_{batt}	Battery investment costs	[€/kWh]
C_{cable}	Costs for upgrading electricity cable	[€/km]
C_{el}	Total electricity costs	[€/year]
C_{grid}	Annualized grid reinforcement costs	[€/year]
C_{system}	System costs	[€/year]
C_{trans}	Costs for upgrading a transformer	[€]
CF	Correction factor	[%]
CP	EU-ETS CO ₂ price	[€/tCO ₂]
CVR_c	Capacity value ratio of technology c	[%]
D	Degradation	[%]
E_{G2L}	Electricity flow from grid to consumer	[Wh]
$E_{\text{PV-feed-in}}$	Electricity flow from PV system to grid	[Wh]
E_{S}	Energy supplied to the system	[Wh]
$E_{\text{batt,max}}$	Maximum amount of energy that can be charged in battery	[Wh]
$E_{\text{batt,min}}$	Minimum amount of energy that should be charged in battery	[Wh]
E_{batt}	Energy content of battery	[Wh]
$E_{\text{ch,max}}$	Maximum accumulated charging energy	[Wh]
$E_{\text{ch,min}}$	Minimum accumulated charging energy	[Wh]
E_{ch}	Charged energy	[Wh]
E_{disch}	Discharged energy	[Wh]
EF	Emission factor of fuel	[tCO ₂ /MWh _t]
EF_{car}	Emission factor for car transport	[kgCO ₂ -eq/MJ _t]
EF_{heat}	Emission factor for heat supply	[kgCO ₂ -eq/MJ _t]

FP	Fuel price	[€/MWh _t]
g	Emission intensity electricity	[kgCO ₂ -eq/MWh]
G_{battdeg}	Battery degradation emissions	[kg CO ₂ -eq/year]
G_{batt}	Battery manufacturing emissions	[kg CO ₂ -eq/kWh]
G_{cable}	Emissions associated with electricity cable	[CO ₂ /km]
G_{el}	Total electricity emissions	[kg CO ₂ -eq/year]
G_{grid}	Annualized grid reinforcement emissions	[kg CO ₂ -eq/year]
G_{system}	System emissions	[kg CO ₂ -eq/year]
G_{trans}	Emissions associated with upgrading a transformer	[kg CO ₂ -eq]
GHG_{cons}	GHG emissions of electricity consumption	[kgCO ₂ -eq]
GHG_{gen}	GHG emissions of electricity generation	[kgCO ₂ -eq]
GHG_{HV}	GHG emissions of electricity on high-voltage lines	[kgCO ₂ -eq]
H	Number of households	[-]
HEF_{cons}	HEF of electricity consumption	[kgCO ₂ -eq/MWh]
HEF_{gen}	HEF of electricity generation	[kgCO ₂ -eq/MWh]
HEF_{HV}	HEF of electricity on high-voltage lines	[kgCO ₂ -eq/MWh]
I_{cable}	Cable length	[km]
L	Lifetime	[years]
l	Battery age	[days]
L_{actual}	No. of actual cycles until end of life	[-]
L_{ca}	Calendric lifetime	[years]
L_{cy}	Cyclic lifetime	[years]
L_{cy}	No. of FEC until end of life under 100% cycle depth	[-]
M	Big-M constraint	[-]
m	Cyclic degradation exponent	[-]
MC	Marginal costs	[€/MWh]
ME	Marginal emissions	[tCO ₂ /MWh]
NC	Net-metered consumption	[Wh/year]
NPV	Net present value	[€]
$P_{\text{batt,max}}$	Maximum power to / from battery	[W]
$P_{\text{ch,max}}$	Maximum charging power	[W]
P_{ch}	Charging power	[W]
$P_{\text{disch,max}}$	Maximum discharging power	[W]
P_{disch}	Discharging power	[W]
$P_{\text{gen,CBS}}$	Average power generation according to CBS	[W]
$P_{\text{gen,missing}}$	Missing power generation in ENTSO-E Transparency	[W]
$P_{\text{gen,Transp}}$	Power generation according to ENTSO-E Transparency	[W]
P_{gen}	Power generation	[W]
$P_{\text{grid,max}}$	Maximum power to / from grid	[W]

P_{grid}	Power to / from grid	[W]
$P_{\text{L,agg}}$	Aggregated residual load	[W]
$P_{\text{load,Powerst}}$	Total load according to ENTSO-E Powerstats	[W]
P_{max}	Power capacity of a technology	[W]
P_{net}	Net power (consumption-production)	[W]
$P_{\text{pre-charging}}$	Power to pre-charge battery	[W]
P_{PV}	PV electricity generation	[W]
$P_{\text{rated,PV}}$	PV system size	[kWp]
P_{rated}	Maximum charging / discharging power battery	[W]
P_{res}	Residential load	[W]
$P_{\text{S,agg}}$	Aggregated surplus PV power	[W]
$P_{\text{tr,max}}$	Transformer capacity	[kVA]
PDI	Price difference increase	[%/year]
PH	Number of peak hours	[-]
ps	Power stabilizer	[%]
Q_{cap}	Battery charge capacity	[Ah]
r	Discount rate	[%]
S	Target variable	[-]
s_{opt}	Optimal storage size	[kWh]
SF	Scale factor	[-]
SOC	State of charge battery	[%]
SOC_{max}	Maximum allowable state of charge battery	[%]
SOC_{min}	Minimum allowable state of charge battery	[%]
T	Number of time steps in assessment period	[-]
VOC	Variable operation cost	[€/MWh]
x	Net PV power surplus (binary)	[-]
y	Fraction of PV surplus that fits in battery	[%]

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1 Introduction

1.1 Motivation

Over the period 1880 to 2012, the global average combined land and ocean surface temperature has increased by approximately 0.85°C [1]. An important anthropogenic driver of climate change is the emission of greenhouse gases (GHG) CO_2 , CH_4 and N_2O . Compared to pre-industrial levels, the atmospheric concentrations of CO_2 , CH_4 and N_2O have increased by 40%, 150% and 20%, respectively [1]. The Representative Concentration Pathway 8.5 (RCP8.5) by the IPCC, characterized by an absence of climate change mitigation policies, high population, low income growth and modest rates of technological change [2], is projecting a further global average temperature increase of 2.6°C to 4.8°C in 2080-2100 compared to the average of 1986-2005 [1]. Already, climate change has resulted in changing precipitation and/or melting of snow and ice in many regions, causing alterations in hydrological systems [3]. Climate-change-related extreme weather events, such as heat waves, extreme precipitation, and coastal flooding, comprise moderate risks for ecosystems and our modern societies at present, whereas these risks are expected to increase with further temperature rise. Additional global temperature increase is expected to cause adverse impacts on biodiversity and the global economy [3].

These developments have led governments across the world to develop policies for mitigating the adverse effects of anthropogenic climate change. In December 2015, the Paris Agreement was adopted under the United Nations Framework Convention on Climate Change. In this agreement, representatives from 196 countries agreed to strive for containing temperature increase “well below 2°C above pre-industrial levels; and to pursue efforts for limiting the increase to 1.5°C ” [4, page 22]. In recent years governments have adopted policies to decrease energy-related GHG emissions; already in currently stated policies, with low-carbon technologies supplying half of the growth in energy demand according to the World Energy Outlook of the International Energy Agency (IEA) [5].

Scholars have attempted to translate the climate mitigation goals to sustainable development pathways: scenarios that are in line with containing temperature increase below 2 or 1.5°C [6]. Combinations of technological solutions differ per integrated assessment model and on assumptions and constraints applied [6]–[11]. A main division in GHG emissions has been made between emissions related to land use and emissions related to the burning of fossil fuel use and industry [7]. The former is also referred to Agriculture, Forestry and Other Land Use (AFOLU) emissions. Although the share of AFOLU in total GHG emissions is small compared to fossil fuel and industry-related emissions [7], a rapid transformation in land use is expected to obtain the 1.5°C target [6]. Examples can be afforestation and the

sustainable use of land for bio-energy crops [12]. Non-energy related emissions come mostly from cement production, because of the emissions released in the process of converting calcium carbonate to calcium oxide. These emissions can be decreased by reducing the demand for cement or by improving the so-called clinker-to-cement ratio [6], [13]. Energy-related emissions are the largest contributor to GHG emissions [7], [11]. This can be energy needed for industrial processes, transportation, heating and cooling, or electricity generation. This prompts the need for an energy transition, to decrease the adverse impact of the energy sector on the global climate. One important mitigation option is fuel switching in end-user sectors, for example the electrification of heating (e.g. through deploying heat pumps) and transport (e.g. switching from internal combustion engine (ICE) vehicles to electric vehicles (EVs)) [7]. Also, much emphasis is placed on energy efficiency measures, i.e. decreasing the energy use per unit of output or service [7]. Furthermore, there is a wide consensus on the need for a deep decarbonization of electricity generation [7], [8], [14]. Again, the combinations of technological solutions differ per model and/or scenario. Electricity generation technologies associated with low GHG emissions include fossil-fuel based power plants that employ carbon capture and storage (CCS) techniques, and technologies that convert nuclear, bio-, hydro-, solar or wind energy to electricity. Battery technologies can play a role as enabler for fuel switching in the transport sector and for the integration of variable renewable energy sources (VRES) in the power system.

From the above mentioned mitigation options, this thesis focuses on the use of solar energy to generate electricity and its integration in the power system using battery-based storage. In the context of fuel switching, the focus is on EVs as a substitute for ICE vehicles. The technologies are studied in the residential sector. In the next sections, first the energy transition technologies under study are explained in more detail, and subsequently the role of bottom-up approaches as used in energy communities in the residential sector is explained.

1.2 Energy transition technologies: PV solar energy, energy storage and EVs

1.2.1 Photovoltaics

Photovoltaic (PV) systems are able to convert solar irradiation directly into electricity. Driven by a rapid reduction in manufacturing costs [15], the globally installed PV capacity has experienced strong growth in recent years, with a year-on-year increase of 33% in the period from 2013 to 2018 [16] (see Figure 1.1). At the end

Figure 1.1: Development in deployment of Photovoltaic power generation, behind-the-meter storage and battery electric vehicles. Sources: [16], [21], [22]/

of 2019, PV systems amounted to a total of 635 GWp¹ globally installed capacity [17]. When determining a cost-optimal electricity generation mix in line with the climate targets, different models indicate a required global installed PV capacity of 10 TWp in 2030 and 30-70 TWp in 2050 [18], [19] or 0.7 TWp [20] to 2 TWp [19] in Europe alone. Because of the variability or intermittency in electricity generation by PV systems, and present limitations in accurate solar forecasting, solutions need to be developed in order to ensure proper integration of PV electricity generation in the power system. One of the possible solutions is energy storage.

1.2.2 Energy storage

Energy storage technologies encompass a large set of technologies both in terms of centralized and decentralized installations. Historically, because of its low costs and large-scale potential, the most deployed energy storage technology is pumped hydro storage. In mid-2017, this technology represented 169 GW² of the total of

¹The use of the letter 'p' in the unit GWp comes from the fact that PV capacity is always given as peak (p) capacity, i.e. the power generated at full sun intensity.

²Note that some sources prefer to report power capacity (e.g. GW) while others prefer energy capacity (e.g. TWh). These are connected through the power to energy ratio of storage, i.e. C-rate

176 GW global storage capacity (96%) but its further growth is limited since most appropriate locations in Europe are already explored [23]. In recent years, the deployment of behind-the-meter storage has seen rapid growth. This is storage that is connected through the electricity meters of commercial, industrial and residential consumers, typically sized between 3 kW and 3 MW and often connected to PV systems [24]. Even though in 2013 only 0.11 GW behind-the-meter storage was installed, this amount increased more than ten-fold to 1.24 GW in 2018 [22] (see Figure 1.1). There is much uncertainty to what extent energy storage is going to play a role in a sustainable future. Lower estimates are provided by [25] and [20]; the IEA estimates an additional storage need of 0.48 TWh for Europe in their 2 degrees scenario (where VRES supply 27% to 44% of power generation) [25], Zappa et al. estimate an amount of 0.64 TWh for Europe in a 100% renewable power system [20]. Other studies estimate much higher storage capacities [14], [19], [26]. Child et al. estimate a storage capacity of 3.3-4.0 TWh for Europe [14], Breyer et al. estimate 10-19% of all electricity demand must be supplied by storage [19] and Bussar et al. estimate a storage capacity of 4.3 TWh, while also showing how optimal storage capacity differs per scenario [26]. Important moderating factors in these studies are the assumptions on transmission capacity, the role EVs can play as storage units and the level of detail on which the distribution grid is modelled. Hence, despite these individual differences, consensus exists on the importance of energy storage deployment. Important drivers are the efficient use of power system resources, increasing the use of VRES, increasing self-consumption, increasing energy access and growing emphasis on grid stability and reliability [5], [23], [25]. As suitable locations for additional pumped hydro energy storage installations e.g. in Europe are limited, batteries may play an increasingly important role [14]. It is estimated that behind-the-meter small capacity and grid-connected larger capacity batteries will represent a 63-75% share of the required storage in 1.5 degree scenarios [19], or on average 32 %, with a range 0-80%, depending on the specific scenario [26]. In recent years, lithium-ion based batteries (LiBs) have become the most important storage technology both for mobile and utility scale applications, pumped-hydro excluded, increasing its share in the energy storage technology mix from 41% in 2011 to 88% in 2016 [22]. This technology has experienced a rapid decline in manufacturing costs [27], and because of its high values of specific energy (in Wh/kg) it is currently the predominant battery technology in EVs.

1.2.3 Electric vehicles

Fuel switching in the transport sector is regarded as vital in the effort to decrease GHG emissions. Many 2050 mitigation scenarios envision only minimal emissions from the transport sector, as a result of electrification of transport combined with decarbonization of electricity generation [7], [10], [28]. Electric vehicles encompass plug-in hybrid EVs, battery electric vehicles, as well as fuel cell electric vehicles. The main difference between the plug-in hybrid electric vehicles and the battery electric vehicles is that the former also have an ICE, whereas the latter is fully electric. The battery electric vehicle is currently the most-deployed electric vehicle technology [21], and it is the focus of this thesis. Therefore, in the remainder, the acronym “EV” is used to represent solely battery electric vehicles. The global EV fleet has shown a large expansion in recent years, from 0.23 million EVs in 2013 to 3.29 million EVs in 2018; an increase of 1330% [21]. Many governments have set policies in place to abolish the sale of ICE-based vehicles and to promote deployment of EVs, and/or set targets for future EV sales; based on both policies in place and announced policies, the global EV fleet size is expected to exceed 155 million in 2030 [21].

1.3 Energy transition in the neighborhood

For PV and batteries, a distinction can be made by deploying systems in a centralized and decentralized manner. For example, PV can be deployed in solar farms on a utility scale at multi-MWp sizes, or as rooftop PV systems on households (typically a few kWp in size). This thesis focuses on decentralized PV and batteries by studying these technologies at the district level.

The EU has recognized the importance of user empowerment. In 2011, the Energy Roadmap 2050 was published, stating that public engagement is crucial for the energy transition [29]. In the recently proposed “Green Deal” the European Commission declares to “continue work to empower regional and local communities, including energy communities” [30, p.23]. The European Commission regards citizens as the driving force of the transition; one of the strategies that the EU aims to deploy is to facilitate grassroots initiatives on climate change and environmental protection [30].

Deploying PV systems on rooftops in the residential sector puts citizens in a more active role in the energy transition: they generate electricity themselves. This can have much impact on households’ energy balance by substantially increasing the self-sufficiency of households [31]. Energy technologies and the built environment are becoming more and more intertwined [32]. Rooftop PV systems hold a number

of further advantages compared to utility-scale PV (solar farms). First, rooftop PV is more efficient regarding use of land by default, since solar farms are placed on land which can often also be used for different purposes. Furthermore, solar farms can have impact on soil and biodiversity; local and micro-climates are influenced because of changes in irradiation and precipitation distributions [33]. Although this impact can be mitigated to some extent, this potential downside is absent in rooftop PV. Lastly, and possibly related to the former two, rooftop PV holds a consumer preference over solar farms, which underlines the EU focus on public engagement. Consumers are willing to pay more for PV installed on roofs than in solar farms [34]. An indirect advantage of rooftop PV is that it can strengthen the consumer's environmental self-identity; past behavior (e.g. the purchase of a PV system) may influence in how far a person sees her- or himself as environmentally friendly [35]. This in turn is related to a higher probability of increased pro-environmental behavior in the future [36].

Social aspects are often overlooked in technical research on the energy transition [37]. A more active role of end-users is captured in the concept of renewable energy communities, which has gained attention in recent years [38]. Energy communities entail people in a neighborhood who jointly invest in renewable energy technologies, thereby both producing and consuming electricity (i.e. prosuming) [38]. This has given rise to new prosuming concepts, like the aggregation of self-consumption on community level [39]. Bottom-up, community-led and owned energy projects are associated with higher levels of public acceptance than alternative commercial or top-down schemes [40]. Energy communities hold additional value from a social perspective in several aspects [41]. Firstly, people in energy communities are able to learn from each other. Secondly, energy communities can play a role in the general energy transition because they are often connecting various important ("regime") actors [41]. Among the motives to form an energy community, financial and environmental considerations are the most important [38]. Recent techno-economic research on energy communities shows that both financial and environmental objectives can be obtained simultaneously [42]. Taken together, this shows the importance of taking a more integrated approach in research, connecting technology, market and stakeholder aspects [37].

1.4 The integration of distributed PV and EVs in the power system: challenges and solutions

Within the electricity system, energy communities are physically connected to the low voltage (LV) distribution grid. Table 1.1 provides an overview of some of the

Table 1.1: PV-related challenges and possible solutions on the LV-grid.

	PV curtail- ment	Grid ex- pansion	Demand Response	Energy storage
<i>Maintain voltage range</i>	X	X	X	X
<i>Avoid thermal overload trans- formers and power cables</i>	X	X	X	X
<i>Matching demand with sup- ply</i>			X	X

challenges related to the large-scale integration of PV, and potential solutions. Curtailment of PV can be a cheap and effective solution to prevent voltage fluctuations and to avoid overloading of cables or transformers. However, with deeper penetration of PV, this would entail increasing electricity losses and concomitant lower economic revenues [43]. Therefore, grid expansion measures are often undertaken for PV integration [44]. These comprise of extending the network and upgrading and/or replacing existing grid assets with new ones, e.g. replacing the LV / medium voltage (MV) transformer, segmenting local grids, installation of parallel cables and upgrading cables/feeders in terms of thickness or material.

An alternative to PV curtailment and grid expansion is attempting to match electricity demand with electricity generation. This entails a shift from the traditional power system, where supply is adjusted to meet the demand. In this context, increasing the self-consumption of PV-generated electricity has received much attention from scholars and policy makers. Next to the PV-related challenges addressed in 1.1, an advantage of increasing self-consumption can also be a reduction of losses associated with the transportation of distributed PV-generated electricity [45]. Policies to increase PV self-consumption have been adopted in a wide range of countries [46]. In general, self-consumption is stimulated when the feed-in tariff for PV-generated electricity is lower than the electricity retail price [47]. Demand response covers a wide range of measures at the demand-side [48]. This can for example reduce peak demand, which can reduce the needs for investments in distribution grids [49]. Scheduling flexible appliances such as washing machines and dish washers to hours with high PV electricity generation can increase PV self-consumption with 2-15% points [50], [51]. Demand response through scheduling EV charging holds more potential to increase self-consumption: 13-38% points [52]. Battery storage with a size of 0.5-1.0 kWh per kWp of installed PV increases the self-consumption by 13-24% points [50].

For demand response, the energy demand of appliances need to be flexible to some extent, and able to respond to external signals. For example, heat pumps can respond to market signals to provide ancillary services to the energy system

resulting in economic profit for the end user [53], [54]. In this context, the term "smart grid" is of importance. Compared to a conventional power grid, the main contribution of the smart grid is the possibility of bidirectional flow of energy and communication signals [55]. It is thus connected both to the technical aspects of the power system, because of the need for information and communication technologies, and the more active role of the end user as an important stakeholder. In the smart grid environment technology and end users can evolve together towards a sustainable and cost-effective energy system [56].

Research into PV systems coupled with batteries or EVs has received much attention from scholars in recent years. It has been found that PV-battery systems are an essential part of the cost-optimal solution for households in a wide range of geographical regions in 2050; the role that batteries can fulfill in the grid can also be fulfilled by batteries of EVs provided that these can supply electricity back to the grid [57]. Already today, small and efficient storage is considered highly beneficial for the integration of VRES [58]. Batteries can have various applications when coupled to a PV system: increasing PV self-consumption, demand load-shifting, demand peak shaving and avoidance of PV curtailment [59], [60]. However, costs of standalone batteries are still considered high, which makes the use of EV batteries an attractive alternative [61].

The impact EVs can have on the stress on the grid is equivocal. In case of uncontrolled charging, the EV charging demand peaks typically coincide with household electricity demand peaks which can lead to congestion problems in the local grid, high investment requirement for capacity reinforcement, less efficient power supply, and power quality issues [62]–[64]. So-called smart charging, also called coordinated or controlled charging, is often presented as a potential solution. This entails the redistribution of charging demand over the period in which the EV is connected to the charging point, to meet an external objective. This objective can be similar to peak shaving. In the Netherlands, it has been found that 59% of the aggregated EV demand can be delayed for more than eight hours [65]. By studying EV penetration rates of up to 20% in the United Kingdom, it has been found that there is no impact from domestic EV charging on the peak electricity demand when smart charging is implemented [66]. For a 100% penetration rate of EVs in the Flemish residential grid, it was found that there was no need for upgrading the transformer capacities in case of smart charging under a peak minimization objective [67]. The same study, using a combination of voltage droop charging and EV-based peak shaving as a charging strategy, found that voltage levels in the 100% penetration scenario were never below 0.85 p.u. in case of smart charging, and with a maximum of 1.4% of the time per week between 0.85 and 0.90 p.u. which is in line with the EN-50160 standards [68]. Next to charging during off-peak

hours, numerous objectives have been addressed by smart charging algorithms to further increase the value of smart charging. For example, a cost minimization approach can be implemented, mostly resulting in valley-filling type of charging [69], [70]. EVs can also be used to provide ancillary services with smart charging, for example by providing upwards and downwards regulation reserves around a given set point of charging power or mitigate voltage fluctuations caused by PV [71], [72]. Another use of smart charging is to increase the utilization of renewable energy, particularly PV energy [52]. EVs could contribute further to the reliability of the electricity grid by providing Vehicle-to-Grid (V2G) services, i.e. delivering power from the EV battery back to the electricity grid. V2G would increase the potential for providing ancillary services [73], open up possibilities for EVs to serve as back-up for renewable electricity generation [74] and contribute to peak shaving [75]. However, barriers for the deployment of V2G exist as currently most commercially available EVs are not capable of delivering V2G services, and concerns exist that V2G could hamper the lifetime of the battery of an EV [76].

On the transmission level, the concept resource adequacy receives much attention in the context of increasing shares of VRES [77]. Resource adequacy encompasses the ability of a power system to provide long-term adequate supply in meeting electricity demand [78]. As briefly mentioned before, one of the challenges of the deployment of PV is the mismatch between PV electricity generation and electricity demand. Being directly related to solar irradiation, PV electricity generation is diurnal and susceptible to weather variations [79]. A potential downside of PV, and VRES in general, is the potential need for back-up power generation facilities for times without sufficient solar or wind energy available. This can be economically inefficient [80], or lead to higher GHG emissions if these facilities have high emission factors and a high load factor. Potentially, distributed flexible resources stationary and EV batteries can also be used to decrease the need of back-up capacity [81].

In existing literature on PV coupled with batteries some areas of research are still under-explored. First, coupling PV with batteries is currently not economically viable in most regions, making it extremely important to combine different applications of a battery in support of multi-revenue business models [59]. In the research presented in this thesis, self-consumption of PV-generated electricity using a battery is always combined with at least one or more applications. Second, most studies focus on battery operation optimization to grid applications and overlook the possibility to minimize GHG emissions in the operation of batteries. This while it is known that coupling batteries with PV can increase GHG emissions [82], which evidently is not a desired outcome in the context of climate change mitigation. Third, most studies are aimed at either the macro (transmission system)

or the micro (distribution system) level; there is a lack of studies bridging the gap between these levels [83]. Specifically, the value flexibility resources deployed on the distribution level can have for resource adequacy on the transmission level is not well established.

1.5 Research questions

The research gaps described above are addressed by the following main research question:

What benefits can be obtained from PV systems coupled with batteries?

Batteries of interest are stationary batteries (either aggregated small-sized home batteries or a larger-sized community battery) and EV batteries. Benefits are subdivided into environmental, economic and technical benefits. The environmental benefits are addressed by focusing on the GHG emission reductions that PV coupled with batteries can have. To determine the potential economic benefits of the investigated technologies, economic optimization is performed both in the investment phase and in the operational phase. The technical benefits are investigated in terms of the potential contribution of PV and batteries to peak demand reduction at different levels of the grid. This resulted in the following three sub-questions:

1. What is the greenhouse gas reduction potential of PV systems coupled with batteries?
2. What is an economically optimal way to combine PV systems and batteries?
3. What is the capacity PV systems coupled with batteries can provide at different levels of the grid?

In this research, we investigate PV and batteries deployed at the distribution system level. Our analysis is mainly focused on the Netherlands in terms of data collection and definition of case studies. The basis of our research is PV self-consumption; all standalone battery applications should be seen as additional applications next to the self-consumption of PV-generated electricity. For EVs this is of less importance, as they already fulfill an important other application, i.e. transport.

1.6 Thesis outline

Table 1.2 provides an overview of all chapters in this thesis, where and whether it has been published with contributing co-authors, and which research question(s) they address.

In the first part of this thesis, **Chapter 2** to **Chapter 4**, the impact that PV coupled with batteries can have on the short term is assessed, by focusing on the operational cost and emissions. **Chapter 2** determines the GHG emission reduction potential of energy communities in which PV systems, batteries, EVs and heat pumps are deployed in eight European countries. The study uses an economic optimal configuration of these technologies as input. Taking the full life cycle of these technologies into account, it is determined how a country's hourly electricity generation mix affects GHG emission reduction potential of the energy communities. **Chapter 3** proceeds on the notion that accounting for the hourly GHG emissions of a power system is important for the environmental impact of a battery. Herein, marginal emission profiles are constructed to be used as input for emission reduction optimization. The method description and the constructed marginal emission profiles are included in **Appendix A** of this thesis. The marginal emission profiles are subsequently used to perform a multi-objective optimization of cost and emissions. This analysis is expanded to study smart charging and V2G when deploying EVs in **Chapter 4**, which also addresses whether grid reinforcements are beneficial from a cost and/or emissions perspective.

In the second part of the thesis, **Chapter 5** and **Chapter 6**, the limited availability of PV-generated electricity during peak demand hours is addressed. This becomes an increasingly relevant topic in parallel with the further deployment of VRES. **Chapter 5** addresses the optimal battery size when coupling batteries to a PV system, using high resolution measured power data (10 seconds). Furthermore, the impact that these batteries, optimally sized for PV self-consumption, can have on the neighborhood residual load peaks is explored, using various algorithms. In **Chapter 6** it is investigated what effects PV systems, batteries and EVs, deployed at the distribution level, can have on the power system level. Insights are provided on important factors determining the contribution to the power system's resource adequacy.

The results of this thesis are synthesized in **Chapter 7**. This chapter also contains the answers to the research questions and policy recommendations as well as recommendations for future research.

Table 1.2: Overview chapters.

Chapter	2	3	4	5	6
Article title	Comparison of the Greenhouse Gas Emission Reduction Potential of Energy Communities	On the trade-off between Environmental and Economic Objectives in Community Energy Storage Operational Optimization	Should we reinforce the grid? Cost and emission optimization of electric vehicle charging under different transformer limits	Photovoltaic systems coupled with batteries that are optimally sized for household self-consumption: Assessment of peak shaving potential.	Insights on the Capacity Value of PV, Stationary Storage and Electric Vehicles.
Co-authors	A. Louwen, I. Lampropoulos and W. van Sark	T. AlSkaif, I. Lampropoulos, S. Henein and W. van Sark	N. Brinkel, T. AlSkaif, I. Lampropoulos and W. van Sark	I. Lampropoulos and W. van Sark	H. Aghaie, I. Lampropoulos and W. van Sark
Journal	Energies	IEEE Transactions on Sustainable Energy	Applied Energy	Applied Energy	Sustainable Energy, Grids and Networks
Publication status	Published (2019)	In press (2020)	Accepted (2020)	Published (2018)	Submitted (2020)
DOI	10.3390/en12234440	10.1109/TSTE.2020.2969292	-	10.1016/j.apenergy.2018.04.023	-
Research questions addressed	1	1 and 2	1 and 2	2 and 3	3

2 Comparison of the greenhouse gas emission reduction potential of energy communities

This chapter is based on the publication:

W.L. Schram¹, A. Louwen¹, I. Lampropoulos, and W.G.J.H.M. van Sark, “Comparison of the Greenhouse Gas Emission Reduction Potential of Energy Communities,” *Energies*, vol. 12, no. 4440, 2019. DOI: 10.3390/en12234440

¹These authors contributed equally to this work.

Abstract

In this research, the greenhouse gas (GHG) emission reduction potentials of electric vehicles, heat pumps, photovoltaic (PV) systems and batteries were determined in eight different countries: Austria, Belgium, France, Germany, Italy, the Netherlands, Portugal and Spain. Also, the difference between using prosuming electricity as a community (i.e. energy sharing) and prosuming it as an individual household was calculated. Results show that all investigated technologies have substantial GHG emission reduction potential. A strong moderating factor is the existing electricity generation mix of a country: the GHG emission reduction potential is highest in countries that currently have high hourly emission factors. GHG emission reduction potentials are highest in southern Europe (Portugal, Spain, Italy) and lowest in countries with a high share of nuclear energy (Belgium, France). Hence, from a European GHG emission reduction perspective, it has most impact to install PV in countries that currently have a fossil-fueled electricity mix and/or have high solar irradiation. Lastly, we have seen that energy sharing leads to an increased GHG emission reduction potential in all countries, because it leads to higher PV capacities.

2.1 Introduction

In this chapter, the greenhouse gas (GHG) emission reduction potentials of PV systems, stationary batteries and EVs are determined. Chapter 3 and 4 will expand on this topic by studying the additional GHG emission reduction potential when implementing optimization techniques.

EU strategies for a low carbon built environment include the electrification of transport which combines vehicles with efficient power trains and the opportunity of using renewable energy sources [84], and electrification of heating systems in buildings through heat pumps [85]. Currently, heat pumps account for 5% in sales for heating requirement and 3% in energy for heating, however, in the International Energy Agency (IEA) scenarios towards a sustainable future, heat pumps make up from 10% to 30% of the heating equipment stock [86]. At the same time, the global EV fleet has shown a large expansion in recent years, from 1.3 million EVs in 2015 to 5.1 million EVs in 2018 [86], and this development will only be intensified since electric light duty vehicles are expected to reach cost parity with internal combustion engine (ICE) vehicles around 2025 in many major markets, driven mainly by declining battery costs [87]. PV technology has evolved in the past decades into a major renewable electricity supplying technology with a total installed capacity of 600 GW [88]. As a result of the large deployment of PV systems, there is an ongoing transition from centralized to decentralized electricity

generation. Hence, the role of households on the electricity market is changing, from being solely consumers of electricity, to becoming so-called prosumers, i.e. both producing and consuming electricity [89].

The integration of EVs and heat pumps into the electricity system provides opportunities but also poses challenges. Both technologies are synergistic with renewable energy sources, and especially PV generation, in terms of a primary renewable energy input and increased self-consumption [90], [91]. However, the electrification of heating and transport systems also poses challenges to the electricity grid, since heating and charging requirements often coincide with peak electricity demand hours. Staffell & Pfenninger (2018) found that heat supply electrification could increase peak electricity demand in the UK by 20% within 15 years [92], whereas another study found that a 50% penetration rate of heat pumps can result into an increase of 27.5% in peak electricity demand in the UK [93]. Similarly, in the case of uncontrolled charging, the EV charging demand can lead to congestion problems, high capacity reinforcement investment needs and less efficient power supply [62]–[64]. To enable an effective transition to an electrified and sustainable energy system, the concepts of electricity storage, smart grids, and demand response are getting increased attention. Especially, battery energy storage systems (BESS) are expanding fast, with the aim of providing short-term storage. A BESS can improve the efficiency of the power system by providing additional flexibility to grid operators, such as the provision of ancillary services, peak shaving, congestion management and reduction of reserve provision from conventional units [54], [94]–[96]. Battery storage capacity is growing fast, actually tripled in less than three years, largely driven by lithium ion batteries, which now account for just over 80% of all battery capacity [87]. In this context, PV systems, battery-electric vehicles (Battery EVs), battery energy storage systems (BESS), and heat pumps (HPs) are key technologies in decarbonising cities. However, this development will require integration technologies such as smart grids and ICT to enable a seamless operation.

The term “smart grid” generally refers to an electricity grid which uses information and communication technologies tools to balance electricity demand and generation, taking into account the intermittent nature of variable renewable energy sources (VRES), demand side management (DSM) and electricity storage [97]. The main aim of smart grids is to ensure cost-optimal use of VRES electricity while minimizing the need for grid re-enforcement due to the strong increases in electricity demand and intermittent decentralized generation. The research on smart grids also includes the concepts of energy communities or energy sharing [38]. An energy community can be broadly defined as a group of consumers and/or prosumers, that together share energy generation units and electricity storage. The

idea is that it is financially beneficial to exchange energy within this community, rather than exchanging it with the grid. This would decrease requirements for grid re-enforcement, and thus allow for a larger deployment of VRES (such as PV systems) in urban environments.

To analyze different business cases for PV prosumers, taking into account electricity storage, EVs and other technologies, the EU-funded PVP4Grid project was initiated [98]. The main project aim is to increase the market share and value of PV, by enabling consumers to become prosumers, in a system-friendly manner. Among other activities, the project has analyzed different grid concepts or scenarios: 1) consumers purchasing electricity individually from the grid, 2) consumers purchasing and producing electricity individually (with the possibility to invest in PV and/or BESS), and 3) consumers forming energy communities, together optimizing purchasing electricity and investments in PV and BESS. The objective is to show how the overall costs for consumers change, and what the benefits are of forming energy communities. The results indicate that investments in BESS and especially PV systems are more than offset by savings in electricity purchase, and that these benefits are further increased when forming energy communities [99].

Next to financial considerations, environmental concerns also play an important role in investments decisions of homeowners [100]. Furthermore, an important underlying rationale of offering incentives for decentralized renewable electricity generation is the mitigation of GHG emissions. Therefore, in this study an assessment is performed on the GHG emission reduction potential of various decentralized energy technologies of a reference European community, taking their full life cycle into account. The focus in this chapter is on technologies that enable the electrification of heating and transport systems. As explained above, EV and HP technologies are key in decarbonizing cities, and at a state of technological development that result into growing market shares worldwide. However, electrification will only be viable if power generation is decarbonized in parallel [101], and supported by grid integration measures. To further increase the comprehensiveness of the GHG impact assessment, it is performed for eight different countries: Austria, Belgium, France, Germany, Italy, the Netherlands, Portugal and Spain. These eight countries are the target countries defined in the PVP4Grid project and they provide a comprehensive selection from Southern, Western and Central Europe in terms of climate and generation mix. In this way, it can be determined in which countries the prosumer concepts have the highest climate mitigation potential.

Since the electrification of heating and transport is primarily aimed at reducing GHG emissions, numerous authors have performed life-cycle assessments (LCAs)

of these technologies, to establish a.o. their GHG emission reduction potentials. Of the technologies considered here, PV systems likely have the longest history of LCA studies, with first examples of somewhat basic LCA studies dating back roughly forty years [102], [103]. Since the publication of those early works, the field of LCA has developed significantly, with many analyses of PV modules and systems (see e.g. a comprehensive review in [104]), and renewable energy technologies in general have been thoroughly studied [105], [106]. For all technologies studied here, a large number of LCA studies are available. Many publications focus on the manufacturing of the technologies, but additionally, publications are available that also include or even focus on the use-phase.

For EVs, most commonly a comparison is made for passenger vehicles, focusing on a comparison between traditional ICE vehicles vs. EVs or plugin hybrid-electric vehicles (PHEVs), hence the results are expressed as environmental impact per passenger-kilometer [107]–[114]. Also for heatpumps, LCAs conducted often make a comparison between the novel technology and its incumbent competitor, which is in the case of heating mostly a natural gas fired boiler [115]–[122]. LCAs of battery storage systems are much less widespread, as was discussed by Pellow et al. [123], especially those including use-phase impacts. For all technologies mentioned here, the use-phase makes a substantial contribution to the overall life-cycle environmental impact. Since the increased attention for the concept of decarbonisation of the built environment, several LCAs have also been conducted that analyse e.g. zero-energy buildings or even neighborhoods and micro-grids [124]–[126].

In traditional LCA approaches, average emission factors (AEFs) are used to reflect the GHG intensity to account for the electricity consumption during the lifetime of a technology. This implicitly assumes emission factors are constant during the year. In reality, emission factors fluctuate during the season and the day because of variable renewable electricity generation, which have low emission factors, and as a result of the economic dispatch of conventional technologies, which have large individual differences in GHG intensity [127]. In a future energy system with a very high share of VRES, the demand even has to adjust to the electricity supply of variable renewable electricity generation, i.e. DSM. This stresses the importance of using time-varying emission factors instead of AEFs. For most of the LCA studies mentioned above, AEFs were used, with the exception of two studies focusing on the application of batteries [82], [128]. Time-varying emission factors have also been used to more accurately determine the impact of energy efficiency measures [129], [130] and for deployment of wind power [131], but never in a such comprehensive manner as in our study. As part of this study, the hourly emission factors (HEFs) of the eight aforementioned countries are determined for the year

2017 and used to determine the scope 2 emissions (i.e. emissions related to the use of electricity) of the prosumer concepts.

The contribution of this study is threefold. First, different policy scenarios are compared, quantifying the climate impact of different policy options. Second, eight European countries are compared, which provides insight in how differences between countries influence the GHG mitigation potential of a technology, and simultaneously gives a practical indication of where prosumer concepts have the largest mitigation potential. Third, hourly emission profiles are constructed and the impact of their use is assessed. This is an improvement to current LCA methodology, and moreover the emission profiles are added as supplementary material to enable their use by other scholars and practitioners.

The chapter is further structured as follows. In Section 2.2.1, all used methods are explained. Section 2.3, the Results section, is divided into four subsections. First, the HEFs are presented. Then, the GHG emissions of the European Communities are compared. Subsequently, GHG impact of individual technologies will be compared per country. Lastly, the impact of using HEFs, as opposed to AEFs, is examined. The chapter concludes with the discussion and conclusions in Section 2.4.

2.2 Methods

2.2.1 Goal and scope

The typical EU community has been defined in [99] and is shown in Figure 2.1. This all-electric community consisted of four single housing units, two stand-alone commercial consumers and one apartment building that consisted of one commercial consumer and six apartments. In total, 23 people lived in this community, and they owned a total of 11 EVs. All rooftops had potential for PV, and heating was supplied by HPs. Also, there was space available for installing one central battery.

Three scenarios were defined: *Baseline* scenario, the *All-electric - No sharing* scenario and the *All-electric - Sharing* scenario. The *Baseline* scenario entailed one metering point per household and no investment options in PV or BESS. In this scenario, the transport need was assumed to be met by ICE vehicles and heating was supplied by largely fossil fuel-based heating (see section 2.2.3.3). The *All-electric - No sharing* also entailed individual metering points, but with investment options in PV and BESS. Lastly, the *All-electric - Sharing* scenario entailed possibility for investment and one central metering point (i.e. energy sharing is allowed). Both the *All-electric* scenarios had HPs and EVs deployed. The economic optimization

Figure 2.1: Overview of the 'typical EU community' analyzed here. Source: [99].

in [99] determined the final configuration of installed PV and BESS capacity. This differed per country because of difference in household electricity profiles, solar irradiation and national policies. To calculate the GHG emissions, life-cycle emissions of the aforementioned technologies were taken into account, as well as the household electricity consumption. Construction and decommissioning of the buildings themselves and of other household appliances were outside of the scope of this research. The year of focus was 2017.

2.2.2 Hourly emissions factors

In general, an emission factor can be defined as emissions GHG over an amount of Energy E . For the HEFs, a distinction can be made between the HEFs of electricity generated in a country and the HEFs of electricity consumed in a country. The HEF_{gen} of country j in time step t (hourly resolution) can be calculated according to equations 2.1a and 2.1b:

$$GHG_{gen,jt} = \sum_{g=1}^G E_{gen,gjt} * EF_{gj} \quad (2.1a)$$

$$HEF_{gen,jt} = \frac{GHG_{gen,jt}}{\sum_{k=1}^G E_{gen,gjt}} \quad (2.1b)$$

where EF is the Emission Factor of generator $g \in (1, 2, \dots, G)$. For the EF of a generator, the weighted average of generators with the specific fuel type in the accordant country was taken from the ecoinvent v3 database [132]. When calculating this weighted average EF , we accounted for the annual generation from different types of generators within each fuel type (e.g. combined cycle vs. conventional generators).

A shortcoming of taking the HEF_{gen} to account for GHG emissions of electricity consumption, is that it neglects import and export of electricity. In reality, electricity consumed is a mixture of electricity generated in a country j and electricity imported from country $l \in (1, 2, \dots, L)$ with L being the number of countries that country j has interconnection lines with. So as an intermediate step, the HEF on the high-voltage (HV) lines of a country is calculated according to equations 2.2a and 2.2b:

$$GHG_{\text{HV},jt} = GHG_{\text{gen},jt} + \sum_{l=1}^L E_{\text{import},jlt} * HEF_{\text{gen},tl} \quad (2.2a)$$

$$HEF_{\text{HV},jt} = \frac{GHG_{\text{HV},jt}}{E_{\text{gen},jt} + \sum_{l=1}^L E_{\text{import},jlt}} \quad (2.2b)$$

For countries that were the focus of this study, the HEF_{gen} calculated in eq. 2.1b was taken, for other countries the AEF was used from ecoinvent. This resulting mix was exported to neighbouring countries l . So finally, the HEF_{cons} was calculated by using equations 2.3a and 2.3b:

$$GHG_{\text{cons},jt} = GHG_{\text{HV},jt} - \sum_{l=1}^L E_{\text{export},jlt} * HEF_{\text{HV},jt} \quad (2.3a)$$

$$HEF_{\text{cons},jt} = \frac{GHG_{\text{cons},jt}}{E_{\text{gen},jt} + \sum_{l=1}^L E_{\text{import},jlt} - E_{\text{export},jlt}} \quad (2.3b)$$

Electricity generation data were taken from ENTSO-E [133], which reports the hourly generation per fuel type for the EU28 member states. The fuel types encompass Biomass, Fossil Brown Coal/Lignite, Fossil Coal-derived gas, Fossil Gas, Fossil Hard Coal, Fossil Oil, Fossil shale Oil, Fossil Peat, Geothermal, Hydro (pumped, Run-of-river and Water Reservoir), Marine, Nuclear, Solar, Waste, Wind Offshore and Wind Onshore. The treatment of missing data can be found in Appendix 2.A.

2.2.3 GHG emissions of applied technologies

To account for a shift in technologies, from a scenario with traditional space heating, ICE vehicles and without any installed PV capacity towards a scenario with HPs for space heating, EVs and installed PV and BESS, we took into account the GHG emissions related to manufacturing of all mentioned technologies. Using data from the ecoinvent v3 database, we expressed the GHG emissions released during manufacturing in functional units that allowed us to calculate *annual* GHG

emissions attributed to manufacturing of the selected technologies. In sections 2.2.3.1-2.2.3.3 we describe in more detail the underlying data and assumptions made to select the appropriate input data.

2.2.3.1 Manufacturing of PV and BESS

In the all-electric technology scenarios, investments in PV and BESS were made. To assess the effect that these investments have on annual emissions, we took into account the GHG emissions from manufacturing of these technologies.

For PV systems, we assumed the installation of multi-crystalline, roof-mounted PV systems. Here, we distinguished between flat-roof mounted systems for the apartment and commercial buildings, and slanted-roof systems for the three detached houses (all shown in Figure 2.1). We chose multi-crystalline systems as these currently have lowest installed system cost, hence they would be the optimal choice in a cost-optimization exercise.

It must be noted that the data in ecoinvent v3 for PV systems is outdated, hence the emissions associated with manufacturing of these systems are much higher than they would be for modern PV systems. However, as we discussed in section 2.2.1, we wanted to base all results on LCA data from a single database for consistency between different technologies.

However, for BESS there is unfortunately no complete dataset available in ecoinvent v3 that includes both the battery cells as well as the energy management system and inverter. Hence, for BESS, we based our results on data presented in [91] for the storage and balance-of-system components of BESS. In this study, we assumed a battery C-rate of 0.5, which is in line with most currently commercially available BESS.

2.2.3.2 Manufacturing of ICE vehicles and EVs

To account for the annual emissions related to the operation of passenger vehicles, we compared conventional ICE vehicles in the baseline scenario with EVs in the full-electric scenarios. The GHG emissions of both were modelled based on data in ecoinvent v3. This database includes LCA data for a large variety of ICE vehicles of different sizes and fuel types. For EVs, there is only one type of passenger vehicle in ecoinvent. For this study, we compared medium EURO5 passenger cars with this single type of EV. To account for fuel type, we used data from Eurostat [134], which describes the share of diesel vs. petrol engine cars. For Italy we assumed the shares to be the weighted averages of the seven other countries since there were no data available for Italy in the Eurostat dataset.

Since the data from ecoinvent include both the manufacturing of the vehicles, as well as the energy use while driving, we corrected the data for EVs to exclude electricity use, since the emissions from charging the EVs were modelled separately.

2.2.3.3 GHG emissions related to heat supply

In the baseline scenarios, GHG emissions related to space heating and hot water demand were modelled based on the current shares of different heating technologies in the eight target countries. The Heat Roadmap Europe 4 project published a dataset in 2015 [135] detailing the heating and hot water technologies in several European countries, including our eight target countries. Using these shares, we calculated an average emissions factor for each unit of heat demand ($\text{gCO}_2\text{-eq/MJ}_{\text{th}}$), using as input country specific emissions factors from ecoinvent for each of the heating technologies.

For the all-electric scenarios, we assumed all heat (and hot water) demand to be fulfilled by means of air source HPs. Since the electricity use of the HPs were modelled separately, emissions related to the electricity use of HPs were calculated directly by using the HEFs. Emissions related to manufacturing of the HPs were modelled based on data from ecoinvent v3 that expresses the impact of manufacturing and other auxiliary processes per MJ of heat demand.

2.2.4 Community-level GHG emissions

Using the HEFs, the time series of electricity flows to and from the grid and within the community, and the emissions related to manufacturing of the selected technologies, we calculated the annual emissions for each building in the community, and for the community as a whole. Broadly speaking, GHG emissions in our study can be attributed to:

- Electricity consumption from the grid
- Fuel combustion in ICE vehicles in the baseline scenario
- Fuel combustion for heating in the baseline scenario
- Manufacturing of vehicles, PV and battery systems, and heating technologies
- Electricity feed-in to the grid from PV (avoided or “negative” emissions)

The GHG emissions from grid electricity consumption were calculated by multiplying the two time series of HEF_{con} and grid electricity consumption E_{G2L} :

$$GHG_{\text{grid},t} = HEF_{\text{con},t} \cdot E_{\text{grid},t} \quad (2.4)$$

Similarly the emissions avoided by feed-in of PV electricity to the grid were calculated by multiplying the time series of HEF_{con} and PV grid feed-in $E_{\text{PV-feed-in}}$. The emissions for fuel combustion for car transport and heating, were calculated by multiplying the annual driven kilometers and annual heat demand by the emission factors for transport (EF_{car} , in gCO₂-eq per passenger·km) and heating (EF_{heat} , in gCO₂-eq/MJ_{th}), respectively. These emissions factors, taken from ecoinvent v3, also include the GHG impacts of manufacturing the respective technologies.

In the all-electric scenarios, heating and car transport are obviously fully electrified, hence there was no direct fuel combustion. In these scenarios, we attributed the emissions to each process by taking into account the time series of EV charging and HP electricity demand. Since we modeled the impacts of electricity use for these processes directly, the emission factors EF_{car} and EF_{heat} in this case only included the impacts related to manufacturing. Additionally, in the all-electric scenarios PV systems were installed, hence the emission factors attributed to EV charging and heat-pump demand were corrected for the share of PV electricity in the overall household electricity demand. Hence, if the complete electricity demand at time t was met by PV electricity, the emission factor at time t for electricity use was 0 gCO₂-eq/kWh.

2.2.5 Input data

The results from the economic optimization from Fleischhacker *et al.* [99] can be found in Table 2.1. As mentioned above, these results were the result of national policies, country-specific solar irradiation and the country-specific electricity profiles. These numbers were taken as input for calculating the GHG emissions reduction potential, together with the timeseries of electricity demand from [99]. The study of Fleischhacker *et al.* analyzed the electricity flows from and to the grid, battery, EV, HP and PV systems, for the eight target countries, and for each of the building units as shown in Figure 2.1.

As mentioned above, the generation data per fuel type were taken from [133]. This is a database where individual Transmission System Operators, associated in ENTSO-E, upload the hourly load values per production type of the individual countries.

The life-cycle emissions of the technologies as well as the AEFs of countries outside of the scope of this study are taken from ecoinvent v3 [132]. This is a highly regarded, comprehensive life-cycle inventory (LCI) database with LCI data on a vast amount of processes, materials and energy flows.

Table 2.1: Results of economic optimization, from [99].

Country	Installed PV Capacity No Energy Sharing (kW)	Installed Capacity Energy Sharing (kW)	PV En- ergy Sharing	Installed Bat- tery Capacity No Energy Sharing (kWh)	Installed Bat- tery Capacity Energy Shar- ing (kWh)
Austria	71.8	74.5		10.9	12.8
Belgium	121.7	146.7		19.5	30.6
France	72.9	86.6		5.6	15.6
Germany	123.5	155.8		22.4	34.9
Italy	121.9	146.7		18.9	31.4
Netherlands	113.9	124.6		16.4	24.3
Portugal	123.7	146.7		23.5	37.1
Spain	120.8	124.6		25.0	36.5

The time series of the heat demand, electricity demand and EV charging demand were supplied by the individual country members of the PVP4Grid project. The PV generation time series and battery charging and discharging profiles were a result of a combination of the data supply of the individual countries in the PVP4Grid project and the model results of [99].

2.3 Results

The results consist of four parts. First, the HEFs are analyzed. Second, the absolute emissions of the previously defined typical European communities are analyzed. This provides insight into the GHG emission reduction potential that of current national policies, as well as the impact of allowing energy sharing. Third, the normalized GHG emission reduction potential are shown for the eight target countries. This provides insight into which technologies have most impact in which location. Lastly, we elaborate on the difference between using AEFs and HEFs. This shows what technologies consume or produce, and times with high or low emission factors.

2.3.1 Hourly emission factors

To use time-varying emission factors in the LCA of the prosumer concepts, HEFs for all seven bidding zones were constructed. Note that Austria and Germany were still combined in one bidding zone in 2017, before being separated in late 2018. The time series of the HEFs of the seven bidding zones in 2017 are added to this chapter as a supplementary file.

Figure 2.2 shows the distribution of all HEFs for the seven bidding zones in 2017. A bidding zone is a geographical area where electricity trading takes place without transport restrictions within their boundaries [85]. From this figure, several observations can be made. The differences between HEF_{gen} and HEF_{con} is caused by the electricity import of a country: when imported electricity has a lower EF than the HEF_{gen} of a country, this results in a lower HEF_{con} of that country. This is seen most in Italy and the Netherlands. Italy imports much electricity from Switzerland and France, which have low EFs. The Netherlands has very high HEF_{gen} , which means import of electricity mostly results in a lower HEF_{con} , but the main difference is caused by the substantial electricity import from Norway which has a low EF. Belgium, on the other hand, has a higher HEF_{con} than HEF_{gen} because it imports a lot of electricity from the Netherlands. This relates to the low HEFs in general for France and Belgium, which is largely due to a high share of nuclear power generation in these countries (72.6% and 49.4%, respectively). Nuclear power generation has the lowest emission factor of all sources; around 12 kg/MWh. The multi-modal shape of these distributions also reflects the general load profile; the first mode reflects night hours where nuclear has an even larger share.

Figure 2.2 also shows the large variation in HEF_{con} for some bidding zones, especially Spain, Portugal, Germany and Austria. Figure 2.3 explores this in more detail, showing the HEF_{con} depicted against a country's total electricity load. Germany and Austria have a large variation both in load and in HEF_{con} . Spain and especially Portugal on the other hand, have a large variation in HEF_{con} , while having relatively low variation in load. This could be explained by having a high share of VRES in the generation mix. Also, some countries show an upward trend in HEF_{con} with increasing load, mainly France and Belgium, while others show a negative trend (mainly the Netherlands). This is related to nuclear energy supplying the base load in the former, while coal serves as base load in the latter. The correlations between the load and the HEF_{con} are shown in Figure 2.4. This figure also shows the correlation between PV-generated electricity and HEF_{con} . A negative correlation can be expected, because in general the EF of PV is lower than the average of the generation mix. This is true for all countries, except for Portugal. A possible explanation is that electricity load serves as a confounding variable; an increased electricity demand in hours with high shares of PV-generated electricity, for example because of air-conditioning, could also lead to more coal-fired electricity generation, ultimately increasing the HEF_{con} . This means that PV systems can have additional GHG emission reduction potential in Portugal, because new systems would replace a relatively dirty electricity mix.

In sections 2.3.2 to 2.3.4, HEF_{con} is used for the determination of emissions

Figure 2.2: Violin plot of distribution Generation and Consumption Hourly Emission Factors per bidding zone. Solid line indicates mean, dashed lines the 25% and 75% percentiles. Country codes: BE = Belgium, DE = Germany, AT = Austria, ES = Spain, FR = France, IT = Italy, NL = Netherlands, PT = Portugal.

related to electricity and for readability purposes is referred to as HEF (i.e. without subscript “con”).

2.3.2 GHG emissions of European communities

In Figure 2.5 we provide an overview of the total annual community-level GHG emissions among the different technologies and grid-interaction scenarios for all countries. In this figure we see that for most countries the switch towards fully electrified heating and personal transport has a profound effect on total GHG emissions of the communities. This effect is moderated by the HEFs of a country: e.g. in France, the effect is much lower than in the other countries. Furthermore, investments in (mainly) PV can decrease the annual emissions of communities substantially, provided that the economic parameters of installing and operating PV systems are suitable. Also here, we see large differences between the countries. In France, the PV and battery result in more emissions than not having PV and a

Figure 2.3: Country electricity load depicted against its HEF_{con} .

Figure 2.4: The y-axis depicts the correlation between a Country's electricity load and its HEF_{con} , the x-axis depicts the correlation between a country's PV-generated electricity and its HEF_{con} .

battery; this can be explained by the higher emission factor of PV compared to nuclear: 84 kg/MWh versus 13 kg/MWh, respectively. Furthermore, PV electricity is generated in hours with a relatively low HEFs (see Figure 2.4), which results in a lower impact of PV installment. PV and battery can have the most impact in Portugal. This is the result of favourable policies in Portugal combined with high solar irradiation, which leads to a high value of installed PV capacity. Furthermore, the HEFs of Portugal are relatively high, and especially high in hours with much PV-generated electricity. This even leads to the Portuguese Community having negative net emissions. The high GHG emission reduction potential of PV in the Netherlands is also remarkable, as this is the country with the lowest solar irradiation of all investigated countries. Policies in the Netherlands are relatively favourable, but the very high hourly emission factors also play an important role. Energy sharing leads to GHG emissions reduction in all countries: emissions are lower in the *All-electric - Sharing* scenario than in the *All-electric - No Sharing* scenario. This can mostly be explained by the higher amount of installed PV capacity as a result of energy sharing (see Table 2.1). However, the differences are larger in some countries than in other countries; the higher the self-consumption benefits, the larger the impact of energy sharing (through higher installed capacity).

2.3.2.1 Baseline scenario

In the baseline scenario, generally speaking, the largest shares of the total community emissions are from heating and using the passenger car. Due to a relatively low heat demand in especially Spain and Portugal, contributions of heating, car and household electricity use in the baseline scenario are roughly equal.

The differences between the countries for the emissions from heating result mainly from the different heating demand in each of the countries, but are also a result of the different technologies used for space heating. Across Europe, the predominant heating technology is based on (condensing) natural gas boilers, but some countries, like Austria, also have large shares of biomass based district heating, with relatively low emission factors. Warm countries like Portugal and Spain have a relatively low heating demand, resulting in low emissions for heating.

For car usage, the difference between the countries are solely the result of the different driving behaviors (km driven per car per year), as we have assumed the same types of cars are used in each country. Car usage contributes a significant share of overall emissions for the baseline scenario.

Figure 2.5: Overview of total annual greenhouse gas emissions of the whole community. Results are shown for all countries, for the baseline and two all-electric scenarios.

2.3.2.2 All-electric scenarios

In the all-electric scenarios, we observe a strong reduction in overall community GHG emissions for most countries. Due to the shift from ICEs to EVs, and from largely fossil fuel-based heating to fully electric heating, emissions are reduced strongly for most countries.

Austria, having a relatively low emission factor for heating in the baseline scenario, shows a relatively modest reduction in heating emissions, compared to for instance Belgium, where the application of electricity for space heating, combined with the low grid emission factor results in a strong decrease of GHG emissions. In Portugal and Spain, the low heat demand, high PV yield, and application of HPs nearly reduces the emissions from heating to zero in the scenarios with installed PV.

Emissions from car usage also strongly drop in all countries. The application of electricity for personal transport strongly reduces GHG emissions, despite the fact that manufacturing of EVs is much more GHG intensive compared to manufacturing of ICE vehicles. Especially in countries with very low grid emission factors (France, Belgium) or in scenarios with high PV generation (Spain, Portugal, Italy), emissions from personal transport are lowered very substantially.

2.3.2.3 Benefits of community energy-sharing

One of the goals of the PVP4Grid project was to establish the benefits of energy sharing in European communities. Our results indicate that the benefits of energy sharing, in terms of GHG emissions, are affected by a variety of parameters.

In six of the eight countries, energy sharing in the community (further) reduces the GHG emissions compared to the No sharing scenario. In most cases, this is the result of increased deployment of PV. In the energy-sharing communities, more of the generated PV electricity can be used within the community, which reduces grid feed-in, and thus allows for a higher installed PV capacity in countries with financial constraints for grid feed-in. The fact that less electricity is fed into the grid can however also hamper the GHG emission reduction potential in countries with high grid emission factors.

2.3.3 Normalized GHG emission reduction potentials

To assess the effects of several specific technology transitions, we have analyzed the normalized GHG emission reductions of EVs, heat-pumps and PV and BESS. In Figures 2.6-2.9 we show the reduction in GHG emissions resulting from the transition towards these technologies. To focus on the specific technologies, and avoid the effects from country-level differences of e.g. installed PV capacity resulting from the economic modelling, we normalize the values to a consistent functional unit: 1 EV for car usage, 1 building for heat supply, 1 kWp for PV systems, and 1 kWh for BESS.

2.3.3.1 Transition from ICE vehicles to EVs

In Figure 2.6 we see that for all countries, in both scenarios with EVs, a strong reduction is observed in the GHG emissions resulting from car usage. Emissions from car usage are reduced by 46 to 73%, depending on the source of electricity used for charging, and its associated emission factor.

Absolute reductions in car usage emissions are largest in Belgium and France, where emissions from burning fossil fuels are replaced with EVs charged with very low-emission grid and PV electricity. In Spain and Portugal, due to the high yield of PV systems, a large part of the charging of EVs is performed with PV electricity, and hence relative reductions are of similar magnitude compared to Belgium and France. Smaller absolute and relative reductions in emissions are observed for the other countries, where the grid emission factor is relatively high and/or PV system yield is substantially lower, hence less charging is performed with PV electricity.

Figure 2.6: Greenhouse gas emission reduction potentials for battery electric vehicles in the eight selected countries. Data are shown as the change in annual emissions related to car use, per car, and includes both energy use (fuel or electricity) and upstream emissions related to manufacturing of the vehicles.

2.3.3.2 Transition from fossil fuel heat to heat pumps

The results for the transition in heat supply from largely fossil fuel-based heat generation to electrified heat generation using HPs is shown in Figure 2.7. Here, we see a much larger variation between the countries, both in observed absolute and relative changes. Overall, emissions from heat supply drop by 38% to 94%, depending on the GHG intensity of the current heat supply, overall heat demand, and the GHG intensity of the country electricity mix.

In Belgium, the largest absolute reduction of GHG emissions from heat supply is observed. The shift from fossil fuel-based heating to electrified heating with heat-pumps benefits from the low grid emission factor in this country. In France a similar relative reduction is observed, but the absolute reduction is much lower since the heat demand in France is also lower.

In Portugal and Spain, the largest relative reduction in heat supply emissions are found. Due to a combination of low heat demand in these countries, high generation of PV electricity which can be applied in HPs for large parts of the year, emissions are strongly reduced, almost to zero in the Sharing scenario.

2.3.3.3 Transition from grid consumption to PV generation

To see and compare the potential for GHG emission reduction of PV systems in the eight countries, we show in Figure 2.8 the total reductions in GHG emission from electricity supply in the communities in $\text{tCO}_2\text{-eq.kWp}^{-1}\text{year}^{-1}$. We also present the relative reduction in percent per kWp average per building in the community.

In the all-electric scenarios, the relative reduction of GHG emissions from

Figure 2.7: Greenhouse gas emission reduction potentials for heat supply with heat-pumps (HPs) in the eight selected countries. Data are shown as the change in annual emissions related to heat supply, expressed as the average per building in the community, including both energy use (fuel or electricity) and upstream emissions related to manufacturing of the heat supply technologies.

electricity supply ranges from 6% to 12%, due to the much higher electricity demand in the all-electric scenarios. Absolute reductions are roughly equal for Austria, Germany, Spain, Italy and the Netherlands, and much lower for France and Belgium. In these latter two countries, emissions from electricity consumption are already quite low due to the low grid emission factors in these countries. In Portugal, absolute and relative reductions are the highest, which results from the fact that there is a positive correlation between PV generation and grid emissions factor (as shown in Figure 2.4). In other words, during the time that PV electricity is generated, grid emission factors are high, and thus the PV electricity that is generated in Portugal mostly replaces electricity from the grid with high emission factors.

2.3.3.4 Application of batteries for enhanced self-consumption of PV electricity

In the modelling scenarios, relatively small amounts of battery capacities are installed, compared to the installed PV capacities. The batteries are used mainly to store PV electricity that cannot be consumed directly. In theory, batteries could reduce GHG emissions by storing energy at times that grid emission factors are low, and subsequently discharging electricity to the consumers at times that grid emission factors are high. However, since electricity costs for the consumers in the communities do not vary throughout the day in the modelling scenarios from [99], the batteries are used only to store excess PV electricity. In this case, the annual emissions from battery operation in country j are calculated as follows:

Figure 2.8: Greenhouse gas emission reduction potentials for PV systems in the eight selected countries. Data are shown as the change in annual emissions related to electricity supply, expressed per kWp of installed PV system capacity. The data presented includes both reductions due to reduced electricity consumption, as well as due to feed-in of PV electricity to the grid. The percentages shown indicate the average relative reduction per kWp per building in the community.

$$GHG_{\text{batt},j} = \sum_{t=1}^{t=8760} (E_{\text{ch},t,j} \cdot HEF_{\text{con},t,j}) - \sum_{t=1}^{t=8760} (E_{\text{disch},t,j} \cdot HEF_{\text{con},t,j}) + G_{\text{batt}} \quad (2.5)$$

Here, the first summed term represents the emissions attributed to BESS, as PV electricity is prevented from being fed into the grid, which would replace grid electricity and thus create “negative” emissions. The second summed term represents the emissions that are avoided by BESS discharging, replacing the need for grid consumption with the associated HEFs. The final term in eq. 2.5 represents the emissions resulting from manufacturing of the BESS denoted as G_{batt} .

As shown in Figure 2.9, the installation and operation of batteries results in added GHG emissions in all countries. Emissions are increased when installing batteries, due to the facts that feed-in of PV electricity reduces GHG emissions in our modelling scenario, battery charging/discharging has an efficiency lower than 100%, and the difference between HEFs during daytime and nighttime is relatively small. The largest increase in emissions is observed for Portugal, where the HEFs are higher during the daytime (as discussed before), hence it would be more beneficial to feed-in PV electricity during the day, rather than storing it for use at a later time.

Figure 2.9: Greenhouse gas emission reduction potentials for BESS in the eight selected countries. Data are shown as the change in annual emissions related to due to charging and discharging of the BESS, including upstream emissions related to manufacturing of the BESS. Note that positive bars imply an increase in emissions.

2.3.4 Difference between AEF and HEF in determining GHG emissions

As we discuss in the introduction, the benefits of using HEFs instead of AEFs is that with HEFs the time-based aspect of variable renewable energy generation as well as variable electricity demand is taken into account. Since emission profiles of electricity generation varies throughout the day and over the year, and the all-electric technologies discussed here also do not have constant electricity demand during the day and throughout a year, using HEFs should more accurately account for the effects of these variation on calculated annual GHG emission. In Figures 2.10 and 2.11, we compare the application of HEFs vs. AEFs.

In Figure 2.10, we show the differences between using HEFs and AEFs for our results for car usage, heat supply and PV electricity generation. This figure mainly reflects the different intra-day and seasonal profiles of grid emission factors.

For both heat demand and car usage, we mostly see that the use of HEFs results in higher emissions than when using AEFs. This is especially the case for France and Belgium. For these countries, especially for heat supply, the electricity demand occurs during periods in the year when emission factors are higher than average. As PV systems are added to the communities, the difference between HEFs and AEFs becomes larger, as a relatively larger share of heat demand related electricity from the grid is used during winter. Since car usage is constant throughout the year the difference between HEFs and AEFs for the baseline scenario is much smaller, but grows more strongly as PV systems are added. Contrasting to the results for most countries, are the results for Portugal. Here, grid emission factors are somewhat lower during winter, and during times of limited or no PV generation.

Figure 2.10: Difference between GHG emissions calculated using hourly emission factors vs. average emissions factors for heat supply, car usage and PV electricity. Positive bars indicate that with HEFs, calculated emissions are higher.

In most countries, the difference between HEFs and AEFs is negative for emission reductions of PV systems. This means that when using HEFs, the emission reductions calculated for PV systems are smaller compared to when using AEFs. This is the result of the fact that in most countries, emission factors are generally lower during the day (and in summer). Only in Portugal, where grid emission are in fact higher during the times of PV generation, this result is not observed. In Figure 2.11, we present the comparison of using HEFs vs AEFs for BESS. In this figure, we only show the emissions related to charging and discharging of the BESS, without manufacturing emissions, to highlight the effects of HEFs vs AEFs (otherwise the emission were calculated according to eq. 2.5).

The results show that the emissions attributed to battery charging and discharging are generally lower when using HEFs compared to AEFs, except for Portugal and France. Using HEFs, the emissions in the other countries are lower, as batteries are charged during the day, when grid emission factors are low, and discharged during the night, when grid emission factors are higher. For Austria, Germany and Italy, the difference between HEFs and AEFs is especially large, due to the clear

Figure 2.11: Difference between GHG emissions calculated using hourly emission factors vs average emissions factors for battery usage. Positive bars indicate that with HEFs, the emissions are higher. The results presented here only include the emissions related to charging and discharging of the battery, to highlight the effects of using HEFs vs AEF.

difference of HEFs between charging (daytime) and discharging (nighttime).

2.4 Conclusions and discussion

In this research, the GHG emission reduction potential of EVs, HPs, PV and BESS was determined in eight countries: Austria, Belgium, France, Germany, Italy, the Netherlands, Portugal and Spain. Hereby, HEFs were being used to determine the emissions related to electricity use. The selection of technologies and countries represents the important role of electrification in the built environment in transitioning to a sustainable future, taking into account different climatic regions in Europe. Results show there are large differences between countries regarding their HEFs, with France and Belgium being on the lower end of the spectrum (because of high shares of nuclear power plants in their generation mix) Austria, Germany and the Netherlands on the higher end of the spectrum (high shares of coal-fired power plants) and the southern countries Italy, Portugal and Spain in the middle of the spectrum (high shares of renewables, medium shares coal-fired power plants). These results have a strong moderating effect on the GHG emission reduction potential of the technologies. Most technologies have substantial GHG emission reduction potential in all countries. BESS are the exception, as these increase emissions in all countries because of losses in the conversion of electricity. These results imply that from a European GHG emission reduction perspective, it is important to not only focus on e.g. installing PV in countries with high values of solar irradiation, but also look at the current electricity mix of the countries. Furthermore, we have seen that energy sharing leads to an increased GHG emission

reduction potential, because energy sharing leads to higher PV capacities - this can be an important notion in designing policies stimulating the deployment of renewable energy. Lastly, we have demonstrated the importance the timing of consuming electricity, signifying the added value of HEFs over AEFs. This is an important finding both from a practical as a scientific perspective, as the AEF is more commonly used in GHG impact assessments.

These findings may be somewhat limited by the data accuracy. As our study entails an extensive amount of data, large databases were used to generate the results (i.e. the transparency data set of ENTSO-E [136] and the ecoinvent database [132]). In some cases, these databases can have missing data (as shown in 2.A) or are not up-to-date for individual data points (as in the case of e.g. the PV emission factor). Furthermore, the GHG emission reduction potentials of the European Communities are necessarily impacted by the specific configuration of the community, hence, it is important to interpret these results along with the normalized GHG emission reduction potentials that we also reported.

Future research could increase both the geographical and time scope. It should be taken into account that our study focused on one year, namely 2017. With changing generation mixes, the GHG emissions of the technologies almost certainly will change in the future due to electricity consumption or feed-in. Changes in generation mixes can be included in future research in order to make a full LCA. As we have found large differences in HEFs between countries, the analysis can be extended to include even more countries, e.g. other regions within Europe, or countries on different continents. Furthermore, we have shown that fluctuation of HEFs impact the GHG emissions of a technology. Some technologies, mostly BESS and EVs, have the potential to shift demand over time. The generated HEF profiles can be used as data input for optimization frameworks. This could further increase their GHG emission reduction potential, or in case of BESS reverse the adverse impact. Future research could attempt to quantify this additional potential, and in similar fashion of our study, determine in which countries flexible assets can have the most climate mitigation impact. In this context, the use of marginal emission factors (i.e. the emissions of the power plant that operates at the margin, reflecting the change in emissions as result of a change electricity demand or supply [137]) should also be considered.

Table 2.2: Shares of other categories and correlation transparency and power stats ENTSOE-E [133][136].

Country	Other (% of total generation)	Other Renewable (% of total generation)	Correlation with ENTSOE-E power stats
Belgium	6.2	N.A.	0.950
France	N.A.	N.A.	0.988
Germany and Austria	6.8	0.3	0.981
Italy	31.5	0.0	0.973
Netherlands	N.A.	N.A.	0.548
Portugal	0.6	N.A.	0.941
Spain	0.2	0.3	0.950

2.A Explanation for treatment of missing data

2.A.1 Explanation for treatment of “Other” categories

ENTSOE-E reports two other generation categories: Other - Actual Aggregated and Other Renewable. The share of these categories in the total electricity generation is reported in Table 2.2. Furthermore, to validate the generation data, a check was performed with the power stats reported in (ENTSO-E, 2019c). Table 2.2 also shows the correlation between the generation (minus the net export) and this total load. What stands out in Table 2.2 is the high share of Other for Italy (31.5%), and the low correlation with the power stats for the Netherlands (0.548). Therefore, data of two countries received more attention, which is elaborated on later. For the other six countries, the Other categories are proportionally attributed to the known generation data. So Other Renewable is proportionally attributed to the generation of renewable sources (biomass, hydro, solar, geothermal and wind) in the relevant hour. Other - Actual Aggregated is proportionally attributed to non-renewable generation for that hour.

2.A.2 Explanation for allocation of missing data in Italy

Attributing the Other generation proportionally to the known generation values could lead to incorrect results, for example if one generation source has better data availability than the other. Therefore, data report by the Italian TSO Terna was directly investigated, to be able to validate the generation data per source.

Figure 2.12: Reported coal generation in Italy in 2017 in [133] and the average coal-based electricity generation reported by [138].

2.A.2.1 Biomass

Terna reports the hourly electricity generated from biomass [138]. These values are substantially higher than the values obtained from data transparency: average of 344 MW over 2017 on transparency, while the data reported by Terna have an average of 1943 MW. This explains 17% of the Other category.

2.A.2.2 Coal

As can be seen in Figure 2.12, the coal-fired electricity generation in the second half of 2017 as reported in (ENTSO-E, 2019a) is in line with the yearly average from 2017 as reported by Terna (Terna, 2019). On 26 June, the coal-fired electricity generation increases from 495 MW from 22:00-23:00 to 3968 MW from 23:00 to 24:00.

It can be concluded that data are missing for the first half of 2017. There are two options to scale up the coal generation for the first half of 2017:

Figure 2.13: Average hourly coal-fired electricity generation in Italy in first half 2017 (left y-axis) and second half 2017 (right y-axis).

- Assume coal provides baseload power, take a fixed load factor and calibrate the load factor to be in line with the total of coal as reported by Terna.
- Multiply the available data by a factor which is calibrated to be in line with the total of coal as reported by Terna.

To decide this, we analyzed if coal could be seen as purely baseload fuel; Figure 2.13 provides insight on this. As can be seen, the first half and the second half show a similar pattern, with slightly higher generation in a few hours in the morning and the evening. As the data from the second half of 2017 can be considered reliable, we conclude that coal does not serve solely as baseload. Therefore, we decided to increase the coal load by a flat factor for the first half of 2017. For the period with missing data, we see two distinct periods: until 7 April 23:00, the average coal-fired electricity generation was 1104 MW, from 7 April 23:00 to 26 June 23:00 423 MW. For both periods, the data are scaled to be in line with the Italian average.

2.A.2.3 Fossil oil and fossil gas

For fossil oil and fossil gas, no long periods of missing data were found. Therefore, it was concluded that these only part of generation from these sources was reported.

The totals taken from the transparency data base were 71.7 TWh for gas and 1.34 TWh for oil. Terna reported totals of 140 TWh and 4.1 TWh, respectively. Therefore, we multiplied the generation values from transparency data by 1.96 for gas and 3.13 for oil.

2.A.3 Explanation missing data the Netherlands

For the Netherlands, we assumed that coal would run as baseload, based on [127]. Two of the six coal-fired power plants were closed on 1 July 2017. We set the electricity generation from coal as a fixed percentage of the capacity in that hour (i.e. the load factor over 2017). This load factor was determined using the total electricity generated from coal that was reported by the Dutch statistics agency CBS [139]. The remaining gap between generation values in transparency data, and total load reported in power stats, was attributed to gas-fired power plants. The new total is 9.6% higher than the statistics reported by CBS. In [140], Dutch TSO TenneT states that the data should be corrected after official statistics are reported by CBS. We followed this notion, and corrected the total gas-fired electricity generation to be in line with the official statistics.

3 On the trade-off between Environmental and Economic Objectives in Community Energy Storage Operational Optimization

This chapter is based on the publication:

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Abstract

The need to limit climate change has led to policies that aim for the reduction of greenhouse gas emissions. Often, a trade-off exists between reducing emissions and associated costs. In this chapter, a multi-objective optimization framework is proposed to determine this trade-off when operating a Community Energy Storage (CES) system in a neighbourhood with high shares of photovoltaic (PV) electricity generation capacity. The Pareto frontier of costs and emissions objectives is established when the CES system would operate on the day-ahead spot market. The emission profile is constructed based on the marginal emissions. Results show that costs and emissions can simultaneously be decreased for a range of solutions compared to reference scenarios with no battery or a battery only focused on increasing self-consumption, for very attractive CO₂ abatement costs and without hampering self-consumption of PV-generated electricity. Results are robust for battery degradation, whereas battery efficiency is found to be an important determining factor for simultaneously decreasing costs and emissions. The operational schedules are tested against violating transformer, line and voltage limits through a load flow analysis. The proposed framework can be extended to employ a wide range of objectives and / or location-specific circumstances.

3.1 Introduction

In the Chapter 2, it was shown that stationary batteries lead to an increase in CO₂ emissions when no optimization algorithms are deployed. In this chapter, it is investigated whether stationary batteries can also decrease CO₂ emissions when deploying optimization techniques, also taking economic objectives into account.

In recent years, there has been a sharp increase in the deployment of PV systems for generating electricity. While this plays an important role to mitigate climate change, it can also pose challenges, such as voltage fluctuations and grid capacity issues, when large amounts of PV-generated electricity are simultaneously fed into the grid. Therefore, emphasis has recently been placed on the self-consumption of PV-generated electricity in households [46], [141]. To encourage self-consumption the surplus injected PV electricity is not remunerated in some countries, and thus potential revenue for prosumers is lost [46]. An option to maximize PV self-consumption is to deploy batteries in households by storing surplus of PV-generated electricity during the day to use it in the evening.

Instead of installing a battery in every household, deploying a Community Energy Storage (CES) system is emerging as an alternative and more cost-effective

solution in residential communities because of scale advantages and lower installation costs [142], [143]. For example, when providing ancillary services, a CES system would require only one measurement and communication system and battery Energy Management System (EMS) whereas aggregating individual batteries would require these with every battery. CES systems can result in higher utilization of renewable energy sources [141], [143]–[145], and provide ancillary services to grid operators; such as balancing, peak shaving, load levelling, large-scale integration of renewable energy sources, voltage optimization, and reliability improvement [146]–[148]. Furthermore, CES can play an integral role in direct current (DC) micro-grids [149].

Several lines of evidence suggest that coupling a PV system with energy storage can be economically attractive, with the most important economic parameters that determine the economic viability being the battery investment costs and the self-consumption benefits (i.e. the difference between the retail electricity price and the PV electricity feed-in tariff). Viable business cases for battery systems have been found by combining a battery price of 781 €/kWh investment costs and 0.26 €/kWh self-consumption benefits [150], investment costs between 265 and 465 €/kWh combined with self-consumption benefits of 0.25 €/kWh to 0.34 €/kWh [151], and investment costs of 234 €/kWh combined with self-consumption benefits of 0.16 €/kWh [94]. However, it is uncertain whether such economic circumstances will arise in the future. Therefore, scholars have shifted their attention on multi-revenue applications of energy storage [152], for example the hierarchical optimization for energy arbitrage in the day-ahead spot market and the contribution in system balancing [153], and the combination of self-consumption benefits and provision of frequency restoration reserves [47]. In this research, the use of a CES for PV self-consumption is expanded by two other applications, namely minimizing electricity costs on the day-ahead market and minimizing the emissions associated with the consumption of electricity.

Many studies see a role for batteries in mitigating climate change in an indirect manner, namely by supporting the integration of renewable energy [154], [155]. Fares and Webber [82] found that integrating a PV system with a battery can actually increase CO₂ emissions, mainly because of the conversion losses that result in a higher electricity demand. This stresses the importance of addressing the impact on CO₂ emissions that are related to the operation of a battery system. Given that the operator of a sufficiently large CES can purchase/sell electricity from/to the grid, e.g. based on forecasted day-ahead spot market prices, this can be achieved by converting emissions to costs and incorporating these in a cost minimization approach [156]. An alternative is to incorporate time-varying CO₂ emission factors as input data, which enables the separate minimization of

emissions. In this regard, the Pareto frontier can be used to address the trade-off between different objectives [157], for example to decide between different energy devices for satisfying heat and electricity demand [158]. The Pareto frontier has been applied to address the trade-off between costs and emissions in portfolio optimization [42] and for demand side management of flexible load [159]. In this research, we establish a multi-objective optimization framework based on the Pareto frontier approach to demonstrate the trade-off between economic and environmental objectives for the operation of a CES system, using a spot market electricity price profile and a marginal emission profile as inputs.

This chapter anticipates on a future energy system with a high share of decentralized energy sources, and the possibility for residential prosumers to collectively own a battery system. This entails new market designs such as decentralized electricity markets (also called local markets), energy communities and microgrids. In these designs, regulation and other economic arguments – such as licensing and certification, data and employment regulation – are fundamental but still open topics. In the current regulatory environment, multiple CES systems should be coupled through an aggregator to meet the entrance requirements of a specific electricity market.

The contribution of our research is threefold. Firstly, to our knowledge, it is the first study to use marginal emission profiles as input for optimization, instead of hourly average profiles. As we elaborate on later, the use of marginal emission profiles reflects reality more accurately for the specified application. Secondly, we demonstrate the impact of important battery characteristics like battery degradation and efficiency on the Pareto frontier of optimal solutions for a multi-objective optimization of costs and emissions. In addition, since we treat self-consumption of PV-generated electricity as a constraint, this becomes effectively the third purpose of the battery (next to cost and emission optimization), which is a novel approach. Thirdly, we assess whether the use of our algorithms lead to violation of grid constraints based on a load-flow analysis.

The chapter is structured as follows: The methods are presented in Section 3.2. The numerical evaluation of the proposed framework is presented in Section 3.3. We conclude the chapter and provide recommendations for future research directions and some limitations in Section 3.4.

Figure 3.1: Scheme of the considered system layout.

3.2 Methods

3.2.1 System layout and boundaries

The topology and system boundaries of the investigated community are shown in Figure 3.1. We modelled interaction between the a CES and H households, indexed by h , where $h \in \mathcal{H} = \{1, 2, \dots, H\}$, each with an on-site PV system (i.e. prosumers). Households are connected to the main grid and to a CES in their neighbourhood via alternating current (AC) power lines. The surplus PV-generated electricity is stored in the CES that is controlled by an EMS. The EMS is responsible for optimizing the day-ahead charging schedule, in order to satisfy the households' residual load, while accommodating their aggregated surplus PV-generated electricity. Households are connected to the main grid to secure their residual load during times when PV-generated electricity is not sufficient and there is no available energy stored in the CES.

In a certain time slot, the community could either store some of its surplus PV-generated electricity in the CES, or request energy from the battery for satisfying its residual load. The average power of household h for time step $t \in \mathcal{T} = t_0, t_0 + \Delta t, t_0 + 2\Delta t, \dots, T$ is denoted as $P_{t,h}$. In the remainder, all power flows P are in [kW]. The duration between two consecutive time steps is Δt , which can represent different timescales (e.g. one hour). The community power $P_{agg,t}$ is an aggregation of the net loads of all households at time step t :

$$P_{agg,t} = \sum_{h=1}^H P_{t,h}, \quad (3.1)$$

where $P_{agg,t}$ represents either a net surplus PV power $P_{S,agg,t}$ (i.e. $P_{agg,t} < 0$) or a

net amount of power demand for residual load $P_{L,agg,t}$ (i.e. $P_{agg,t} > 0$). Hence, we define residual load as a non-negative value where PV-generated power is subtracted from the actual load, whereas we define surplus PV power as a non-negative value where actual load is subtracted from PV-generated power.

3.2.2 Battery degradation

Battery performance is affected over time and upon usage [160]. Important battery parameters that decline are the efficiency (e.g. through the increase of internal resistance), the pulse power capability and the capacity [161]. Regarding capacity fading, two important battery ageing components are cyclic ageing and calendric ageing. These processes occur independently from each other and thus should be added together to obtain the total degradation [150], [161]. According to [150], calendric ageing is linearly dependent on time. The relation between ageing and charging cycles is less straightforward. Wöhler curves (also called S-N curves, reflecting Stress and Number of cycles) are historically used to predict the material fracture under cycle loading [162]. Using these has also become common practice in estimating the number of full-equivalent cycles (FECs) a battery can withhold as a function of cycle depth [150], [163], [164]. The basic notion is that with equal energy throughput, lower cycle depths lead to reduced aging compared to higher cycle depth. From [150], we can derive eq. 3.2 to estimate the cumulative degradation D_l (in %) at the l^{th} day of battery operation:

$$D_l = 20\% * \left(\frac{m}{L_{ca}} + \sum_{n=1}^N \frac{0.5}{L_{cy} * \delta_n^{r-1}} \right) \quad (3.2)$$

Herein, 20% reflects the capacity loss that is generally considered end of life. The quotient of battery age l (in [days]) and calendric lifetime L_{ca} (in [years]) denotes the calendric ageing. Cyclic ageing is estimated by summing the incremental degradation of each half cycle $n \in \{1, 2, \dots, N\}$ in which N is the number of half cycles since the start of battery operation. L_{cy} is the number of FECs if cycle depth would be 100% for every cycle and m is the cyclic degradation exponent that corrects for actual cycle depth δ . Using eq. 3.2 and assumptions on the parameters' values (see Section 3.3.1), we update the remaining battery capacity in our model every day. A literature review on the parameter values can be found in Section 4.3.

Figure 3.2: Schematic representation optimization process.

3.2.3 Optimization problem formulation

3.2.3.1 Pareto frontier and ϵ -constraint method

The main objective is to find a trade-off between electricity cost and CO₂ emissions when setting a charging schedule for the CES. This trade-off can be studied through the Pareto frontier. In the proposed scheduling framework, the ϵ -constraint method is used to calculate the Pareto frontier [157]. In this method, first each optimization problem is solved separately (i.e. electricity cost minimization problem and CO₂ emission minimization problem). By doing so, the two endpoints of the Pareto frontier are calculated, and the range of possible electricity cost and CO₂ emissions becomes known. After that, the range of electricity cost is divided into K equally spaced bins ϵ_k , where $k \in \mathcal{K} \{1, 2, \dots, K\}$. The optimization process and minimization functions are visually depicted in Figure 3.2.

The electricity cost and CO₂ emission functions can be defined as:

$$C_{\text{total}} = \sum_{t=1}^T c_t P_{\text{grid},t} \Delta t, \quad (3.3)$$

$$G_{\text{total}} = \sum_{t=1}^T g_t P_{\text{grid},t} \Delta t, \quad (3.4)$$

where $P_{\text{grid},t}$ is the power absorbed from or injected into the grid and c_t is the DAM-price (in [€/kWh]), both at time-slot t (in [h]). The CO₂ emission function can be described in the same way as the cost function, with c_t replaced by the

emission input g_t (in [kg CO₂/kWh]), obtaining total emissions G_{total} . Both the electricity tariff and the CO₂ emissions are considered as demand response signals and are piecewise constant with possible jumps at a subsequent time step.

The objective functions are subject to a number of constraints.

3.2.3.2 Power conservation

The conservation of power property for the entire system is given by the familiar local balancing formula:

$$P_{\text{grid},t} + P_{\text{S,agg},t} + P_{\text{disch},t} = P_{\text{L,agg},t} + P_{\text{ch},t}, \forall t, \quad (3.5)$$

where $P_{\text{disch},t}$ and $P_{\text{ch},t}$ are the discharging and charging power of the battery.

3.2.3.3 Battery dynamics

The battery's coefficient φ (in [kWh-1]) is related to the battery charge capacity (i.e. Q_{cap} in [kAh]) and open circuit voltage (i.e. V_{oc} in [V]) as:

$$\varphi = \frac{1}{Q_{\text{cap}} V_{\text{oc}}} \quad (3.6)$$

The battery State of Charge SOC at time step $t+1$ is a function of $P_{\text{ch},t}$, $P_{\text{disch},t}$ and the SOC at time step t , and can be calculated by:

$$SOC_{t+1} = SOC_t + \Delta t (\phi \eta_{\text{ch}} P_{\text{ch},t} \frac{P_{\text{disch},t}}{\eta_{\text{disch}}}), \forall t, \quad (3.7)$$

where η_{ch} and η_{disch} represent the charge and discharge efficiency of the battery, respectively. Eq. 3.7 represents the discrete-time battery dynamics.

The SOC of the battery is constrained as follows:

$$SOC_{\min} \leq SOC_t \leq SOC_{\max}, \forall t, \quad (3.8)$$

where $SOC_{\min}$ and $SOC_{\max}$ are the minimum and maximum allowed SOC of the battery, respectively. We set these at 0% and 100%, respectively, because we only treat usable capacity.

Besides, a global balance of the battery is included to ensure equal or better conditions for the next day of simulation when the model is run over an extended period of time:

$$SOC_{t=T} \geq SOC_{t_0} \quad (3.9)$$

By convention, we set the SOC_{t_0} at 50%.

3.2.3.4 Self-consumption

A Big-M constraint [165] is used to ensure that the proposed operation of the CES is not at the expense of the self-consumption of PV-generated electricity:

$$y_t P_{S,agg,t} - P_{ch,t} \leq M(1 - x_t), \quad \forall t, \quad (3.10)$$

where x_t is a binary input variable that is 1 when there is surplus PV electricity. On days where the total $P_{S,agg,t}$ exceeds the battery capacity, this constraint cannot be met without the fraction y_t . This is an input variable that represents the fraction of $P_{S,agg,t} \Delta t$ that fits in the battery without violating the battery's energy constraints on such days. The value of M should be sufficiently large, resulting in that the artificial variable would not be part of any feasible solution.

3.2.3.5 Power boundaries

Finally, we assume the grid power $P_{grid,t}$ and battery power $P_{batt,t}$ are limited in every time step t according to the following inequality constraints:

$$-P_{grid,max} \leq P_{grid,t} \leq P_{grid,max}, \quad \forall t, \quad (3.11)$$

$$0 \leq P_{ch,t} \leq P_{batt,max}, \quad \forall t, \quad (3.12)$$

$$0 \leq P_{disch,t} \leq P_{batt,max}, \quad \forall t, \quad (3.13)$$

where $P_{grid,max}$ and $P_{batt,max}$ are the maximal power that can be received from the grid and the battery, respectively.

3.2.3.6 Optimization problem

The ϵ -constraint multi-objective optimization problem [157] can now be formulated as:

$$\begin{aligned} & \text{minimize} && \sum_{t=1}^T g^t P_{grid,t} \Delta t \\ & \text{subject to} && \sum_{t=1}^T c^t P_{grid,t} \Delta t \leq \epsilon_k, \\ & && \text{eq. 3.5} - \text{3.13.} \end{aligned} \quad (3.14)$$

3.2.4 Battery targeting solely PV self-consumption

The optimal solutions are compared with a reference scenario. The reference scenario in this study is a CES that is solely aimed at increasing the consumption of on-site generated PV electricity; we will denote this as the “Self-consumption only battery”. This battery is charged when $P_{agg,t} < 0$ and discharged when $P_{agg,t} > 0$. Operation of the battery is controlled using constraints enforced by the battery management system, for example the power and energy constraints of the battery, but no further optimization is applied.

3.2.5 Load flow analysis

A load flow analysis is performed to assess whether LV grid limits would be violated, for three different optimal schedules. The network used is a Kerber network [166] for suburban areas, using 58 nodes (57 households and one CES) and a 160 kVA transformer station, which is in line with Dutch standards [167]. A time-resolution of five minutes was chosen.

3.3 Numerical evaluation

3.3.1 Data input

3.3.1.1 Consumption and surplus PV profiles

The consumption and surplus PV profiles are taken from 60 prosumers located in the neighbourhood Nieuwland of the Dutch city of Amersfoort. Net-metered power measurements were obtained as part of the “Smart Grids: Benefit for all” project [168], from 1 November 2013 to 1 October 2014. Data was collected with a time resolution of 10 seconds, but for this research it was averaged over an hour corresponding to the day-ahead market time resolution. Some days were missing, resulting in a representative total of 295 days for the simulation. These data were used to determine how much electricity could be purchased / sold on the wholesale market, and in that sense we implicitly assume perfect information forecasting. The average PV system size is 2.4 kWp (SD = 0.79), with a range from 0.5 kWp to 6.2 kWp. Average annual residual electricity load is 2.5 MWh (SD=1.1). The maximum PV surplus was 83.7 kWh/h, which was used as $P_{grid,max}$ in the optimization model. This is a conservative constraint, which forces the battery not to discharge excessively in times of high PV electricity generation, and not to charge excessively in times of high electricity demand.

3.3.1.2 Price profile

Day-ahead market (DAM) prices in the Dutch market of the same period as the obtained load profiles are used [169]. We assume that the community is legally allowed to trade electricity on the wholesale market. As mentioned before, currently this is not possible due to minimum bid size requirements. However, the CES can be operated by an aggregator which owns multiple CESs in different communities and aggregate them all together in order to achieve the minimum bid size requirements.

3.3.1.3 Emission profile

We use marginal emission factors to construct the marginal emission profile. The concept of marginal emission factors focuses on the notion that renewably generated electricity replaces the electricity generated by the price setting power plants of that same time slot [20], which is generally seen as a superior method over average emission factors [137]. Using average emission factors implicitly assumes that a change in demand results in a small change in generation of all facilities in the generation mix. However, operating flexible demand does not result in changes of the complete generation mix, but merely of the power plant operating at the margin. Hence, the marginal emissions of the system should be used instead of the average emissions. We take marginal emission profiles as presented in Appendix A [127], which provides both the marginal costs and the marginal emissions of each electricity generation facility in the Netherlands (see Figure 3.3). Using these data, and following the logic that the marginal operating plant is the plant with marginal costs closest to the market price, the emission profile can be generated as the market price profile is known (see Section 3.3.1). Here, for every time step t a value for the marginal system emission g_t is calculated.

3.3.1.4 Battery system parameters

The technical parameters of the Lithium iron phosphate (LFP) battery CES battery that we use can be found in Table 3.1.

3.3.2 Costs and emissions of various operation schedules

Figure 3.4 shows the key results of this work, namely the average electricity costs and accompanying CO₂ emissions in relation to various battery operation schedules for a new battery and a degraded battery. For the new battery, the cheapest operation schedule leads to a cost reduction from 48.1 €/MWh of net electricity consumption of the “Self-consumption only battery”, to 34.3 €/MWh; a reduction

Figure 3.3: Marginal costs and emissions of Dutch electricity generation mix in 2014. Source: [127].

Table 3.1: Battery system characteristics.

Parameter	Quantity	Unit	Source
Battery size	205	[kWh]	[94], [151], [170]
$\eta_c = \eta_d$	$\sqrt{0.89}$	-	[23]
C-rate	0.4	[h ⁻¹]	[171]
Cycle life L_{cy}	4586	[-]	[23], [150]
Cyclic degradation exponent r	-0.5093	[-]	[150]
Calendric life time L_{ca}	20	years	[172]

of 28.8%. However, in this operation the CO₂ emissions would increase from 613 kg/MWh to 960 kg/MWh. The cleanest operation would lead to average emissions of 282 kg/MWh; a reduction of 57.2%. Opting for this operation would lead to an increase in electricity costs to 52.9 €/MWh. There are also many schedules possible that both decrease costs and emissions. For example, in the “Balanced operation”, which we define as the operation of the median of ϵ_k , the costs are 43.6 €/MWh (a reduction of 9.5%) and the emissions 464 kg/MWh (a reduction of 29.7%). Hence, this operation leads to negative CO₂ abatement costs and can be considered as a no regret option if a CES system is already installed. Table 3.2 elaborates on this, presenting cost and emission impact, CO₂ pay-back time (PBT) and CO₂ abatement costs for different Pareto points. The CO₂ PBT entails the period needed to mitigate the emissions associated with production of the battery,

Table 3.2: Optimization schedules versus self-consumption only battery.

Optimization	CO ₂ impact (t)	Electricity Costs impact (k€)	CO ₂ PBT (years)	CO ₂ Abatement costs (€/tCO ₂)
Cheapest	+25.5	-1.18	-	-
2 nd Cheapest	-2.15	-0.78	>20	-365
Balanced	-16.6	-0.39	2.2	-23.5
2 nd Cleanest	-26.8	+0.00	1.3	0.179
Cleanest	-32.1	+0.40	1.1	12.6

which are set at 157 kg CO₂ per kWh battery capacity based on [173]. The second cheapest schedule gives the lowest CO₂ abatement costs, however the CO₂ PBT is high and it is questionable whether that would be within the economic lifetime of the battery. Negative abatement costs are possible because generation is shifted from less efficient to more efficient generating facilities of the same fuel. In this case the cost and emission objective are in synergy as this shift leads to reduction in both costs and emissions. In general, it is apparent that starting from the cheapest operation, large steps in emission reduction can be taken at relatively low costs. The last steps to the cleanest operations entail relatively high costs; this concerns the shift from coal to gas.

A further striking notion from Figure 3.4 is that a self-consumption only CES leads to slightly higher electricity costs and emissions than having no CES. This is simply due to efficiency losses that occur when the electricity is converted to chemical energy and vice versa.

After one year of operation, battery degradation is 3.0%, 2.6% and 2.7%, respectively, for the cheapest, balanced and cleanest schedule. Of this, 2.0%, 1.6% and 1.7% can be attributed to the use of the battery (cyclic degradation). The graph of the degraded battery in Figure 3.4 depicts the Pareto frontier after five years of operation for the same cost and emission input. Energy and power performance of the battery are decreased with 12.9% to 14.8%. The roundtrip efficiency is assumed to be decreased from 89% to 87.6%, based on [174]. From Figure 3.4 it can be concluded that savings on costs and emissions can also be obtained with a degraded battery. To provide more insight in the battery operation and grid interaction within the three charging schedules that are indicated on the Pareto frontier of Figure 3.4 we demonstrate these on a randomly chosen day (1 October 2014) in Figure 3.5.

The DAM price and marginal emissions are shown on Figure 3.5a. Figure 3.5b demonstrates the battery operation and interaction with the grid when the CES control is optimized on cost. The battery is charged from the grid when costs

Figure 3.4: Pareto front of multi-objective optimization of average DAM price and CO₂ emissions of the community. Reference scenario of the situation without a battery and a self-consumption only battery are also shown, as well as the pareto front of a degraded battery.

are lowest, for example between 02:00 and 04:00, between 11:00 and 16:00 and between 22:00 and 24:00. When prices are highest (e.g. between 06:00 and 09:00 and between 17:00 and 19:00, electricity is exported to the grid. Figure 3.5d shows the community's battery operation and grid interaction when optimized on CO₂ emissions. In contrast to the cheapest schedule, the battery is discharged when marginal emissions are relatively high, for example from 0:00-2:00 and from 23:00-24:00, when a coal-fired power plant is the marginal operating facility, and also from 8:00-9:00 and 16:00-19:00 when an inefficient gas-fired power plant is at the margin. Charging occurs when the marginal emissions are low (between 5:00 and 6:00 and between 21:00 and 23:00), and with self-generated PV electricity (between 11:00 and 16:00) when P_{net} is below zero.

Figure 3.5c shows the grid interaction and battery operation in the 'balanced schedule'. In contrast to the cheapest and cleanest operation, note that the battery is barely used between 0:00 and 5:00. The battery is charged whenever an efficient gas-fired power plant is marginal, i.e. between 5:00 and 6:00, in the afternoon and between 20:00 and 23:00.

Figure 3.5b-d all show that the battery operation does not hamper the self-consumption of PV electricity. From 11:00 to 16:00 the community is a net producer

Figure 3.5: DAM price of 1 October 2014 and corresponding marginal emissions (a), Cleanest operation and accompanying battery SOC (b), Balanced operation and SOC (c) and Cheapest operation and SOC (d).

Figure 3.6: Impact of round-trip efficiency on pareto frontier.

of electricity, and this electricity is accommodated in the battery; in all battery operations the battery is at SOC_{min} at the start of the surplus PV period. Since the available battery capacity is larger than the surplus PV on this day, the battery can be additionally charged during the surplus PV period, namely between 13:00 and 14:00, when costs and emissions are relatively low.

Figure 3.6 shows the impact of the round-trip efficiency on the pareto frontier. It becomes apparent that efficiency is a key factor for the potential on saving costs and emissions. This finding advocates using a battery technology with a high efficiency, for example a Lithium Titanate (LTO) [23], but evidently more factors need to be considered. When efficiency is 77%, the pareto frontier almost intersects the “No Battery” reference case, which would make simultaneously saving costs and emissions impossible.

3.3.3 Load flow analysis

Figure 3.7 - Figure 3.9 show the transformer loading, line loading and minimum and maximum voltage, respectively, over the 295 days at 5-minute time resolution, for the balanced operation scenario; the other scenarios render similar results. The results show that LV grid limits were not violated in the load flow simulations. The maximum transformer loading was 140 kVA, or 87.3% of its capacity. This

Figure 3.7: Transformer loading during load flow simulation at 5-minute time resolution for the balanced schedule.

occurs when there is surplus PV electricity generation and simultaneously the battery is exporting electricity to the grid. However, because the grid limits in the optimization model were set at 83.7 kWh/h (see section 3.2.3.2), no transformer loading problems occur. Similarly, the line loading stays well within the limits with a maximum loading of 58.4%. Lastly, the voltage analysis of all nodes in the network shows voltages stay well within the limits as defined by EN-50160, which are $+0.10$ p.u. and -0.15 p.u. for 10-minute average values over a year [68]. Maximum voltage over 5 minutes found was 1.03 p.u. and minimum 0.97 p.u.

3.4 Conclusion and discussion

In this chapter a framework is proposed that enables the multi-objective optimization of cost and emissions by making use of a CES system. Our method ensures that the self-consumption levels of PV-generated electricity are not hampered. The analysis shows that costs and emissions can simultaneously be decreased compared to reference cases without a CES and with a CES only focused on self-consumption. We have found very attractive, even negative, CO₂ abatement costs. Various schedules show low CO₂ pay-back times of fewer than three years. Our framework enables households that co-own a CES to decide between the trade-off of costs and emissions. We also show that the (dis)charging schedules do not exceed LV grid limitations.

Figure 3.8: Line loading at all nodes at 5-minutes time resolution for the balanced schedule.

Figure 3.9: Minimum and maximum voltage at all nodes at 5-minutes time resolution for the balanced schedule.

Some considerations are required when implementing the proposed framework in practice. First, forecast errors could result in different economic results than presented here. The load forecast errors present a practical problem for all traders; the trade-off between profit maximization and risk acceptance. Further elaboration for future work could include hierarchical optimization, i.e. after the DAM optimization, proceed to closer to real-time markets (i.e. supporting multi-revenue streams), or first intra-day markets and then in balancing markets where the hierarchical control compensates for forecast errors by exploiting the real-time balancing market (see e.g. [153]). PV electricity generation forecast errors on the other hand, could result in too much or too few capacity of the CES being reserved for accommodating PV-generated electricity. State-of-the-art machine learning methods have an average day-ahead mean absolute error of six to seven percent for forecasts of hourly totals [175]; operators of a CES could decide to reserve some capacity of the battery to ensure high self-consumption rates. However, forecast errors only slightly affect the Pareto curve, as we found in preliminary work, and the overall results still hold clearly. This is also confirmed in recently published work [96].

The focus of our chapter is on operational aspects and excludes construction, finance and end-of-life. Future research could include these, to determine under what economic circumstances investing in a CES becomes a business case. Furthermore, not all factors influencing battery degradation are taken into account. To limit computational time, we considered temperature to be controlled within acceptable range by the battery management system and maximized the C-rate at $0.4 \text{ [h}^{-1}\text{]}$. However, these factors could also be included in the battery model for a more accurate analysis of battery degradation. A further option is to increase the level of detail in the load flow analysis, e.g. increase the time resolution, and to make it part of optimization model.

The proposed framework can be extended in several directions. First, the trade-offs between emissions and other price incentives can be investigated. Examples are operation on the reserve markets such as Frequency Containment Reserve or Frequency Restoration Reserve. In addition, our framework can be applied to a variety of cases of optimizing flexible resources, such as EVs, heat pumps and industrial electricity loads.

To conclude, in a medium- to long-term future CES systems could even be price setters in electricity spot markets. This could inspire new research, for example on exploring possible bidding strategies of aggregators operating CES systems, but also on how to quantify the marginal emissions of storage systems.

4 Should we reinforce the grid? Cost and emission optimization of electric vehicle charging under different transformer limits

This chapter is based on the publication:

N.B.G. Brinkel¹, W.L. Schram¹, T.A. Alsaif, I. Lampropoulos, and W.G.J.H.M. van Sark, "Should we reinforce the grid? Cost and emission optimization of electric vehicle charging under different transformer limits." Accepted," *Applied Energy*, 2020.

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Abstract

With high electric vehicle (EV) adoption, optimization of the charging process of EVs is becoming increasingly important. Although the CO₂ emission impact of EVs is heavily dependent on the generation mix at the moment of charging, emission minimization of EV charging receives limited attention. Generally, studies neglect the fact that cost and emission savings potential for EV charging can be constrained by the capacity limits of the low-voltage (LV) grid. Grid reinforcements provide EVs more freedom in minimizing charging costs and/or emissions, but also result in additional costs and emissions due to reinforcement of the grid. The first aim of this study is to present the trade-off between cost and emission minimization of EV charging. Second, to compare the costs and emissions of grid reinforcements with the potential cost and emission benefits of EV charging with grid reinforcements. This study proposes a method for multi-objective optimization of EV charging costs and/or emissions at low computational costs by aggregating individual EV batteries characteristics in a single EV charging model, considering vehicle-to-grid (V2G), EV battery degradation and the transformer capacity. The proposed method is applied to a case study grid in Utrecht, the Netherlands, using highly-detailed EV charging transaction data as input. The results of the analysis indicate that even when considering the current transformer capacity, cost savings up to 32.4% compared to uncontrolled EV charging are possible when using V2G. Emission minimization can reduce emissions by 23.6% while simultaneously reducing EV charging costs by 13.2%. This study also shows that in most cases, the extra cost or emission benefits of EV charging under a higher transformer capacity limit do not outweigh the cost and emissions for upgrading that transformer.

4.1 Introduction

In Chapter 3, a multi-objective framework was developed for scheduling the charging and discharging of a community battery. In this chapter, this framework is deployed for an EV fleet, in the context of the question whether grid reinforcements to accommodate EV flexibility make sense from an emission and/or cost perspective.

With the substantial increase in EV charging transactions in low-voltage (LV) grids, optimization of the EV charging process receives growing attention. Currently, most EVs charge in an uncontrolled manner; the EV starts charging directly after connecting to the charging station, until its charging requirement is met. This charging strategy is generally regarded as undesirable, as a large share of the EVs start charging in the evening hours [65], [176], [177]. This causes the EV demand peak to coincide with the evening electricity demand peak of households, inducing

grid congestion and power quality problems [178], [179]. In addition, uncontrolled charging is not always efficient from a financial and/or CO₂ emission perspective.

In the majority of charging transactions, the EV connection time to the charging station largely exceeds the required time to meet its charging demand [65], [176]. This provides the opportunity to optimize the EV charging process by shifting EV charging over time. This process is frequently referred to as smart charging, coordinated charging or controlled charging. Smart charging algorithms have been proposed for a wide range of objectives. The majority of the proposed charging algorithms perform economic optimization of EV charging [180], [181]; these algorithms aim to minimize the charging costs of EV owner or aggregators in case of unidirectional charging, or to maximize their economic benefits using vehicle-to-grid (V2G) technology. Other proposed EV smart charging algorithms aim to minimize CO₂ emissions [182], maximize self-consumption of PV solar energy [52] or mitigate congestion and power quality problems in LV grids [183]–[185]. These research activities were followed by actual implementation and testing of smart charging algorithms in real-life environments [186]–[188].

Numerous business case analyses have demonstrated the economic attractiveness of smart charging in different electricity markets, with potential financial benefits ranging from 106 €/year to 1008 €/year per EV [189]–[191]. Despite previous research having illustrated that the specific hourly electricity generation mix is an important moderator of the CO₂ emission impact of EVs [192], emission minimization through smart charging and V2G has only been addressed in a limited number of studies. Some of these studies operationalize this by minimizing the electricity imported from the grid [193], [194]. The limitation of this approach is that it fails to recognize that the emission factor of the electricity generation mix also shows large fluctuations over time, depending on the actual dispatch of e.g. renewables, coal- and gas-fired power plants [127]. Others translate emissions to costs and subsequently minimize on these adapted cost functions [195], [196]. This eliminates the possibility to do a pure emission-based optimization, and it therefore underestimates the mitigation potential of smart charging and V2G. The limitations of these previous studies can be addressed by constructing emission profiles which can be used as input in the emission optimization process [197], [198]. To the best of our knowledge, only Zakariazadeh et al. [199] and Hoehne et al. [182] have applied this approach to smart charging or V2G. However, both studies only consider a short timescale and neglect day-to-day variations in emissions. Battery degradation is also not considered in both studies, while this can have important implications for the Pareto frontier in battery multi-objective optimization [198]. Furthermore, Hoehne et al. [182] do not determine the trade-off between charging costs and emissions and only consider plug-in hybrid EVs, while Zakariazadeh et al.

[199] consider unrealistic synthetic price and emission profiles which overestimate the variability in emissions and prices by a factor of 10 [127], [133].

A second gap identified in scientific literature is the limited attention of the potential adverse impact of smart charging and V2G on grid congestion. Increasing grid congestion induced by EV charging can occur when a large set of EVs charge simultaneously at moments with low electricity costs or emissions. Distribution system operators (DSOs) are required to accommodate the needs of all system users and requests for new connections in the LV-grid [200], which could result in increasing need for grid reinforcements in order to accommodate smart charging and V2G. However, grid reinforcements result in extra emissions and socialized costs from producing and installing grid assets. This demonstrates the need to determine whether the economic and environmental benefits of smart charging with a higher grid capacity limit outweigh the costs and emissions of grid reinforcements.

This study aims to address the two gaps in literature that were identified above. First, the trade-off between cost and emission minimization of EV charging is determined using multi-objective optimization framework. The second aim is to assess whether it is beneficial from a cost and emission system perspective to reinforce the grid. To do so, the multi-objective framework is used to compare the cost and emission benefits of smart charging with a higher grid capacity limit with the costs and emissions of grid reinforcements. The model uses a method to model the aggregated charging pattern of a large set of EVs at low computational time and considers EV battery degradation, V2G and transformer limits. The model is tested by using an actual case study grid for different EV adoption rates, PV adoption rates, emission profiles and pricing schemes.

This chapter is outlined as follows: Section 4.2 presents the system architecture, discusses a method to model the aggregated charging pattern of a large set of EVs at low computational time and provides the multi-objective optimization problem formulation. Section 4.3 provides a literature review on battery degradation experiments, determining the empirical relationship between cycle depth and battery degradation. Section 4.4 introduces the investigated case study and provides an overview of the data inputs. Section 4.5 presents the multi-objective optimization results, including a sensitivity analysis on the effect of different critical parameters such as EV adoption rate, PV adoption rate and V2G on the outcomes. Lastly, the discussion is presented in Section 4.6 and conclusions and suggestions for future research are presented in Section 4.7.

Figure 4.1: System outline of proposed framework.

4.2 Methods

4.2.1 System architecture

Figure 4.1 shows the system architecture of this study. The system boundaries contain a single LV grid, which connects a number of households, PV systems and EV charging stations. Because this research focuses on the cost and emissions from a system perspective, we assume one central operator that controls all loads. In the assessment timeframe, a set of EV charging transactions is conducted at the EV charging stations in the investigated LV grid. The central operator ensures the power flows through the Medium Voltage (MV)/LV transformer remain within the transformer limits, the residential load is satisfied and the charging needs of the EVs are met. EV demand is assumed to be the only shiftable load and furthermore EVs are able to feed electricity into the grid (i.e. V2G). The central operator can control the charging and discharging of the EVs to optimize economic and/or environmental objectives. This study assumes perfect foresight in residential load, PV generation, time-of-use (ToU) tariffs, emission profiles and EV availability.

4.2.2 System costs and system emissions

A transformer upgrade and/or cable reinforcements provides EV fleet operators more freedom in minimizing EV charging costs and/or emissions without being constrained by the grid capacity. However, to evaluate whether transformer or grid reinforcements are desirable from a system perspective, costs and emissions from the production and installation of a transformer and electricity cables should also be taken into account. Costs and emissions associated with battery degradation

should also be considered to account for the potential extra battery degradation with V2G compared to unidirectional charging. System costs and emissions are defined in eq. 4.1a and 4.1b as follows:

$$C_{\text{system}} = C_{\text{el}} + C_{\text{battdeg}} + C_{\text{grid}}, \quad (4.1a)$$

$$G_{\text{system}} = G_{\text{el}} + G_{\text{battdeg}} + G_{\text{grid}}, \quad (4.1b)$$

where C_{system} and G_{system} are respectively the annual system costs and emissions, C_{el} and G_{el} are the total annual electricity costs and emissions for the whole LV grid, C_{battdeg} and G_{battdeg} are the total annual costs and emissions resulting from EV battery degradation and C_{grid} and G_{grid} are the annualized costs and emissions from grid reinforcements.

Grid reinforcement costs C_{grid} and emissions G_{grid} are annualized by using equations 4.2a and 4.2b:

$$C_{\text{grid}} = \frac{(C_{\text{trans}} + l_{\text{cable}} C_{\text{cable}})r}{(1 - (1 + r)^{-L})} \quad (4.2a)$$

$$G_{\text{grid}} = \frac{G_{\text{trans}} + l_{\text{cable}} G_{\text{cable}}}{L}, \quad (4.2b)$$

where C_{trans} and G_{trans} represent the total costs and emissions of producing and replacing a transformer, C_{cable} and G_{cable} represent respectively the costs and emissions for reinforcing one kilometer of cable, l_{cable} represents the total cable length that is reinforced and L represents the assumed lifetime of the grid, assuming that the transformer and the cables have the same lifetime. Grid reinforcement costs are discounted to consider the time value for money; r represents the discount rate.

4.2.3 Modelling aggregated EV charging patterns

Nearly all EV optimization models optimize the charging behavior of individual EV transactions, since each charging transaction has its unique plug-in time, plug-out time, charging requirement and maximum charging rate (e.g. [201], [202]). With high EV penetration, optimization of individual EV transactions could result in a significant computational burden, as each individual EV transaction adds a set of variables to the optimization problem. This computational burden can hinder policymakers and DSOs to perform techno-economic scenario studies for a long time horizon and for a large number of case-specific grids, considering a large number of parameters.

A study by Tang et al. [203] has proposed a method to model the aggregated charging behavior of a large pool of EVs in a LV grid at one timestep as a single

variable, inducing a considerable reduction in the computational time. The method converts the required charging volume, maximum charging power, plug-in time and plug-out time of individual EV charging transactions into an aggregated maximum charging power ($P_{\text{ch,max},t}$), minimum accumulated charging energy ($E_{\text{ch,min},t}$) and maximum accumulated charging energy ($E_{\text{ch,max},t}$) per timestep for a set of charging transactions, as described in Table 4.1. This method allows the charging behavior of this set of charging transactions to be modelled as a single community battery with a variable (i.e. time-dependent) battery capacity.

This study proposes two modifications to the methods of Tang et al. [203]. First, this study proposes to model accumulated EV charging behavior as multiple community batteries with a variable battery capacity instead of as a single community battery, since Tang et al.'s methods can underestimate the costs or emissions of EV smart charging: The maximum charging power $P_{\text{ch,max},t}$ is aggregated for multiple EV charging transactions, which allows the model to meet the charging requirement of individual charging transactions by charging with a higher charging power than physically possible for an individual charging transaction. This study proposes to divide the set of EV-transactions into S subsets, where $s \in \mathcal{S} \{1, 2, \dots, S\}$, in a chronological order based on the plug-in time. Subsequently, $P_{\text{ch,max},t,s}$, $P_{\text{disch,max},t,s}$, $E_{\text{ch,max},t,s}$ and $E_{\text{ch,min},t,s}$ are determined for every timestep and for every subset. The contributions compared to previous work (Tang et al.) are twofold. First, the number of subsets S is varied to determine a balance between computational time and accuracy of the model. Second, this study proposes to extend the method of Tang et al. to V2G-systems by introducing a maximum discharging rate ($P_{\text{disch,max},t,s}$) for the aggregated EV charging model. Table 4.1 discusses the proposed methods for determining $P_{\text{disch,max},t,s}$.

4.2.4 Multi-objective optimization model formulation

4.2.4.1 Objective functions and ϵ -constraint

A common approach to address a problem with multiple objectives is to determine the Pareto frontier using the ϵ -constraint method [204]. Each optimization is first solved separately, calculating the two endpoints of the Pareto frontier. The cost and emission objective functions are formulated in equations 4.3a and 4.3b:

$$\text{minimize } \sum_{t=1}^T (C_{\text{el},t} + C_{\text{battdeg},t}), \quad (4.3a)$$

$$\text{minimize } \sum_{t=1}^T (G_{\text{el},t} + G_{\text{battdeg},t}), \quad (4.3b)$$

Table 4.1: Overview of parameters for optimizing the aggregated charging demand of EV transaction subset s , adapted based on Tang et al. [203].

$E_{ch,max,t,s}$	The maximum accumulated charging energy at timestep t of EV set s is equal to the required charging energy of all EVs of transaction set s that connected to the grid between $t = 0$ and t .
$E_{ch,min,t,s}$	The minimum accumulated charging energy assures that the charging requirement of individual charging transactions is met before unplugging. $E_{ch,min,t,s}$ is equal to accumulated charging volume of all EVs in transaction set s that connected to the grid between $t = 0$ and t in the 'latest charging scenario'. The 'latest charging' scenario assumes that the charging schedule of an EV is delayed to the latest and that an EV charges at maximum charging power in the required number of timesteps to meet its charging demand before unplugging.
$P_{ch,max,t,s}$	The maximum charging power of EV set s at timestep t is equal to the maximum charging power of all EVs of EV transaction set s connected to the grid at timestep t .
$P_{disch,max,t,s}$	The maximum discharging power of EV set s at timestep t is equal to the maximum discharging power of all EVs of EV transaction set s connected to the grid at timestep t , excluding EVs that are charging in the latest charging scenario at timestep t . This avoids the model to discharge at maximum power one timestep before an EV unplugs, resulting in unmet charging demand.

where C_{el} represents the electricity costs, $C_{battdeg}$ the battery degradation costs, G_{el} represents the CO₂ emissions related to electricity consumption and $G_{battdeg}$ the CO₂ emissions related to battery degradation. C_{el} and G_{el} can be determined according to equations 4.4a and 4.4b:

$$C_{el,t} = c_t P_{grid,t} \Delta t, \forall t, \quad (4.4a)$$

$$G_{el,t} = g_t P_{grid,t} \Delta t, \forall t, \quad (4.4b)$$

where at timestep t the ToU-tariff is represented by c_t , the emissions related to electricity consumption are represented by g_t and the total amount of electricity withdrawn from (+) or injected to (-) the MV-grid is represented by $P_{grid,t}$.

Additional discharging and charging of an EV impacts the lifetime of the EV battery caused by cyclic ageing [205], [206]. Therefore, it is important to include battery degradation into the objective function, to ensure batteries are only discharged and charged if the benefits exceed the costs associated to battery degradation. If δ represents the cycle depth of an EV battery system, then the battery degradation costs $C_{battdeg}$ and degradation emissions $G_{battdeg}$ at timestep t

can be calculated using equations 4.5a and 4.5b:

$$C_{\text{battdeg},t} = C_{\text{batt}} \sum_{s=1}^S \Phi(\delta_{s,t}), \forall t, \quad (4.5a)$$

$$G_{\text{battdeg},t} = G_{\text{batt}} \sum_{s=1}^S \Phi(\delta_{s,t}), \forall t, \quad (4.5b)$$

where C_{batt} are the battery investment costs and G_{batt} are the emissions from producing a battery. The dimensionless degradation function $\Phi(\delta_{s,t})$ is discussed in Section 4.3.

The minimum and maximum of the range in emissions are the outcome of eq. 4.3b, and the emissions associated to the optimal solution found in eq. 4.3a, respectively. Subsequently, the range in emissions is divided into K equally spaced bins ϵ_k , where $k \in \mathcal{K} \{1, 2, \dots, K\}$. The ϵ -constraint can now be formulated by treating the emission function 4.3b as a constraint for each bin ϵ_k , as in eq. 4.6, and running the problem using the cost objective:

$$\sum_{t=1}^T (G_{\text{el},t} + G_{\text{batt deg},t}) \leq \epsilon_k \quad (4.6)$$

This approach allows to obtain the least-cost solution for a certain intended reduction in emissions. Only the cost minimization runs of the multi-objective optimization are subject to this constraint. The objective functions 4.3a and 4.3b are subject to various other constraints, as discussed in the following sections.

4.2.4.2 Power balance constraint

The power balance constraint is formulated in eq. 4.7:

$$P_{\text{grid},t} = P_{\text{res},t} - P_{\text{PV},t} + \frac{1}{\eta_{\text{ch}}} \sum_{s=1}^S P_{\text{ch},s,t} - \eta_{\text{disch}} \sum_{s=1}^S P_{\text{disch},s,t}, \forall t, \quad (4.7)$$

where $P_{\text{res},t}$ and $P_{\text{PV},t}$ represent the residential load and PV generation in the investigated LV grid at timestep t . These are assumed to be non-controllable. $P_{\text{ch},s,t}$ and $P_{\text{disch},s,t}$ represent, respectively, the charging and discharging power at the EV battery of EV group s at timestep t and η_{ch} and η_{disch} represent the EV charging and discharging efficiencies.

4.2.4.3 Charging power constraints

The aggregated charging and discharging power of each subset of EVs are constrained by a maximum charging and discharging power, which are determined

using the methods presented in section 4.2.3:

$$0 \leq P_{ch,t,s} \leq P_{ch,max,t,s}, \forall t, s, \quad (4.8)$$

$$0 \leq P_{disch,t,s} \leq P_{disch,max,t,s}, \forall t, s. \quad (4.9)$$

4.2.4.4 Accumulated charging energy constraints

To model the charging behavior of a group of EVs as a single community battery, the accumulated charging energy is constrained by a minimum and maximum accumulated charging energy, as discussed in section 4.2.3:

$$E_{ch,min,t,s} \leq E_{ch,t,s} \leq E_{ch,max,t,s}, \forall t, s,, \quad (4.10)$$

where $E_{ch,t,s}$ is a variable that represents the accumulated charging energy of EV group s at timestep t . $E_{ch,t,s}$ is based on the accumulated charging energy in the previous timestep and the charging and discharging power at timestep t :

$$E_{ch,t,s} = 0 \text{ for } t = 1, \forall s. \quad (4.11)$$

$$E_{ch,t,s} = E_{ch,t-1,s} + (P_{ch,t,s} - P_{disch,t,s})\Delta t, \forall t \in \{2 \dots T\}, s. \quad (4.12)$$

4.2.4.5 Transformer capacity constraint

To avoid transformer overloading, $P_{grid,t}$ is constrained by the transformer capacity ($P_{tr,max}$) at every timestep t , as formulated in eq. 4.13:

$$-P_{tr,max} \leq P_{grid,t} \leq P_{tr,max}, \forall t \quad (4.13)$$

Since residential load and PV generation are assumed to be non-controllable in this study, only EV charging behavior is altered to meet this constraint.

4.3 Battery degradation

Wöhler curves, or Stress – Number of cycles curves (S-N curves), are often used to predict material fracture under cycle loading [162]. This relation can also be applied to cyclic battery degradation [207]. Doing this, the relation between number of full equivalent cycles until end of life L_{FEC} and cycle depth δ takes the following general form:

$$L_{FEC} = L_{cy}\delta^m \quad (4.14)$$

By default, parameter L_{cy} reflects the number of cycles under cycle depth of 100% (i.e. $\delta = 1$), whereas cyclic degradation exponent m determines the specific shape

of the curve. To obtain the number of actual cycles L_{actual} until end of life, one needs to correct for the actual cycle depth:

$$L_{\text{actual}} = \frac{L_{\text{cy}} \delta^m}{\delta} = L_{\text{cy}} \delta^{m-1} \quad (4.15)$$

The degradation per cycle of the battery is the inverse of L_{actual} . Considering half cycles instead of full cycles, this can be translated to the dimensionless degradation function $\Phi(\delta_{s,t})$:

$$\Phi(\delta_{s,t}) = \frac{0.5}{L_{\text{cy}} \delta^{m-1}} = \frac{0.5}{L_{\text{actual}}} \quad (4.16)$$

Note, as this function is non-linear, equations 4.5a, 4.5b and 4.6 are treated as piecewise linear functions in the optimization model by using four segments.

A literature review was performed to determine appropriate values for the parameters L_{cy} and m for lithium-ion EV batteries. Figure 4.2 shows the results of seven different studies; all studies comply to the general form presented in eq. 4.14, with the R^2 for each individual study ranging from 0.92 to 1.00. For every cycle depth that was researched by more than four studies, the average value of y was taken. A trendline with the form of eq. 4.14 was fitted using the MATLAB curve fitting toolbox; values of L_{cy} and m were determined at 4084 (± 367 ; 95% confidence) and -0.7514 (± 0.0324), respectively, with an adjusted R^2 of 0.997. These values are used as battery degradation parameters in this study.

4.4 Data inputs

4.4.1 Case study specifications

This research considers an LV grid in a residential area in the Lombok district in Utrecht (the Netherlands) as a case study grid. This part of the distribution grid is used as a living lab in the Smart Solar Charging research project [186] to determine the impact of EV charging and PV generation on LV grids. For this research project, EV charging transaction data is logged from 26 EV charging stations and the PV generation from three PV systems is logged on a 5-minute basis.

The investigated grid has a radial outline and is connected to the MV grid through a 400 kVA transformer. The total cable length equals 3.3 km, divided over 19 feeder lines. Most cables in the grid are made out of copper, with cross-sectional areas ranging from 25 to 95 mm², as described in [72]. The total electricity demand in this grid equaled 1251 MWh in 2017.

The grid is connected to the MV grid through a 400 kVA transformer, which can be upgraded to a capacity of 630 kVA. This study will compare the system costs and system emissions with and without transformer upgrades.

Figure 4.2: Cycle depth versus number of full equivalent cycles. Data from [206], [208]–[212]. Trendline is an exponential fit of the averages of the studies; the 95% CI is the confidence interval of the mean for every cycle depth.

4.4.2 EV charging transactions

The analyses in this study are performed for different EV adoption rates, as depicted in Table 4.2. Future sets of EV charging transactions are generated to reflect high EV adoption rates, using the methods described in [65] and using two years of logged EV charging data from the investigated grid. The different EV adoption rates in Table 4.2 represent the share of EVs in total number of cars possessed by households connected to the investigated grid, considering the current car possession rate of 0.4 car/household in the Lombok district [213]. Table 4.2 makes a distinction between local EVs and other EVs (e.g. visiting EVs), using the classification method in [65]. It is assumed that all EVs in the future are battery electric vehicles and that the ratio between local EVs and other EVs is the same as in the logged EV data.

Table 4.2: Details of the sets of EV transactions used.

EV adoption	No. EVs charging per year		No. charging transactions per year	EV charging volume per year
	Local	Other		
25%	34	916	7339	132 MWh
50%	68	1832	14464	257 MWh
75%	102	2749	20778	372 MWh
100%	136	3665	28355	506 MWh

Table 4.3: Overview of parameter grid reinforcement costs and emissions.

Parameter	Value	Unit	Source
C_{trans} (630 kVA)	15,000	€	[214]
C_{cable}	120,000	€/km	[214]
G_{trans} (630 kVA)	136.3	tCO ₂ eq	[215] ²
G_{cable}	12.5	tCO ₂ eq/km	[216] ³
r	3	%	[214]
L	40	years	[214]
l_{cable}	3.3	km	-

4.4.3 Grid reinforcement costs and emissions

Table 4.3 shows general values for the costs and emissions of grid reinforcements used in economic and environmental assessments about grid reinforcements. In this study, we consider both scenarios with only transformer upgrades and scenarios in which 25%, 50%, 75% and 100% of the cables in the grid are reinforced. Table 4.4 presents the annualized reinforcement costs and emissions for each considered scenario, which are based on eq. 4.2a and 4.2b.

4.4.4 Emission profiles and other data input

Table 4.5 provides an overview of the data inputs used in this study. The emission profiles form an important input for this study. Two different profiles are composed for the Netherlands in 2018: an average emission profile and a marginal emission profile. These are constructed according to the methods presented in [127] and

²Jorge et al. [215] determined the life-cycle emissions for a 315 kVA transformer. This has been scaled to a 630 kVA transformer by using a scale factor of 0.8 [217]. Emissions from transformer losses were not considered, assuming that a transformer upgrade of 400 to 630 kVA does not result in additional transformer losses.

³This study assumes that underground copper cables are replaced with aluminum cables. The emissions from the production and installation of an aluminum cable are combined with the end-of-life emission benefits of copper cables.

Table 4.4: Shares of cable reinforcements versus reinforcement costs and emissions.

Share cables reinforced	Annualized costs	Annualized emissions
0%	649 €/year	3.41 t CO ₂ eq/year
25%	4955 €/year	3.67 t CO ₂ eq/year
50%	9262 €/year	3.93 t CO ₂ eq/year
75%	13568 €/year	4.19 t CO ₂ eq/year
100%	17225 €/year	4.44 t CO ₂ eq/year

[192]; the method for determining marginal emission profiles can be found in Appendix A. Average emission profiles are constructed by taking the weighted average emission factors of all electricity generating technologies in a certain time frame (15 minutes in this study). This makes them especially suitable for CO₂ accounting purposes. Marginal emission profiles take the emission factor of one specific power plant, namely the one that is the price-setting unit in a certain time frame (typically one hour). An increase or decrease of demand leads to altered electricity generation of this power plant, which makes these profiles very suitable to determine impact of charging optimization [218].

The assessment time horizon equals one year. To limit the computational burden of the simulation, the EV charging optimization is split into individual months, which are subsequently combined to obtain the annual total electricity and battery costs. The simulation of each month also considers the EV charging transactions starting in the five days before the start of the month to assure that a representative number of EVs is charging at the beginning of the month. In addition, five days after the last day of the month are considered in each monthly optimization to allow EVs to finish their charging transaction. Battery degradation was only considered in simulations with V2G-functions, as V2G can increase battery degradation compared to unidirectional EV charging. The number of EV subsets S equalled 50 for 25% EV adoption, 150 for 50% EV adoption, 200 for 75% EV adoption and 250 for 100% EV adoption, based on section 4.5.3. Simulation was performed in Python [219] with the Gurobi [220] solver, using a laptop equipped with an Intel i7-5600U processor and a 16GB RAM.

4.5 Results

4.5.1 Multi-objective optimization results

The Pareto frontier showing the trade-off between cost minimization and emission minimization for EV charging is presented in Figure 4.3. This figure shows the

Table 4.5: Overview of data inputs in this study.

Input	Explanation
PV-generation profiles	Normalized 15-minute data (kW/kWp) from three logged PV systems in the Lombok district in Utrecht, the Netherlands.
Residential load profiles	Standardized household load profiles from NEDU [221] and the total annual electricity consumption of all grid connections in the investigated grid in 2017.
Price data	Day-ahead market prices in the Netherlands in 2018 in most runs. automatic Frequency Restoration Reserve (aFRR) imbalance prices in the Netherlands in 2018 in section 4.5.2.2
Emission profiles	Average emission profiles are determined using the method in [127] and 15-minute generation data in 2018 from the Netherlands from [133]. Marginal emission profiles are determined using the methods in [192] and Dutch day-ahead market prices in 2018. Specific assumptions can be found in Appendix 4.A.
η_{ch}, η_{disch}	$\sqrt{0.87}$ [222]
Δt	15-minutes
Battery degradation parameters	Parameters presented in section 4.3.
Battery investment costs	130 €/kWh [223]
Battery production emissions	104 kg CO ₂ eq/kWh [224]

trade-off for both marginal and average emissions and identifies the impact of a transformer upgrade from 400 kVA to 630 kVA on system costs and emissions.

4.5.1.1 Unidirectional charging

Figure 4.3 indicates that cost minimization of unidirectional EV charging with a 400 kVA transformer results in a reduction of charging costs of 22.7% compared to uncontrolled charging. Emission minimization of EV charging with a 400 kVA transformer can reduce charging emissions by 8.0% when considering average emission profiles and by 23.6% when considering marginal emission profiles. Even with 100% emission minimization of EV charging, costs are reduced by 7.8% compared to uncontrolled charging when considering average emission profiles and by 13.2% when using marginal emission profiles.

Marginal emission profiles show a larger spread in emissions compared to average emission profiles (standard deviations in 2018 of 0.190 kg CO₂eq/kWh and 0.045 kg CO₂eq/kWh respectively, see also Figures 4.8 and 4.9 in Appendix 4.A), as a change in marginal power plant (e.g. from a coal- to a gas-fired power plant)

Figure 4.3: Pareto frontier for multi-objective optimization of costs and CO₂-emissions of EV charging, considering average and marginal emission profiles and considering unidirectional charging (left) and V2G (right). Pareto frontiers are presented for an EV adoption rate of 100% and an installed PV capacity of 400 kWp. Battery degradation costs and emissions are considered for all Pareto frontiers. For V2G, the costs and emissions are presented per net charged kWh (i.e. charging volume minus discharging volume).

has a direct substantial impact on the marginal emission factor. The impact of a different marginal power plant on the average emission factor is limited, since a large share of the total emissions are determined by relatively constant baseload generation.

Figure 4.3 indicates that the increase in costs when shifting from cost minimization to emission minimization is higher when using average emissions profiles than when using marginal emission profiles. An explanation can be found in the input data: the lowest values of marginal emission factors coincide with lower prices than the lowest values of average emission factors. The lowest marginal emission factors are found in hours in which the most efficient gas-fired power plant is marginal; this implies a relatively low residual electricity demand, and thus relatively low prices.

Overall, the CO₂-abatement costs⁴when shifting from cost-based optimization to emission-based optimization range from 2.8 to 22.6 €/tCO₂eq with increasing levels of emission abatement when considering marginal emission profiles with a 400 kVA transformer. The CO₂-abatement costs range from 21.8 to 310.6 €/tCO₂eq

when considering average emission profiles.

4.5.1.2 V2G

V2G functions allow for a larger reduction in charging costs and emissions, as EVs can inject electricity to the grid at moments with high costs or emissions. Figure 4.3 shows that the cost reduction potential of V2G compared to uncontrolled charging equals 32.4%, whereas the emission reduction potential equals 8.7% when using average emission profiles and 67.3% when using marginal emission profiles. This emission reduction with V2G is most profound for marginal emission profiles due to its high volatility in emissions. This high volatility causes that the emission benefits of discharging exceed the extra battery degradation emissions, resulting in high discharging volumes when minimizing emissions with marginal emission profiles. This also explains why the increase in EV charging costs with V2G is higher with marginal emission profiles when shifting from cost-based optimization to emission-based optimization. EV discharging volumes are higher when optimizing emissions using marginal emission profiles. This causes EVs to inject electricity to the grid at moments with high emissions and corresponding to low electricity prices, thus increasing the net charging costs of EV charging. The CO₂-abatement costs when shifting from cost-based optimization to emission-based optimization range from 5.9 to 43.8 €/tCO₂eq for marginal emissions and from 82.7 to 434.8 €/tCO₂eq for average emissions when considering V2G functions with a 400 kVA transformer.

4.5.1.3 Impact of transformer upgrade

Comparing the Pareto frontiers corresponding to 400 kVA and 630 kVA transformers in Figure 4.3 provides insight on the effect of a transformer upgrade on system costs and emissions. The results indicate that EV charging costs and emissions are lower with a 630 kVA transformer from the perspective of the central operator (i.e. when neglecting transformer upgrading costs and emissions), since this Pareto frontier is located below the 400 kVA Pareto frontier in all scenarios. A transformer upgrade causes that EVs are less constrained in their charging behavior by the transformer capacity, providing more freedom to EVs in minimizing their charging costs or emissions. However, Figure 4.3 shows that a transformer upgrade is never beneficial from a system perspective in terms of both costs and emissions

⁴CO₂-abatement costs are calculated by dividing the increase in system costs when shifting from cost minimization towards a partly emission-based charging optimization by the decrease in system emissions when making this shift.

with unidirectional charging when also considering the costs and emissions for producing and installing a transformer.

A transformer upgrade has a more pronounced impact on system costs and emissions with V2G, since EVs are not only less frequently constrained by the transformer capacity during charging, but also less constrained during discharging. This allows EVs to inject more electricity to the grid at moments with beneficial prices and/or emissions. With V2G, the Pareto frontiers corresponding to the transformer capacities of 400 and 630 kVA (including transformer upgrading costs and emissions) intersect at EV charging emissions of 0.45 kg CO₂eq/kWh. This indicates that grid reinforcements are attractive from a system perspective in the investigated case study when constraining the EV charging emissions to 0.45 kg CO₂eq/kWh or lower when EVs optimize their charging schedule using V2G.

4.5.2 Sensitivity analysis on system impact of grid reinforcements

To provide better insights under what circumstances grid reinforcements are beneficial from a system perspective, this section elaborates on how the system impact of grid reinforcements changes with different values for critical parameters, including the EV adoption rate, installed PV capacity, selected pricing scheme and level of grid reinforcement. These sensitivity analyses focus on the impact on system costs, since most DSOs still base decisions for grid reinforcements on financial grounds.

4.5.2.1 Impact of EV adoption rate and installed PV capacity

Figure 4.4 presents a breakdown of the change in system costs with a transformer upgrade from 400 kVA to 630 kVA for different EV adoption rates and different installed PV capacities for both unidirectional charging and V2G. Figure 4.4 indicates that in all cases with both unidirectional EV charging and V2G, the annualized investments outweigh the reduction in EV charging costs due to a transformer upgrade, resulting in an increase in system costs. An increase in total system costs implies that, under the assumptions in this study, it is not economically attractive to reinforce the grid from a system perspective.

A transformer upgrade leads to a larger decrease in EV charging costs with higher EV adoption rates. As a high EV load can cause transformer overloading, the number of times that EVs are constrained by the transformer capacity in charging at moments with low prices increases with the number of EVs connected to the grid. Subsequently, a transformer upgrade leads to a larger reduction in EV charging costs with higher EV adoption rates.

Figure 4.4: Annualized transformer investments, change in EV charging costs and change in system costs with a transformer upgrade of 400 kVA to 630 kVA in the investigated grid for different EV adoption rates and installed PV capacities with unidirectional charging (top) and bidirectional charging (bottom). No cable reinforcements are considered in this figure.

Figure 4.5: Annualized transformer investments, change in electricity costs and change in electricity costs with a transformer upgrade of 400 kVA to 630 kVA in the investigated grid for different shares of cars charging using aFRR and day-ahead (DA) prices in optimizing their charging process. Results are presented for an EV adoption rate of 100% and an installed PV capacity of 200 kWp.

The decrease in EV charging costs with a transformer upgrade is lower with a higher installed PV capacity in the grid. PV generation causes that less power withdrawal from the MV grid is required to fulfil the electricity demand of EVs. As a consequence, EVs can meet a larger share of their charging demand at moments with low electricity prices without causing transformer overloading, thus a transformer upgrade has a less pronounced effect on the EV charging costs.

4.5.2.2 Impact of selected pricing scheme

With increasing integration of renewables into the electricity system, electricity prices could become more volatile. In addition, it is unlikely that all EVs will be subject to the same price-incentives as inputs in the optimization of their charging process, since EVs are optimized in the context of different (sub-)markets via the central operator. To determine how these developments could affect the impact of grid reinforcements on system costs, additional simulations were performed in which different shares of the EV fleet used the more volatile Dutch automatic Frequency Restoration Reserves (aFRR) prices in optimizing their charging schedule.

Figure 4.5 indicates that the decrease in EV charging costs with grid reinforcements outweighs the grid reinforcement investments when a large number of EVs bases its charging schedule on aFRR prices, using the scenario of 100% EV adoption with a 200 kWp installed PV capacity in the considered LV grid. This highlights

Figure 4.6: Annualized grid investments, change in electricity costs and change in electricity costs with a transformer upgrade of 400 kVA to 630 kVA in the investigated grid for different grid reinforcement scenarios. Results are presented for an EV adoption rate of 100% and an installed PV capacity of 200 kWp. All EVs in this scenario used aFRR prices to optimize their charging demand.

the major impact of the volatility of the selected pricing scheme on the outcome of the analysis. The effect is less pronounced with a low share of EVs use aFRR prices to optimize their charging behavior compared to a situation where all EVs use day-ahead market prices in their optimization process, as the most beneficial prices for EV charging do not occur at the same moments for both pricing schemes. Consequentially, EV demand peaks are better distributed over time, resulting in fewer moments in which the charging demand is constrained by the transformer capacity.

4.5.2.3 Impact of level of grid reinforcement

Figure 4.6 presents the change in system costs with different levels of cable reinforcement for a situation where 100% of the EVs are optimized based on the aFRR prices.. This is the situation with the largest decrease in EV charging costs with grid reinforcements. The annualized grid investments rise sharply when grid reinforcements are required next to a transformer upgrade, since cable reinforcements require costly excavations. If a large share of the cables in the grid require reinforcements, then grid reinforcements are even with very high price volatility not beneficial from a system cost perspective.

Figure 4.7: Underestimation in model outcome and relative computational running time of the aggregated EV charging model proposed in section 4.2.3 using different numbers of EV charging transaction subsets. The model outcome and computational time of a conventional EV charging model formulation is taken as the reference. Installed PV capacity equals 200 kWp. EVs used marginal emission profiles to optimize their charging demand.

4.5.3 Accuracy of EV community battery modelling method

Figure 4.7 compares the computational time and objective outcome of conventional methods for optimizing EV charging behavior (i.e. creating variables for every individual charging transactions) with the computational time and objective outcome when using the methods proposed in section 4.2.3. The results indicate that when the aggregated EV charging demand is optimized using one subset of EV charging transactions, as proposed by Tang et al. [203], the annual EV charging emissions are underestimated by 7.0% with a 100% EV adoption rate when considering marginal emission profiles. The underestimation in objective outcome equals 1.8% when optimizing using average emission profiles, 6.6% when optimizing using day-ahead prices and 12.5% when optimizing using aFRR prices. Increasing the number of subsets rapidly reduces this charging cost or emission estimation error, until this error is completely eliminated. The computational running time increases with a larger number of subsets, allowing users of the proposed method to make a trade-off between computational time and estimation error in results. Figure 4.7 indicates that aggregated EV charging demand can

be optimized using a cost estimation error of 1% at a relative computational time of below 20% compared to conventional EV charging optimization methods. With lower EV adoption, a lower number of subsets is required to eliminate the inaccuracy in optimizing EV charging costs.

4.6 Discussion

This study presented Pareto frontiers to get insight in the trade-off between cost-based optimization and emission-based optimization of EV charging in an LV-grid under different transformer capacity limits. A model was developed to be able to optimize EV charging for a large group of EVs at lower computational cost compared to conventional EV optimization models, without losing accuracy in results. The results show that grid reinforcements to mitigate grid congestion caused by EV charging are in most situations not beneficial from both a cost and emission perspective; the additional costs and emissions in case of reinforcement outweigh the potential additional EV charging optimization benefits that can be obtained as a result of the higher transformer capacity. These results are robust for various future scenarios regarding the penetration of PV and EVs, but not with much more volatile electricity prices. A second major finding was that even with the current transformer limitations, the costs and emissions related to EV charging can be decreased substantially. For example, emission-based charging optimization can reduce charging marginal emissions by 23.6% compared to uncontrolled EV charging, while also reducing the costs by 13.2%. With V2G, marginal emission savings of up to 67.3% are possible, while charging costs can be reduced by 32.4%.

These findings have important practical implications. For example, a transition from internal combustion engine vehicles to EVs can have a larger impact on emissions than often assumed - also on the short term. This could help countries in attaining their climate goals. Many studies consider the average generation mix to estimate the impact of this transition, whereas this study shows that EVs are adept to be charged with electricity that is less CO₂ intensive than the average of a country's generation mix.

Further, it was shown that a high penetration of EVs is possible under the current transformer limit for the investigated grid, and moreover, the current transformer limit provides ample possibilities for smart charging and V2G. In order for such a system to function, various options exist. One option is that the DSO enforces central operators to stay within the overall capacity limits. the DSO as single buyer, and the charging fleet operators providing ancillary services (e.g. see [96]). Both options will require investments in communication infrastructure.

Currently DSOs are legally obliged to accommodate the needs of all system users [200], which could mean that charging fleet operators should be financially compensated when they are constrained by the grid capacity. It should be reconsidered whether this system can be maintained in the future in grids with high EV adoption. An important recommendation is to think of a new framework which allows for a socially fair distribution of costs and benefits.

Two main categories of uncertainty should be considered when interpreting the results: uncertainty in input data and uncertainty in forecasting accuracy. One of the main sources of uncertainty in the input data are the used emission profiles. To determine the marginal emission profile, this study assumed marginal emissions are equal to the emissions of the plant with marginal costs closest to day-ahead market price. As discussed in [127], it is not always possible to determine the actual marginal power plant. More accurate marginal emission profiles can only be constructed if each balance responsible party (BRP) publishes the CO₂ intensity of their scheduled generation based on the unit commitment of their power plants. Given the large emission reduction potential of EV charging when optimizing EV charging using marginal emission factors, this study recommends countries or regions to publish live marginal emission factors to facilitate adoption of emission-based smart charging. These emission factors should be published in such a way that market-sensitive information of electricity generating companies is not revealed.

In addition, there is uncertainty regarding the future robustness of the price input data. The trade-off between cost minimization and emission minimization EV charging is heavily dependent on the CO₂-price. With higher CO₂-prices, gas-fired power plants can become cheaper than coal-fired power plants, resulting in a merit order with alternating coal- and gas-fired power plants. A further increasing CO₂-price could make the trade-off between costs and emissions less severe, as electricity can be shifted to times with low emissions for lower or low additional costs. A last important notion in this context is the penetration of renewables. Higher penetration of renewables leads to a higher variation in emission profiles [192] and potentially leads to higher price volatility, which would increase the width of the Pareto frontiers.

This study assumed a perfect forecasting accuracy in PV generation, residential load, electricity prices, electricity generation emission factors and EV availability when scheduling the charging behavior of EVs. Although multiple studies have developed forecasting methods which could be applied to LV grids, forecast errors could be relatively large, especially since this study looks at a relatively small aggregation level (a single LV grid). Due to these forecast errors, grid congestion problems cannot be fully eliminated, causing that real-time correction

of the charging schedule of EVs is required to mitigate risks on grid congestion problems. In addition, due to these imperfect forecasts, EVs might be charged more conservatively in practice to avoid grid congestion or unmet EV charging demand requirements. Thus, the actual potential of EVs to minimize costs or emissions may be lower than the theoretical potential identified in this study.

Although this study has concluded that grid reinforcements are not attractive in terms of cost and emissions from a system perspective when the focus is on congestion problems caused by deep penetration of EV charging in LV grids, our sensitivity analysis also suggested that this could be different with more volatile prices. Furthermore, it should be noted that the decision whether to reinforce the grid is based on multiple factors. Grid reinforcements are not only a solution to grid congestion problems, but could also be necessary to mitigate power quality problems [44]. Next to the large-scale integration of EVs, these problems could also be caused by i.a. greater penetration of variable renewable energy sources in the LV grid or electrification of space heating and cooking in buildings.

4.7 Conclusion and future research

This research addressed the question whether grid reinforcements are attractive from a cost or emission perspective in the context of a deep penetration of EVs. It was shown that the costs and emissions of grid reinforcements outweigh the benefits in costs and emissions in EV charging optimization resulting from increased grid capacity. However, substantial reductions in EV charging costs and emissions can be achieved under the current transformer capacity.

Future research could study to what extent it is possible to avoid grid congestion problems when using forecasts of the expected grid load when scheduling EV charging with a transformer capacity constraint. This research should compare the grid congestion levels with different forecasting methods that are used with EV charging scheduling and should also evaluate different methods to mitigate grid congestion induced by forecast errors. Also, future research could look further into the economic and environmental attractiveness of grid reinforcements by using more-realistic EV charging schedules, which consider different electricity markets and uncertainty in EV departure times. Furthermore, future research could address when LV grid reinforcements are required from a technical perspective when considering congestion and power quality problems caused by greater penetration of variable renewable electricity generation in the LV grid, as well as the electrification of end-uses in buildings.

4.A Assumptions emission profiles

The 15-minute average emission profiles and marginal emission profiles can be found in Figures 4.8 and 4.9. The same methods were used as in [127] and [192], respectively. However, some assumptions and modifications were made to adapt the profiles to the year 2018.

4.A.1 15-minute Average emission profiles

Because of missing data in [133], some data modifications had to be performed. When generation data of a specific technology for one hour was missing, data was filled using the forward fill method, i.e. data of the previous hour was used. When data of more than one hour was missing, the data of the previous day was used.

ENTSO-E Transparency Platform [133] provides generation values for biomass generation and solar generation. However, these values are low compared to official Dutch statistics [225]. Therefore, data was scaled to be in line with these statistics.

Subsequently, the remaining missing power generation in time step t was determined using the following equation:

$$P_{\text{gen,missing},t} = P_{\text{load,Powerst},t} + P_{\text{net export},t} - \sum_j^J P_{\text{gen,Transp},j,t} \quad (4.17)$$

i.e. the sum of the net export and the total Dutch electricity load taken per timestep from ENTSO-E Powerstats [226] was subtracted by the total known generation power of technology j , with J being the total number of technologies provided by ENTSO-E Transparency Platform. For gas-fired and coal-fired electricity generation, ENTSO-E Transparency Platform provides for 2018 a part of the data and no data, respectively. For these technologies, it was determined which fraction M_{corr} of the $P_{\text{gen,missing},t}$ could be attributed the generation of technology j :

$$M_{\text{corr},j} = \frac{\sum_t^T (P_{\text{gen,Transp},j,t}) - P_{\text{gen,CBS},j}}{\sum_t^T P_{\text{gen,missing},t}} \quad (4.18)$$

Now, the $P_{\text{gen},j,t}$ of coal- and gas-fired power plants could be determined using:

$$P_{\text{gen},j,t} = P_{\text{gen,Transp},j,t} + M_{\text{corr},j} * P_{\text{gen,missing},t} \quad (4.19)$$

4.A.2 Marginal emission profiles

Three modifications were carried out compared to [192]. First, data for the fuel prices was taken from [227]. Second, the least efficient gas-fired power plant was

Figure 4.8: 15-minute average emission profile for the Netherlands in 2018.

Figure 4.9: Marginal emission profile for the Netherlands in 2018.

assumed to be the Merwede-11 plant. Hence, the Velsen-24 plant, which is fired by blast-furnace gas, was excluded from the analysis. Third, a factor representing the upstream emissions was included, taken from [228].

5 Photovoltaic systems coupled with batteries that are optimally sized for self-consumption: Assessment of peak shaving potential

This chapter is based on the publication:

W.L. Schram, I. Lampropoulos, and W.G.J.H.M. van Sark. 2018. "Photovoltaic systems coupled with batteries that are optimally sized for household self-consumption: Assessment of peak shaving potential," *Applied Energy*, vol. 223, pp. 69-81. DOI: 10.1016/j.apenergy.2018.04.023

Abstract

As the share of renewable energy sources in the energy mix is increasing, new challenges arise regarding the grid integration. This research focuses on a solution for one of these challenges, namely the employment of batteries to address the mismatch in electrical power between electricity supply from photovoltaic systems and household electricity demand. Herein, the optimal sizing of batteries for household self-consumption is combined with peak shaving at district level, whereas previous studies only looked at these questions in isolation. Our analysis makes use of a unique set of power measurement data from 79 households in the Dutch city of Amersfoort, in 295 evenly distributed days, with a resolution of 10s. By using simulation of batteries and Net Present Value analysis, the average optimal storage size for self-consumption in the case of net metering abolishment for households with photovoltaic systems was determined to be 3.4 kWh. Large differences were observed between different households; photovoltaic system size, total net metered consumption and specific characteristics of load profiles resulted into optimal storage sizes in the range of 0.5–9 kWh. The impact of these optimally sized batteries on neighborhood peak demand was assessed and found to be limited, corresponding to a decrease of 5.7%. The peak shaving potential was further assessed under different control strategies of the batteries. Results show that the impact could be amplified to a decrease of 22% or 51% when the batteries are controlled by using heuristics or by assuming perfect foresight together with a power minimization algorithm, respectively. The findings of this chapter emphasize the importance of collaboration between households and other stakeholders, such as distributed system operators and retailers in transitioning to a sustainable power system.

5.1 Introduction

In this chapter and in Chapter 6, the attention shifts to the technical benefits of coupling batteries to PV. The main focus of this chapter is the potential contribution of distributed batteries to peak residual load reduction on the neighborhood level. Chapter 6 also includes EVs and the transmission system level.

One of the viable options to cut greenhouse gas emissions in order to combat climate change is to generate electricity from renewable energy sources. Photovoltaics (PV) are expected to play an important role in this [229]. The global generation capacity of PV systems has increased from approximately 7 GW in 2006 to about 300 GW at the end of 2016 [230]. At the same time, a significant growth in electricity consumption due to electrification of the transport system and residential heating is expected [231], [232]. As these trends will predominantly take place in the residential sector, this will pose challenges for the operation of

low voltage (LV) electricity grids. Batteries installed in households could alleviate some of these challenges, by shaving peaks and filling valleys in the household demand profiles [233].

Several scholars have assessed the economic value that can be created by using storage in the smart grid context, i.e. by providing flexibility services to the electricity system, by addressing the power quality, reducing the negative effects of renewable energy, reducing the peak demand and system costs [234]. Furthermore, batteries can be used for market optimization; for instance by combining self-consumption with minimizing costs on the day-ahead market [235], or control battery operation on the day-ahead market and in the imbalance settlement system in an economically optimal way [153]. Malhotra et al. [236] stated that demand charge reduction, residential solar integration and frequency regulation are the most attractive grid-connected applications, whereas load following, renewable energy integration and ancillary services are the most attractive island-mode and microgrid services [236]. Another review study on energy systems in island-mode reported that PV-diesel-battery systems were proven to be competitive, feasible and having positive environmental impact [237]. Collectively, these studies outline a critical role for batteries in the integration of PV-generated electricity. Increasing self-consumption of households can decrease the stress on the grid by limiting the maximum feed-in of PV-generated electricity [238], [239]. Storage is reported to increase self-consumption by 13-24% for battery sizes of 0.5-1.0 kWh per kWp of PV system size [50]. With sufficient self-consumption incentives, the coupling of PV and batteries can become an attractive option from a households' economic perspective [151], [240].

While using batteries to increase self-consumption limits the impact of PV-generated electricity to the grid, several other studies have investigated the role batteries in reducing the peak power demand of a household or neighborhood. For instance, in a fast-charging infrastructure for EVs batteries can allow for efficient fast-charging with reduced impact on the main grid [241]. In a DC micro-grid, batteries are especially suitable as they can operate on DC, just like PV electricity production and EV charging [242]. Research on the exact peak shaving potential of PV-battery systems is still inconclusive. De Oliveira e Silva and Hendrick [243] found that the peak power consumption does not decrease when a battery is added to the PV system. This is in contrast to Fares and Webber [82], who found that peak power on neighborhood level can be reduced by 8-32%. The difference largely depends on geography: households in the United States [82], which have consumption peaks in summer due to the use of air conditioning versus households in Belgium [243], where consumption peaks occur in winter when there is much less solar irradiation. In different climatological conditions peak shaving can also

occur in the winter [244]. Our research aims to present a generic solution by addressing also the peak shaving potential under low solar irradiation conditions.

There are several limitations in current literature about the coupling of PV systems with batteries. Firstly, many studies focus on single households [151], [239], [243], or small samples of households [238], [245]–[247], regarding the consumption or PV generation profiles. A disadvantage of these approaches is that they lack the statistical power to determine the differences that exist between households. Furthermore, for peak shaving, aggregation of many households is essential as problems for grid operators mostly arise at neighborhood or district level. Secondly, most studies make use of synthesized generation or consumption profiles instead of measured data, and only a few studies [82], [240] are exceptions to this. For PV generation profiles, sometimes solar irradiation is used as the only input [248], occasionally combined with temperature [249], [250]. In practice, PV-generated electricity depends on many more factors, such as tilt and orientation of the PV system [251], and the output can be influenced by location-specific shadow impacts, especially in residential areas [252]. Thirdly, most studies use measurements with a resolution of 15 minutes to one hour. Beck et al. [253] found that these time resolutions could be insufficient: for households with large amounts of electricity consumption or production exceeding 2 kW, using 15 minutes resolution data results in substantial errors ($>5\%$) in determining self-consumption. Furthermore, for determining peak power demand, which plays an important role in this research, higher time resolutions are also preferred [50]. Lastly, all reviewed studies have a single focus, particularly maximizing self-consumption or minimizing household electricity costs, whereas our study is focused on whether batteries can be used for additional applications in support of multi-revenue business models. The aim of this chapter is thus to determine the economically optimal battery size for high self-consumption for a large variety of PV households in the Netherlands, while assessing the potential of these batteries for consumption peak shaving. The novel contributions of this research address five aspects. Firstly, this study adds new results to the body of literature on optimal storage sizing by determining the influence of many different technical and economic factors. Secondly, we provide insight in the impact on optimal storage size due to differences between individual household production and consumption profiles by making use of a large set of 79 households. Thirdly, we assess the peak shaving potential by mutually combining optimal sizing of batteries from a household's economic perspective with peak shaving on neighborhood level, which reflects a realistic future use case. Fourthly, we present two novel pre-charging algorithms which are employed for determining both the minimum and maximum peak shaving potential. When grid assets are mainly dimensioned to transport PV-generated electricity, this leads to

a low utilization rate of these assets [254]. Our approach of coupling a battery to a PV system and pre-charging the battery on days with low PV surplus (i.e. more production than consumption) leads to more efficient use of distribution grid capacity because of two separate factors: a lower distribution grid capacity is needed and the utilization rate of the distribution grid capacity is increased. Lastly, a unique empirical data set of 79 households with PV systems and very high time resolution (10 seconds) of net power measurement data underlies all results.

The chapter is organized as follows: in section 5.2, the mathematical model is presented, followed by an explanation of how the battery size for optimal self-consumption is determined, a description of the pre-charging algorithms, an overview of battery technologies and possible impact of battery degradation, and a description of the input data and the assumptions underlying this research. section 5.3 presents the results regarding the optimal storage sizing and the peak shaving potential, including a sensitivity analysis. The chapter ends in section 5.4 with conclusions and recommendations.

5.2 Methods

5.2.1 Model description

The simulation model was developed in MATLAB. Figure 5.1 shows a simplified flow chart representing all steps that were undertaken in the model, for each household, and various storage sizes. It is similar to the model reported in Ref. [255], with the main difference being the input; net power (P_{net}) in this study compared to separate consumption and generation profiles in [255]. In case of either surplus production and a non-fully charged battery, or residual load (i.e. more consumption than production) and a non-empty battery, the battery can be used to prevent import from or export to the grid. Then, the resulting power from/to the grid (P_{grid}) is either zero or $P_{\text{net}} - P_{\text{rated}}$ (in case of battery power constraint violation). P_{rated} is defined as the power of a battery charged or discharged with a C-rate of 1 (i.e. P_{rated} is 1 kW per kWh of battery size), and is thus dependent on the battery size in kWh; $\eta_{\text{ch}} = \eta_{\text{disch}} = \eta$ is the one-way charging/discharging efficiency of the battery. The energy in the battery E_{batt} at time t can be calculated according to eq. 5.1):

$$E_{\text{batt},t} = E_{\text{batt},t-1} - \begin{cases} P_{\text{net}} * \eta * \Delta t, & \text{if } P_{\text{net},t} \leq P_{\text{rated},t} \\ P_{\text{rated}} * \Delta t, & \text{else} \end{cases} \quad (5.1)$$

This is formulated for surplus production; in case of residual load P_{net} is divided by η .

This model was used to first determine the optimal storage size. Storage sizes were stepwise increased at an interval of 0.5 kWh. Per household and per storage size, the energy consumed from the grid was determined. The benefits of storage could then be determined by multiplying the difference in energy consumed from the grid with and without battery by the difference between the feed-in tariff (FIT) and the retail electricity price. Subsequently, the Net Present Value (NPV) of household h and battery size i was calculated according to eq. 5.2:

$$NPV_{h,i} = -C_{batt} * 3.5 * \left(\frac{s}{3.5}\right)^{SF} + \frac{\sum_{y=0}^L B_{h,i} * CF * (1 + PDI)^y}{(1 + r)^y} \quad (5.2)$$

With

i = Battery size (kWh)

$B_{h,i}$ = Benefits of storage (€/year) of household h with battery size i

CF = Correction factor

C_{batt} = Investment costs battery (€/kWh)

PDI = Price difference increase; increase Δ Electricity price in (%/year)

r = Discount rate

L = Lifetime battery

SF = Scale factor

y = time (years)

Regarding the scale factor, 3.5 kWh is chosen as the reference storage size. The Correction factor (CF) was included to convert the benefits to yearly benefits; this factor is 365/295 (see section 5.2.3). The optimal storage size s_{opt} was defined as the storage size with the highest NPV for that specific household. See Table 5.2 for the values used for each parameter / variable.

Subsequently, the impact on the peak power consumption and evening energy use in winter was determined by simulation using three cases: a) a reference case denoted as REF, where batteries were not controlled, b) a minimum potential case, where batteries were controlled using a heuristics algorithm (HEU), and c) a maximum potential case, where batteries were controlled to minimize peak power assuming perfect information forecasting (PER), see also Figure 5.1.

Table 5.1 shows the differences between HEU and PER algorithms. The rationale behind the HEU algorithm was that the highest energy use of households in the Netherlands occurs in winter, especially in the evening hours after work, while during nights there is still much capacity on the grid for extra consumption. Hence, the battery could be pre-charged during those nighttime hours. The advantage of using heuristics is that the battery would require little additional software and

Figure 5.1: Flow chart of battery use without control (left, REF). For the battery control algorithms (right) the colored blocks change to respective formulae. HEU aims to determine the minimum potential of optimal-sized batteries for peak shaving, PER the maximum potential (see text and Table 5.1 for details of the algorithms).

no digital communication (hence this would already work in a non-smart grid). In the PER algorithm, the batteries were ensured to be fully charged at 14:00 every day and a power limit was set on the aggregated power consumption of the neighborhood.

When P_{net} would surpass this power limit, the power consumed from the grid was corrected to the power limit by a “power stabilizer” (ps in Figure 1), and the remaining proportion of the demand was taken from the battery in such a way that P_{grid} would equal the power limit. The power limit was stepwise decreased in different model runs in order to find the lowest possible maximum power consumption.

5.2.2 Battery technology and degradation

Most prominent battery technologies for household applications are lead-acid (LA) batteries, high temperature batteries (e.g. NaS or NaNiCl, flow batteries and lithium-ion batteries (LiBs) [23]. All technologies have their own specific characteristics and accompanying advantages and disadvantages. Based on the

Table 5.1: Characteristics of two battery control algorithms.

	Heuristics algo- rithm (HEU)	Minimization of power algorithm, per- fect information forecasting (PER)
Pre-charging hours	0:00 to 6:00	0:00 to 14:00
Months	November to March	All
Battery use	17:00	When aggregated neighbourhood power is above certain threshold.
Pre-charging amount	Fixed, Proportional to battery size	Variable, required to have a full battery at 14:00

review studies of Mahlia et al. [233] and Yekini Suberu et al. [256], the following facts are relevant for household applications. The LA battery technology is the oldest technology for household and commercial applications. Being a mature technology, LA batteries are relatively cheap. Most significant disadvantages entail the low cycle depth and fast battery degradation. The most used high temperature battery is the NaS battery. Advantages of this battery are the high energy density, high efficiency, low maintenance and high cycle life. However, safety can be an issue for these batteries because of the high operating temperature, possible explosion when in contact with air and corrosion in insulators caused by the challenging chemical environment. Flow batteries hold some significant advantages against conventional batteries. For instance, the separation of power and energy constraints enables the easy optimization of the configuration, the batteries are safe and have a long life time. However, these advantages are accompanied by high investment costs, and moreover the complex system requirements and related high maintenance costs which make them less attractive for small scale storage applications (e.g. households) [233].

LiBs have rapidly become the most prominent technology for mobile consumer electronics [23]. Advantages are the high energy density, efficiency, cycle depth and cycle life. The most important disadvantage is the high investment costs, although these are rapidly declining in recent years [27], [142]. As lithium-ion is the battery chemistry with the highest investments in recent years [257], and prominent home batteries such as the LG Chem and the Tesla Powerwall use this technology, lithium-ion is the technology of choice in our research. Within the LiB family, currently the three most prominent chemistries are Nickel-Cobalt-Aluminum-Oxide (NCA), Nickel-Manganese-Cobalt (NMC) and Lithium-Iron-Phosphate (LFP) [258]. From these, the NCA battery has the lowest costs, while the LFP performs best on cycle life time [23]. A promising new technology is Lithium-Titanate-Oxide (LTO). The LTO-battery potentially has excellent cycle life characteristics, but currently is in the

research phase and is more expensive compared to the other LiB chemistries [258]. In this research, we use the NMC battery of the Tesla Powerwall as a reference technology. We perform a sensitivity analysis on the critical battery parameters to ensure that our results are also applicable to other battery technologies.

The cyclic degradation of a battery can be approximated with a linear function of the energy throughput of the battery [160]. This relationship is moderated by many variables, of which the three most important are C-rate, temperature and depth of discharge:

- **C-rate:** High C-rates result in faster degradation [160]. However, this mainly holds for very high C-rates, i.e. 3.5C and higher, whereas the difference in degradation between 0.5C and 2C has been found to be negligible [242]. In our research, we assume a C-rate of 1C which varies between 0.5C and 2C in the sensitivity analysis.
- **Temperature (Temp):** In general, higher operating temperatures lead to increased battery degradation [259], [260]. However, at low C-rates capacity loss is shown to be similar for $\text{Temp}=10^{\circ}\text{C}$ and $\text{Temp}=22^{\circ}\text{C}$ [160]. Degradation is accelerated at higher temperatures of $\text{Temp}\geq 34^{\circ}\text{C}$ and especially at $\text{Temp}=46^{\circ}\text{C}$ [160]. As ambient temperatures generally are not that high in the Netherlands, and household battery systems are expected to be in moderate space conditions, we assume that high temperatures have a negligible influence in our research. Moreover, the power requirements for batteries in stationary applications are not very stringent which results in uncomplicated heat management [261]. In this regard it is also relevant to mention that next to very high temperatures, also very low temperatures can lead to acceleration of battery degradation [262]; this is due to lithium plating and dendrite formation [263]. The most effective operating temperature for lithium-ion batteries (LFP batteries in this case) is determined to be 13°C [264]. As batteries are installed inside households, it is unlikely that operating temperature would drop far below this temperature. Therefore we choose to also omit this temperature effect in our degradation model.
- **Depth of discharge:** Higher cycle depth leads to faster degradation [150]. As this can be an issue in our research, we monitor the modelled degradation resulting from the different algorithms employed in our research by using rainflow cycle counting. This method was first introduced by Amzallag et al. [265] and applied to batteries by Stroe et al. [266]. The method records and counts every half cycle, i.e. when operation of battery alters from charging to discharging or vice versa, the state of charge (SOC) of the

battery and the depth of cycle (DOC) of that half cycle. This shows how the algorithm translates to operation of the batteries and gives insight in the battery degradation, for which especially the DOC and number of (half) cycles are important indicators [161].

5.2.3 Input data

Data was obtained from the “*Smart Grids: Profit for all*” [168] project in the neighborhood Nieuwland of the city Amersfoort, the Netherlands. More details about the measurement data can be found in [51]. Measurement equipment was supplied by Net2Grid [267]. In this district 500 small (0.8–4.4 kWp) PV systems were installed between 1999–2001 totaling 1.3 MWp [268]. For 100 households, the power interaction with the grid was measured every 10 seconds. The data concerned net metered power; hence consumption and production could not be analyzed individually. The period of measurement was November 2013 to October 2014. While a full year of measurements was aimed for, three problems regarding data quality were encountered. Firstly, data were missing due to communication issues for 68 days, spread out over the 12-month period. It was assumed that the remaining 295 days were representative of a year. Secondly, data for individual households was found to be often incomplete. The criterion for excluding a household from the analysis was whether more than a month of the remaining data was missing. As a result, 21 households were kept outside of the research. The remaining 79 households had an average residual load of 2637 kWh (standard deviation (SD) is 1120) and an average surplus production of 797 kWh (SD = 638) over the 295 days. For households with substantial surplus production (>50 kWh), the average derived system size was 2.4 kWp (SD = 0.74), which is well in line with previous analysis of the PV systems in Nieuwland [268]. Multiple linear regression was performed to determine the impact of these variables on the optimal storage size. The PV system size was derived from the data by taking the 99.995 percentile value of surplus production, assuming a) the highest surplus production values could be outliers or influenced by the cloud edge / cloud enhancement effect [269] and b) of the 2.5 million data points per household, there are enough values with simultaneous occurrence of peak production and minimal consumption.

Table 5.2 shows the most important input parameters of this research. Since all parameters are under substantial uncertainty, sensitivity analyses have been performed; minimum and maximum input values for the sensitivity analyses are also shown in this table.

The cost of the battery was determined by extrapolating the expected 8% annual cost decline starting from 300 €/kWh in 2014 to 2020 based on [27],

Table 5.2: Input parameters.

	Min	Base	Max	Based on
C_{batt} (€/kWh)	130	234	494	[27]
SF		0.9		[270]
Self-consumption benefits (€/kWh)	0.04	0.16	0.28	Net metering abolishment, [151]
PDI	0%	1%	3%	[271]
r	2%	4%	8%	[151]
1- η	4%	8%	20%	[272]
L (years)	10	15	20	See below
C-rate	0.25	1	2	[160], [170]

resulting in a base material costs of 180 €/kWh. We assumed that these costs are also obtainable for residential storage of size 3.5 kWh as the (marginal) scale effect of larger batteries (as in EVs) [270] could approximately be offset by cost savings accompanying the much lower power, weight and volume requirements of residential batteries. To obtain the battery costs, we assumed the installation costs would add 30% to the material costs. To reflect the fact that smaller systems may require higher installation costs per kWh than larger systems, we implemented a scale factor of 0.9 over the total costs, based on [270] and the fact that batteries are modular, see Eq. 5.2. The self-consumption benefits, i.e. the difference between the retail electricity price and FIT, is completely dependent on the electricity pricing scheme; as a base, this is estimated to be € 0.16/kWh. This was estimated to increase by 1% per year, as the Dutch government announced it would pay investments in renewable energy by increasing existing energy taxes [271]. In our model, the battery was DC-coupled to the PV system; we used the same setup as shown in [150]. Following the example of [272], we took the Tesla Powerwall efficiency of 92% as the reference (i.e. 8% losses), which when combining with a roundtrip inverter efficiency of 96% results in an 88% total round trip efficiency. Constant efficiency and a C-rate of 1 were assumed, following the example of [170]. Regarding lifetime, Tesla guarantees 80% of remaining capacity after 10 years for the Powerwall. As the battery will also be usable with lower capacity remaining [150], we assumed the lifetime to be 15 years.

5.3 Results and discussion

This section is structured as follows: In section 5.3.1, optimal sizes of batteries for household self-consumption are determined. This is done to provide insight in the factors that determine the optimal storage size, and simultaneously serves as input for section 5.3.2 where simulations are performed and the results are analyzed, thus

adding to the knowledge of the peak shaving potential. section 5.3.3 and section 5.3.4 are focused on the external validity of the research. In Section 5.3.3 insights are provided in how the batteries are operated under different charging/control algorithms and how this impacts battery degradation. In section 5.3.4 various sensitivity analyses are performed and recommendations are drawn.

5.3.1 Determining optimal storage size

As explained in section 5.2.1, the NPV was determined for various storage sizes for all households. Figure 5.2 shows the relationship between increasing the storage size and the NPV for three individual households. The optimal storage size is defined as the storage size with the highest NPV for that household (i.e. the red bars in Figure 5.2). The maximum NPV coincides with the storage size where the marginal discounted benefits of increasing the battery size equals the marginal costs of increasing the battery size. Although individual differences are apparent, all curves show a similar pattern: with increasing storage size, the NPV first exhibits a rather steep increase, followed by a diminishing incline until a maximum is reached and finally a gradual decline in NPV is observed. This is explained by the fact that a rather small battery in a household is per definition more often fully charged with PV-generated electricity and therefore has a higher utilization rate compared to a larger battery for the same household.

A histogram of optimal storage sizes of all investigated households is shown in Figure 5.3. A positive NPV was found for 58 out of the 79 households. The optimal sizes for a battery ranged from 0.5 to 9 kWh, with an average of 3.36 kWh (SD = 1.49) and mode and median both of 3.5 kWh. The NPV values ranged from 72.0 € to 1.74 k€, with an average of 697€ (SD=296). The profitability index, i.e. present value per euro invested [273], ranged from 1.1 to 2.0. Note that from an economic point of view the Tesla Powerwall 2 with a size of 13.5 kWh appears to be too large for the Dutch market if it is only used to increase self-consumption: only three households would have a positive NPV for the Powerwall 2, even when the price would drop to the cost assumption made in this research.

Our findings are in line with previous research [170], that found an optimal storage size of 0.75 kWh per MWh of consumption, when combined with a PV system of size 1 kWp per MWh of consumption. A higher optimal storage size was found by [151], mainly due to the assumption of a larger difference between FIT and retail electricity price. Note that both above-mentioned studies describe results for one typical household with PV, whereas our research also encompasses the substantial differences that exist among different households.

Figure 5.2 also shows that increasing the storage size somewhat above optimal

Figure 5.2: Storage size vs. Net Present Value for three different households (colored blue, green and yellow). Red bars represent the optimal storage size for that specific household.

does not result in major decreases in NPV. More details are shown in Figure 5.4, in which the average decreases in NPV are depicted when battery sizes would be increased by different amounts. These decreases are small compared to the assumed reference storage cost of 234 €/kWh. Therefore, this presents an attractive investment opportunity in the case that a second party would be willing to compensate the decrease in NPV of a larger than optimal battery, e.g. in exchange for allowance to operate the battery to provide other ancillary services. Besides, recent research shows that consumers might be convinced to purchase a larger than optimal battery for non-financial benefits such as increased self-sufficiency / decreased grid dependency [274].

Furthermore, by analyzing household characteristics that determine the optimal storage size, it becomes apparent that the optimal storage size has the highest correlation with the total surplus production: $r(56) = .85, p < .001$. The correlation with the derived PV system size is also relatively high, with $r(56) = .75, p < .001$. The correlation with the yearly net metered consumption is found to be insignificant; $r(56) = -.14, p = .15$. Multiple linear regression was used to predict the optimal storage size (s_{opt} , in kWh) by using derived PV system size ($P_{rated,PV}$, in kWp)

Figure 5.3: Histogram of frequency of optimal storage sizes.

and net metered consumption (NC , in MWh/year), as these variables are readily available for most households, also without a smart meter. This results in the empirical relationship depicted in eq. 5.3.

$$s_{\text{opt}} = -0.032 - 0.187 * NC + 1.51 * P_{\text{rated,PV}} \quad (5.3)$$

The adjusted R^2 of this model is 0.579; further statistical details are shown in Table 5.3. The MATLAB prediction slice plot is included as an interactive graph in the online version of this article. Larger PV system sizes result in larger optimal storage sizes. Remarkably, the statistically significant negative regression coefficient of NC suggests that, given certain PV systems size, lower net metered consumption is expected to result in larger optimal storage sizes. This can also be seen in Figure 5.5. For lower values of net metered consumption, fewer dark blue markers (representing low optimal storage size) are visible than in the area with similar PV system size but high values of net metered consumption. The figure also shows that not all variance in optimal storage sizes can be explained by PV system size and net metered consumption, as households with similar values of these variables can have very different optimal storage sizes. Two of the largest optimal storage

Figure 5.4: Investment opportunities for external parties. The y-axis represents the average decrease in NPV per kWh, i.e. ‘storage costs’, if all battery sizes would be increased by the value on the x-axis.

sizes (6 kWh and 7 kWh; red markers with PV size of ~ 3 kWp and NC of ~ 1 MWh/year) have a PV system size and NC that are similar to households with smaller optimal storage sizes. This finding suggests that the residents of these two households are more often not at home during the day, resulting in more days with high surplus PV electricity production (i.e. low self-consumption). This results in a need for larger batteries - even though the PV system size and the yearly NC is similar to other households.

These results indicate that the empirical model needs to be handled with care. Firstly, because 42.1% of the variance is still unexplained, and is thus dependent on specific consumption and production profiles. This finding also stresses the importance of having smart meters (or sub-metering) with high time resolution to enable a more thorough analysis in order to provide tailored advice for each household. In addition, this has important implications for research by stressing that studies about households should always take a sufficiently large sample of households into account. Secondly, because the economic assumptions also have

Figure 5.5: Relationship between net metered consumption, PV system size and optimal storage size.

Table 5.3: Mult. linear regression. Dependent variable: optimal storage size (kWh).

			Regression coefficient	Standard Error	p (one-sided)
Intercept			-.032	.46	.47
Net Metered Consumption (MWh/year)			-.187	.10	.038
Derived	System	Size	1.51	.17	<.001
(kWp)					

a high impact on the optimal storage size. This is explored more in-depth in the sensitivity analysis in section 5.3.4.

In this section we determined the optimal storage size for each individual household. Furthermore, we saw how this optimal storage size is influenced by the PV system size, the yearly surplus of PV and the yearly net-metered consumption. In the next section, we will do simulations with these optimally sized batteries to determine the peak shaving potential of the batteries in this neighborhood.

5.3.2 Simulations with optimal-sized batteries

The total storage capacity in the investigated neighborhood, under the condition of optimally sized batteries, is 195 kWh, thus an average of 2.47 kWh per household including the households with a negative NPV (21 out of 79). Figures 6 – 8 show the impact on the aggregated neighborhood power to / from the grid and battery content of the non-controlled (REF) and the batteries controlled by the heuristics (HEU) and perfect information power minimization algorithms (PER). See Table 5.1 and Figure 5.1 for details on cases. Batteries are a natural partner for PV regarding peak shaving in summer: batteries are charged during the day with surplus PV electricity, and this electricity is used in the evening hours. Figure 5.6 illustrates this concept: the neighborhood is a net producer of electricity from around 10:00 to just before 18:00. This surplus of PV-generated electricity is fed into the grid in the case without batteries, whereas in the REF case this electricity is used to charge the batteries in the neighborhood. Electricity from these batteries is then used in the evening hours resulting in much lower peak power demand. In winter, when electricity consumption peaks, batteries have only a marginal impact on the consumption pattern if they are not pre-charged. As there is little surplus of PV-generated electricity, the batteries are not charged and the peak cannot be shaven. Figure 5.7 shows a comparison between the case without batteries and the HEU case. In the HEU case, the batteries are pre-charged during the night resulting in higher power consumption in these hours. From 06:00 to 17:00 the power consumption of the case without batteries is roughly the same as in the HEU case, however in the HEU case, after 17:00, the peak consumption of the neighborhood is shaven to some extent. Note that in reality, the heuristics would probably have to be designed differently to prevent large voltage fluctuations. However, much of the energy content of the batteries is already used from $\sim 17:00$ to 19:00, which results in batteries being depleted too early and a new consumption peak occurring around 20:00. Figure 5.8 shows the same day but for the case of the PER algorithm. In this case, batteries are also pre-charged; power consumption in the PER case is higher than in the case without batteries, however not as high as in the HEU case because in the PER case the batteries are still partly charged as a result of the previous day. As in the PER case batteries are discharged at such rates that the neighborhood aggregated power does not exceed a certain threshold, and energy from the batteries is used in a more efficient way resulting in the maximum peak shaving capabilities.

Due to the high time resolution of the data, the impact on peak power demand could be determined very accurately. Over the year, the neighborhood net peak power consumption decreases from the original 111.4 kW to 105.1 kW (-5.7%)

Figure 5.6: Demonstration impact battery REF case on a summer day (3 August 2014). The blue graphs on the primary y-axis shows the neighborhood electricity power without batteries and the REF case. When the power is below zero, the neighborhood is a net producer of electricity, hence the simulated batteries are charged in the REF case. The aggregated battery energy content (orange line) is shown on the secondary y-axis. The electricity stored in the batteries is used in the evening, resulting in lower peak consumption when using batteries.

compared to original) for the REF case, to 86.8 kW (-22%) for the HEU case and to 54.9 kW (-51%) for the PER case, i.e. the maximum peak shaving potential. The maximum peak shaving potential found in this research is much higher than in previous research such as [243], [255], despite having a relatively low battery capacity per household; 2.5 kWh in this research, compared to 7 kWh in [255] and 25 kWh in [243]. This finding stresses the importance of the specific algorithm used for determining the peak shaving potential. These results have relevant practical implications, for example when designing grids in new neighborhoods or upgrading existing grids in residential areas. Peak shaving can have various benefits, such as lower grid (re)investment costs, lower generation capacity investment costs and lower marginal electricity costs.

Resulting load duration curves are shown in Figure 5.10, which shows that the power minimization algorithm has a very large impact, but for a small proportion of the time ($\sim 6\%$), whereas the heuristics algorithm has lower consumption than non-controlled batteries for the 13% of peak consumption of both other cases. Due to charging and discharging losses, the utilization of batteries increases the total net electricity consumption compared to the case without batteries; an increase of 2.8%, 3.6% or 1.1% for non-controlled batteries, batteries controlled by heuristics

Figure 5.7: Demonstration HEU case on a winter day (28 November 2013). Blue lines indicate the households' aggregated power without batteries and in the HEU case. Orange line indicates the house-holds' aggregated battery content. In the HEU case, batteries are pre-charged from 00:00 to 06:00 and switched on at 17:00, resulting in lower electricity consumption from the grid in the evening.

and batteries controlled by the power minimization algorithm, respectively. These load duration curves can serve as input for stakeholders such as grid operators and energy retailers to determine which of the cases is preferable from their perspective.

In this section we determined the peak shaving potential of batteries in different use cases. We saw that the PER case led to the highest peak power shaving, while the HEU case led to the largest peak shaving potential. In the next section we provide more insight on the operation of the batteries in the different cases and give an indication of the battery degradation in each of these cases.

5.3.3 Rainflow cycle counting

Rainflow cycle counting was used both to give insights on the impacts of the different algorithms on the battery behavior and to monitor battery degradation indicators. By far most cycle depths are below 2% in all scenarios. This can be detected due to the high time resolution of data; for example, when a cloud

Figure 5.8: Demonstration HEU case on a winter day (28 November 2013). Blue lines indicate the households’ aggregated power without batteries and in the HEU case. Orange line indicates the households’ aggregated battery content. In the HEU case, batteries are pre-charged from 00:00 to 06:00 and switched on at 17:00, resulting in lower electricity consumption from the grid in the evening.

Figure 5.9: Boxplots of the evening four-hour peak energy use over the 295 days for the four cases.

Figure 5.10: Load duration curves of neighborhood of No Batteries, REF, HEU and PER cases). The HEU and PER case perform best in the peak demand area associated with the highest cost.

temporarily blocks direct sunlight this can result in a micro-cycle, or when a household appliance is switched on resulting in a household shifting from being a net producer to a net consumer.

Figure 5.11 illustrates per case the cycles with Depth Of Cycle (DOC) >2%. In the REF case, most cycles have low DOCs and SOC. Other notable bars are at a SOC of 100% and low DOC values, and at a DOC of 100% and SOC of 0% (which represents a full discharge). Charging from 0% to 100% occurs less frequently, which is in line with the intermittent nature of PV electricity generation and possible alternation with net consumption when household appliances are switched on. The rainflow cycle chart of the HEU case looks similar to the REF case, while the most notable difference is the large bar in the middle of the chart: this represents the pre-charging from SOC of 0% to SOC of ~60% during winter nights. This also results in fewer cycles around a SOC of 0%, as the batteries are more often not empty. In the PER case, most cycles occur close to a SOC of 100%, which indicates batteries are often not fully discharged. This is an indication that the capacity of the batteries in the PER case are not used to their full potential, which is a logical consequence of the algorithm design; batteries are switched on only when the aggregated neighborhood power exceeds a certain limit. This occurs only a small proportion of the time (see Figure 5.10).

Figure 5.11: Rainflow cycle counting chart of all 58 batteries (REF (upper left, 11a), HEU (upper right, 11b), PER (lower left, 11c)). Charts of individual batteries would largely lead to a similar picture, as the algorithm works the same for every battery within a use case. For visual purposes, micro-cycles ($DOC < 2\%$) are not depicted, as their amounts dwarf the other cycles.

Table 5.4: Average battery capacity fade per year resulting from calendric and cycle aging for the different cases. Aging assumptions are based on [150].

	REF	HEU	PER
Reference aging	1.57%	1.67%	1.38%
Strong aging	1.74%	1.89%	1.42%

Table 5.4 shows the average battery capacity reduction of all batteries, based on aging assumptions of [150]. Calendric aging (1.33% per year in both reference and strong aging) accounts for the largest part of aging. In the PER case the capacity fade is lowest, again because the batteries are often not fully discharged, which results in lower energy throughput and cycle depths. The battery capacities in the HEU case are only marginally faster reduced than the non-controlled batteries.

5.3.4 Sensitivity analyses

The most important limitations of this research are due to the uncertainty of the economic parameters and the external validity given that the research is essentially a case study. Both issues are addressed by making use of different sensitivity analyses. Figure 5.12 shows the impact of the various input parameters on the average optimal storage size (see Table 5.2 for initial values). The optimal storage size is quite robust for the variables self-consumption benefits increase, discount rate and efficiency. Lifetime and battery costs have larger impact, but the largest impact comes from the self-consumption benefits. This is an important result from a policy perspective, as these benefits can be controlled by policies, thereby directly influencing the amount of residential storage. The relationship between the C-rate and optimal storage is particularly interesting. For very low C-rates (≤ 0.1) the average optimal storage size goes to zero: batteries are not capable to store enough PV generated electricity to obtain a business case. However, C-rates between 0.25 and 0.75 have a moderate positive effect on the average optimal storage size, because power rates increase with battery size. Hence, battery producers may be inclined to manufacture batteries with relatively low C-rates, also because lower C-rates (i.e. lower power requirements for the batteries) represent cost savings. However, this would have important implications to the maximum peak shaving potential, as is shown in Figure 5.13. If batteries would have a C-rate of 0.25, then the theoretical maximum peak shaving decreases from 51% to 33%. The other variables have a similar effect on peak shaving potential as on optimal storage. The peak shaving potential cannot increase much above the found 51%, because the average power of the day with the largest consumption serves as asymptote. On the other hand, even for pessimistic values of the parameters there is still substantial peak shaving potential ($>30\%$).

In the last sensitivity analysis, shown in Figure 5.14, the amount of storage available in the neighborhood is varied in two ways: first, by multiplying all battery *sizes* by a certain factor (depicted as “Size per battery” in Figure 5.14), and second by multiplying the *number* of batteries by a certain factor (depicted as “Amount of batteries” in Figure 5.14). The results on the minimum peak shaving potential (HEU) are especially robust. This is because the new consumption peak (86.8 kW, see section 5.3.2) occurs on a winter day at 2PM, when batteries are not used as a result of the algorithm design. Therefore, this peak shaving potential is less dependent on the amount of storage in the neighborhood: this peak shaving can be obtained by using just a part of the storage capacity (see Figure 5.11b), but cannot be increased when the storage capacity is increased. The maximum peak shaving potential (PER) is more sensitive to varying the amount of storage. Especially

Figure 5.12: Sensitivity analysis on average optimal storage size. See initial values in Table 5.2.

the number of batteries has a large impact; hence, it is preferable to have a large number of small batteries, rather than a few large batteries. This is due to the assumption in this research that households can only use electricity from their own battery. An implication of this finding is that it can be attractive to have community energy storage, so that a larger number of households can use the stored electricity when needed.

5.4 Conclusions

In this study the optimal sizing of batteries for PV self-consumption at household level was combined with determining the peak shaving potential of these optimal-sized batteries at neighborhood level, for a case study in the Netherlands. We have shown that, given certain economic conditions, it can be attractive for PV system owners to couple their system with batteries in case net metering scheme is abolished or not in force. In the Netherlands, the net metering will be abolished and be replaced by an as of yet unknown support scheme in 2020 [275]. If these batteries are operated in a controlled manner, then these can have a large peak

Figure 5.13: Tornado diagram from impact of different battery parameters on the maximum peak shaving potential of the neighborhood, i.e. PER case. See Table 5.2 for maximum and minimum values.

shaving potential. This impact is robust for lower amount of storage capacity in the neighborhood, and has a limited effect on battery degradation. In addition, our analysis has shown the importance of several preconditions for realizing this peak shaving potential, both from battery and policy design perspectives. Firstly, as consumption peaks occur in winter, we propose to pre-charge batteries from the grid instead of solely from PV-generated electricity as it is found to be more beneficial. Secondly, some technical characteristics of batteries, such as the C-rate, can be unimportant for one purpose, but very important for a second purpose. Lastly, it is important that joint investment, e.g. by house owners and grid operators, is made possible; since our economic analysis revealed that NPVs do not decrease much when battery sizes are increased above the economic optimal for self-consumption, making collaboration between different stakeholder very attractive.

A key policy priority should therefore be to encourage this joint investment. This can be done for example by enabling differentiated network tariffs. Another policy recommendation is to investigate alternative compensation mechanisms for replacing the net metering scheme in the case of abolishment. The findings of this study support the argument that a subsidy for batteries could both compensate

Figure 5.14: Impact of varying the number of batteries in the neighborhood [from 18 (optimal storage size factor = 0.31) to base value 58 (factor = 1.0) on peak shaving potential of heuristics (HEU) and perfect information power minimization (PER)] and varying the battery sizes (from on average 0.4×3.4 kWh to 1.3×3.4 kWh) on peak shaving potential of both algorithms.

a PV owner and result into substantial additional societal benefits, however, this option should be investigated further to take other compensation options into account.

Recommendations for future research are to replicate this study for different locations. As we have shown, individual consumption and production profiles have significant influence; performing similar research in different climatological conditions and with different consumption profiles may yield valuable new insights. In addition, this research can be enhanced with a laboratory setup, for example by focusing on the impact of the different algorithms on the voltage level in the LV grid. Furthermore, we advise designing a hybrid algorithm that optimizes between self-consumption and peak shaving objectives. Our research focused on the minimum and maximum potential for peak power shaving of batteries, however the employed algorithms both have disadvantages: the heuristics algorithm fails to capture the full peak shaving potential of the battery, while the impact of the power minimization algorithm may hamper self-consumption. Future research may address a different combination of ancillary services, for example using the

batteries to operate on the markets for operating reserves. Lastly, different storage configurations can be explored, for example the possibility to use the battery of a neighbor, or to have community energy storage instead of individual batteries.

6 Insights on Capacity Value of Photovoltaics, Community Energy Storage and Electric Vehicles

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and

W.L. Schram, H. Aghaie, I. Lampropoulos, and W.G.J.H.M. van Sark, "Insights on the Capacity Value of PV, Stationary Storage and Electric Vehicles. Submitted.," 2020.

Abstract

In the transition to a power system based on renewable energy sources, resource adequacy becomes an increasingly important topic. The part of their capacity that distributed resources can supply during peak residual load hours, i.e. the capacity value ratio (CVR), is still underexplored territory. In this research, we investigate the CVR for a community battery coupled with photovoltaic (PV) systems, by using various algorithms, as well as for smart charging approaches of electric vehicles (EVs) and vehicle-to-grid technology. The analysis is performed both on the distribution level and on the transmission system level of the Dutch power system. On the distribution level, we show that batteries charged only with PV-generated electricity reduce the peak demand with 14.6%, whereas a battery also charged with electricity from the grid can reduce peak demand with 30.0%. On the transmission system level, we approximate a CVR of PV-charged batteries of 25.0% and a CVR of a grid-charged battery of 47.0%. Results are robust for analyses of different years and future loads, but do exhibit large variations between different days. Also, the discharge time of the battery is a very important moderator. Regarding EVs, we approximate the load shifting potential of EV charging at 78.5% and the CVR of vehicle-to-grid at 8.9%. This indicates EVs could play a large role to maintain resource adequacy in the context of a phase-out of conventional power plants, given that this has priority in the optimization of EV charging.

6.1 Introduction

Building on the results of Chapter 5, this chapter explores the contribution to the peak residual load both on the distribution system level and on the transmission system level. A comprehensive analysis is performed, by deploying optimization techniques on these levels for stationary batteries coupled with PV systems and for EVs.

Resource adequacy encompasses the ability of a power system to provide long-term adequate supply in meeting electricity demand [78]. Resource adequacy policies are designed to address the "missing money" problem: in energy-only markets the revenues from energy and ancillary services alone may be insufficient to recoup the investments on facilities that only run for a few hours per year [80]. The capacity value of a generator is an important metric as this value is considered in the reserve margin of the power system. The capacity value can be defined as the expected possible amount of the energy output of a technology during the peak residual load [78]. A second important concept for this research is the capacity value ratio (CVR). This is the capacity value divided by the rated capacity of the

technology. In other words, the proportion of installed capacity of a technology that is used to satisfy the peak residual load. The CVR of conventional generators is mainly above 80%, as the only limiting factor is the forced outages on those generators during peak residual load hours [276]. As the generation from variable renewable energy resources (VRES) depends largely on the weather conditions, the correlation between VRES generation and peak demand is much weaker than in case of dispatching conventional generation. As a result, VRES contribute less to resource adequacy compared to conventional power generation. Therefore, electricity markets with high share of VRES require additional back-up capacity to meet the target generation reliability criterion.

Recently, this topic has received much attention from the European Union in general, and the European Network of Transmission System Operators for Electricity (ENTSO-E) in particular. The recent legislative package on Clean Energy for all Europeans, specifically Regulation 2019/943 of 5 June 2019 on the internal market for electricity, places resource adequacy at a central position in the European energy policy context [277]. According to the initial ENTSO-E's proposal, each European Transmission System Operator (TSO) shall calculate the capacity value for all generation technologies in order to determine the required dispatching back-up capacity to maintain system reliability in the presence of a defined volume of variable renewable capacity [77], [278].

The CVR is often used in modelling energy systems at the transmission system level. Because of computational limits, simulations at the transmission system level have to make simplifying assumptions about the flexibility on distribution system level. For example, Zappa et al. assume a European-wide load shifting capacity of 82 GW [20], based on a report assessing the theoretical demand response in Europe [279]. Energy storage and EVs are left outside of this analysis, despite it is known that batteries can have a large impact on reducing the peak residual load on the distribution system level [94]. With increasing EV charging data availability, opportunities arise to make an assessment for these flexibility resources as well. In the context of resource adequacy, these resources may be especially suitable as they can have multiple applications and thus do not have to stand idle for the time they are not requested to supply power to the grid. Hence, unlike conventional generators they do not rely on the remuneration of selling electricity for the few hours they are needed to ensure sufficient resource adequacy. Also, distributed resources are associated with lower rates of greenhouse gas emissions compared to conventional power plants [192].

In literature, capacity value is also addressed in terms of Effective Load Carrying Capability (ELCC), De-rated Capacity and Capacity Credit [278], [280]–[282]. The calculation of capacity value is always interlinked with reliability assessment of

national power systems. Several studies have estimated the capacity value of VRES, in various countries or TSO/ISO (Independent System Operator) control areas. Holttinen et al. [283] compare the capacity value of wind in several countries and conclude that the capacity value depends on the penetration of wind energy in the power system, the geographical location, weather conditions, peak load season, and electricity generation profile of each country. For instance, as the peak load in central and northern Europe occurs mainly during the cold winter evenings, the capacity value of PV in this region is nearly zero. However, due to the strong correlation between PV electricity generation and peak load in summer afternoons in southern Europe, the capacity value of PV is relatively high in those regions. The CVR of wind generation in Germany is estimated at 8%, but is expected to drop to 5% with increased penetration of wind energy [284], [285]. In general, higher penetration of VRES results in lower capacity value of it [286].

Historically, the contribution of each generation technology to the resource adequacy was evaluated independently from other technologies. However, by increasing penetration of new flexibility resources such as storage technologies, evaluating the capacity value of storage technologies integrated with VRES has been discussed in the literature in the last few years [287]. Sioshansi et al. proposed a dynamic programming approach to estimate the capacity value of storage [81]. Denholm and Margolis [288] show the interaction between PV integrated with battery storage and their integrated capacity value in the Californian electricity system. In an analysis performed for the Singapore power system, Koh et al. [289] found that storage can increase the contribution of PV to decreasing loss of load expectation (LOLE) of a system, especially at higher penetration rates of PV. However, at low penetration rates of PV, storage does not increase the capacity value as PV coincides with the residual load peak. Konstantelos et al. show the capacity value of batteries and emphasize the importance of outage duration on the capacity value of storage [290]. These findings are in line with findings of the British Transmission System Operator, National Grid, which shows the importance of discharge time of duration-limited storage in determining the capacity value [291].

To the best of our knowledge, our study is the first that addresses capacity value of PV combined with storage in the European context. Furthermore, it is the first that investigates the contribution that EVs can have to the resource adequacy of a system. We investigate the CVR of distributed resources PV, a community battery and EVs on a distribution system level as well as on the transmission system level, to investigate the different contributions flexibility resources can have on each level. We connect a detailed model at the community level to the residual load peak at power system level, thereby aiming to bridge the gap between the

power modelling on distribution system level and transmission system level.

This chapter is outlined as follows. First, we examine how to determine capacity value of flexible resources in Section 6.2. In Section 6.3, we present the system architecture, and explain the algorithms used in this study. In Section 6.4, we show the CVRs of the technologies with different algorithms. Subsequently, we reflect on our findings in Section 6.5. Last, we provide concluding remarks in Section 6.6.

6.2 Determination of Capacity Value

In literature, several methods for the CVR calculation have been introduced and described [292]–[294]. Castro and Ferreira [294] cluster the CVR calculation methods into two main categories, namely chronological and probabilistic, and compare them. Chronological methods, also called approximation methods, revolve around calculating the capacity factor over the peak load hours, which is suitable to help the system operation. Probabilistic methods calculate CVR by considering the probability distribution function of generation and demand and their associated uncertainties, which is suitable for system planners like TSOs [294]. Probabilistic methods revolve around the LOLE. The LOLE represents the sum of all loss of load probabilities (LOLPs) during a certain period, e.g. a year. The LOLP is defined as the probability of a system load that is larger than the system available generation capacity. Based on historical data, statistical analysis can determine the LOLE of the current generation mix. Subsequently, a specific technology can be added to the generation mix, and new simulations can determine the updated LOLE. As a last step, the studied technology is removed from the generation mix, and a hypothetical fully reliable power generation unit is added. The capacity of this unit is varied over different iterations, until the same LOLE is found as with the added capacity of the studied technology. The equivalent firm capacity is then the ratio between the capacity of the technology added and the fully reliable capacity.

The disadvantage of the traditional approach is that it involves the use of complex planning models, which is accompanied with substantial cost regarding data analysis, expertise and computational time [295] and could be hampered by lack of available data [293]. In the context of the energy transition, with VRES having very location-specific output due to variations in weather patterns, the traditional methods may not be adequate. Therefore, various approximation methods have been developed to be able to estimate the CVR of VRES [293], [295], [296]. Often, one considers the average output of technologies in a certain amount of peak residual load hours that are considered critical. In that sense, the amount of peak hours is an important design option for the determination of the CVR. This can vary from 0.01% of peak hours (i.e. a single peak load hour) to 30% of

peak residual load hours [20], [293]. VRES may record very different CVRs when different amount of peak hours is studied [20]. This is even more the case for duration-limited flexible resources such as electricity storage. When looking at a few peak hours, these resources may have a high CVR, while the CVR may be low when looking at many peak hours. To date, there are few studies that attempt to determine the CVR of storage and provide insights on these dynamics.

Currently, no consensus exists on the amount of peak hours PH that should be taken into account when approximating the capacity value. Therefore, we vary the amount of PH by looking at the hours associated with the peak residual load of 0.5 GW to 4.0 GW (2.7% to 22% of the Dutch peak residual load in 2018), which is called "Peak Capacity" in the remainder of this chapter. At present, 4.0 GW is equivalent to the current coal-fired power generation capacity in the Netherlands (3990 MW) [127]. This is a relevant upper limit given the discussions on the phase-out of coal-fired generation [297], to comply with national emission reduction targets agreed between EU member states. We sort the residual load hours and determine PH as the hours which fall into the hours of Peak Capacity. For the Netherlands in 2018, which is the focus of this study, the Peak Capacity from 0.5 GW to 4.0 GW relates to five peak hours ($PH = 5$, which is 0.06% of the hours) to $PH = 1017$ (12% of the hours). This approach also provides insights on how the impact of PV, batteries and EVs may change when supplying a larger part of the load.

A set of hours $p \in \mathcal{P} \{1, 2, \dots, PH\}$ is created. We calculated the capacity value by using a commonly used approximation method (e.g. in [293], [295], [296]). The CVR of technology c is calculated by taking the average electricity supplied to the system E_S in the peak hours of a day, divided by capacity of the technology given by $P_{\max}$:

$$CVR_c = \frac{\sum_{p \in \mathcal{P}} E_{Sc,p}}{PH * P_{\max,c}} \quad (6.1)$$

We report the CVRs for a peak capacity of 1.5 GW, but also show how it varies when increasing / decreasing this peak capacity.

6.3 Methods

6.3.1 System architecture

In Figure 6.1 the system architecture of this study is illustrated. The system boundaries of this study contained a single Low-Voltage (LV) grid connected to a Medium Voltage (MV) grid via a MV/LV transformer. It contained a set of households, PV systems and a flexibility source, which was either a community battery or a

Figure 6.1: System outline of proposed framework.

set of EV (bidirectional) charging stations. These loads were also connected in a communication network with one central operator, e.g. an aggregator. The residential load can be satisfied by PV electricity generation, and/or by importing electricity from the grid, and/or by discharging the community battery/EV fleet. All loads were aggregated at the community level.

Perfect foresight in residential load, PV generation and EV charging requirements and availability was assumed.

6.3.2 Modelling EV charging behavior as a community battery

We model the EV fleet in the same manner as in Chapter 3, using 25 virtual power plants. Even though a community battery has fixed power and energy constraints, the power and energy constraints of this EV fleet varies. This was determined using the “Latest charging” scenario developed by [203]. This means that the energy capacity of the EV battery should be at a certain level at the plug-out time, but also at a certain minimum in the hours directly before plug-out time, depending on the maximum charging power $P_{ch,max}$ of a specific EV. The $P_{ch,max}$ varies from 1 to 22 kW per EV, depending on the charging transaction data. The power and energy limits of all EVs are then aggregated and the EV fleet is treated as a community battery.

6.3.3 Optimization problem formulation

The objective function is formulated in eq. (6.2):

$$\text{minimize } \sum_{t=1}^T (P_{grid,t} * S_t) \quad (6.2)$$

Here, $P_{\text{grid},t}$ represents the power through the LV/MV transformer and S_t represents the target variable. Note that the analysis was performed at two levels: the distribution system level and the transmission system level. When the focus is on the distribution system level, S_t is the aggregated residual load within the LV-grid (i.e. $P_{\text{grid},t}$) and operation were optimized to minimize the peaks within the LV-grid. Hence, in this case the problem becomes a mixed-integer quadratic optimization problem. When the focus switches to the transmission system level, S_t is a binary variable reflecting whether it is a peak load hour, and the operation was optimized to have the highest possible capacity value. i.e. S_t in the optimization on the transmission system level is 1 for peak hours and 0 for non-peak hours. Hence, on the transmission system level the problem is a mixed-integer linear problem. The objective function was subject to various constraints, explained below.

The power balance constraint is formulated in eq. (6.3):

$$P_{\text{grid},t} = P_{\text{res},t} - P_{\text{PV},t} + \frac{P_{\text{ch},t}}{\eta_{\text{ch}}} - \eta_{\text{disch}} P_{\text{disch},t}, \forall t, \quad (6.3)$$

where $P_{\text{res},t}$ and $P_{\text{PV},t}$ represent the aggregated residential load and PV generation in the studied LV grid at timestep t . $P_{\text{ch},t}$ and $P_{\text{disch},t}$ represent the charging and discharging power of the community battery / EV fleet at timestep t and η_{ch} and η_{disch} represent the battery charging and discharging efficiencies.

To determine the CVR of distributed resources, it is important to comply with local power constraints. The MV/LV transformer power $P_{\text{tr,max}}$ constraint is formulated in eq. (6.4):

$$-P_{\text{tr,max}} \leq P_{\text{grid},t} \leq P_{\text{tr,max}}, \forall t \quad (6.4)$$

The aggregated charging and discharging power of the community battery / EV fleet are constrained by a maximum charging and discharging power:

$$0 \leq P_{\text{ch},t} \leq P_{\text{ch,max}}, \forall t \quad (6.5a)$$

$$0 \leq P_{\text{disch},t} \leq P_{\text{disch,max}}, \forall t. \quad (6.5b)$$

The energy in the community battery / EV fleet should always be within the energy limits of the batteries:

$$E_{\text{batt,min}} \leq E_{\text{batt},t} \leq E_{\text{bat,max}}, \forall t, \quad (6.6)$$

where $E_{\text{batt},t}$ represents energy charged in the community battery / EV fleet at timestep t and $E_{\text{batt,max}}$ is the battery's (aggregated) energy capacity (we only look at usable capacity). $E_{\text{batt},t}$ is based on the energy in the battery of the previous timestep and the charging and discharging power at timestep t :

$$E_{\text{batt},t} = E_{\text{batt},t-1} + (P_{\text{ch},t} - P_{\text{disch},t}) * \Delta t, \forall t \quad (6.7)$$

A Big-M constraint is used to ensure that the proposed operation of the community battery is not at the expense of the self-consumption of PV-generated electricity:

$$y_t P_{S,t} - P_{\text{charge},t} \leq M(1 - x_t), \forall t, \quad (6.8)$$

where x_t is a binary input variable that is 1 when there is surplus PV electricity (P_S). On days where the total $P_{S,t}$ exceeds the battery capacity, this constraint cannot be met without the fraction y_t . This is an input variable that represents the fraction of $P_{S,t} \delta t$ that fits in the battery without violating the battery's energy constraints on such days. The value of M should be sufficiently large, resulting in that the artificial variable would not be part of any feasible solution. For the optimized battery algorithm (see Section 6.3.4), we also remove this constraint to be able to compare a battery that is coupled with PV and thus increases self-consumption of PV, and a standalone battery which is exclusively aimed at maximizing the capacity value.

One of the developed battery algorithms (see Section 6.3.4) assumes the battery is only charged by PV-generated electricity. This is forced by the following constraint:

$$P_{\text{grid},t} \leq P_{\text{res},t}, \forall t \quad (6.9)$$

To determine the CVR of smart charging, we disable the possibility to discharge using the following constraint:

$$P_{\text{disch},t} = 0, \forall t \quad (6.10)$$

The model is programmed in MATLAB by using the Yalmip toolbox [298] and solved with the Gurobi optimizer.

6.3.4 Community battery and EV algorithms

Four algorithms are deployed. For the community battery, two optimization algorithms are developed. The first only allows charging from PV-generated electricity, thereby determining to what extent batteries affect the CVR of PV. The second allows charging from the grid and thereby determines the CVR of the battery itself, without being constrained to only using PV-generated electricity. For the EV algorithms, we distinguish between smart charging and V2G. In both algorithms the charging is flexible, but only in the V2G algorithm discharging from the EVs is also possible. All algorithms and accompanying constraints are summarized in Table 6.1.

6.3.5 Data inputs

The data input is summarized in Table 6.2. Data represent a single LV-Grid in the neighbourhood Lombok in Utrecht, the Netherlands. Residual system load

Table 6.1: Overview of constraints per algorithm.

Algorithm	Subject to constr.
Community battery (PV-charged)	Eq. 6.3 - 6.9
Community battery (grid-charged)	Eq. 6.3 - 6.8
EV (Smart Charging)	Eq. 6.3 - 6.7, 6.10
EV (V2G)	Eq. 6.3 - 6.7

profiles were taken from the ENTSO-E Transparency platform [133], residential load profiles were taken from [299]. We multiplied the PV installed capacity by a performance ratio of 80% to realistically calculate maximum PV power in relation to the current transformer capacity of 400 kVA. This translates to 1.5 kWp per household (HH), which is well within the rooftop PV potential of this area [91]. We fixed the power capacity of the battery at the peak PV output, corrected by the performance ratio and a direct self-consumption of 30%. This was done to represent the main rationale to install batteries on community level, which is to increase self-consumption. The discharge time of the battery, or the energy capacity, was set at 1.5 hour, but was also varied from 0.5 to 4 hour in a sensitivity analysis. Two years of logged EV charging data from the studied grid were used to generate future sets of EV charging transactions, using the methods described in [65]. The analyses in this study were performed for an EV adoption rate of 100%, considering the current car possession rate of 0.4 car/household in the Lombok district. The focus was on EVs owned by local residents; visiting EVs were left outside of the analysis. In the transmission system level optimization, we assumed that energy already stored in the EV batteries at arrival could be used to some extent; if an EV arrived with an SOC above 50%, all energy above this 50% could be used for V2G. As no measured data on V2G power capacity were available, we set the $P_{\text{disch,max},t}$ at 11 kW per EV, which reflects the power capacity of one charging point. We assumed a technical availability of 96.1% based on [291], which is used to scale the results of the final CVR of the battery.

6.4 Results

6.4.1 Contribution of PV, community battery and EV to peak reduction at distribution level

Figure 6.2 illustrates the load duration curves (LDCs) of the residential loads with PV only and the residential load when batteries under various algorithms are connected to PV. The load duration curves including EVs are illustrated in Figure

Table 6.2: Important data inputs.

Parameter	Value	Unit
Electricity consumption	2678	kWh/HH/y
Number of households	340	-
EV adoption rate	0.4	EV/HH
Installed PV capacity	1.5	kWp/HH
Battery Power Capacity	0.56	kW/kWp
Discharge time	1.5	hour
Transformer Capacity	400	kVA
V2G capacity	11	kW
Assumed V2G SOC limit	50	%
Technical availability Battery	96.1	%

Figure 6.2: Load duration curves of residual load without battery (i.e. PV only), with uncontrolled battery using uncontrolled and optimization algorithms (PV-charged and grid-charged).

6.3. We will address these results in more detail in the following sections.

6.4.1.1 PV only and PV with uncontrolled battery

For the cases of PV only and PV combined with an uncontrolled battery we find the same peak load as the case of the community level without PV: 220 kW. PV does not contribute to satisfy the peak community load; it only has some contribution in the intermediate load hours. Adding an uncontrolled battery to PV does not increase the contribution to the peak load; the LDC with the uncontrolled battery is lower

Figure 6.3: Load duration curves of residual load without EVs and with EVs under various charging procedures.

than the original LDC from approximately hour 1200 to hour 6800 (see Figure 6.2). This is due to peak residual load hours being in winter, when there is limited PV electricity generation. When not controlling the battery, the PV electricity is in most cases used directly, or immediately when $P_L > P_{PV}$. Generally, this does not coincide with the peak residual load.

6.4.1.2 Optimized PV-charged battery

In self-consuming PV electricity, one can prioritize charging the battery over satisfying the load. In that case, the grid is used to satisfy the load, while the PV-generated electricity is used to charge the battery. When we optimize the discharging of the battery to minimize the peak residual load, this peak decreases from 220 kW to 188 kW. Figure 6.2 shows the LDCs of the community with and without batteries. The residual load when deploying batteries with the optimized PV-charged battery lies lower in the peak hours of the year, and higher in the hours with the lowest residual load, compared to the LDCs without a battery and with an uncontrolled battery. When the battery is not controlled, the interaction is zero for many hours; in these hours, the community operates fully on the battery.

The battery operation of a summer and a winter day is shown in Figure 6.4. We can see that on a summer day, a substantial part of the load is satisfied by the battery. During the day, the battery is charged using PV-generated electricity - also

Figure 6.4: Operation of optimized PV-charged community battery on summer and winter day. Graph a) reflects the load and PV generation, b) shows the residual load in red and the optimized residual load in green when power of the battery (in black) is used and c) shows the accompanying SOC of the battery.

the maximum feed-in is minimized. On a winter day, the battery also satisfies a part of the load, but to a less extent, whereas this load is higher than the load on a summer day. The new peak load occurs on a day with both exceptionally low PV electricity generation and high load. On these days, pre-charging the battery with electricity from the grid can further increase the peak reduction of the combined PV-battery system.

6.4.1.3 Optimized grid-charged battery

When charging the battery from the grid is allowed, we can minimize the maximum power extracted from the grid. Executing this, the peak load decreases from 220 kW without PV and batteries, to 154 kW with PV and batteries: a peak reduction of 66 kW or 30%. Looking at the load duration curves in Figure 6.2, we see that the optimized grid-charged battery results in much lower peak grid demand than the situation without a battery and with a uncontrolled battery. This effect is similar to the PV-charged community battery, but rather amplified. Figure 6.5 shows how charging the battery from the grid can increase the peak reduction when compared to Figure 6.5; in winter, the average residual load demand is constant for most of the day.

6.4.1.4 Electric Vehicles

Figure 6.3 shows the load duration curve of the community without EVs, with uncontrolled EVs, with smart charging EVs and with V2G. Uncontrolled charging increasing the peak on the LV-grid from 220 kW to 379 kW. However, when these EVs are charged in such manner to minimize peaks, the community peak increases to 240 kW. In case of V2G, despite adding a large load to the system, EVs can even decrease the peak load to 189 kW (-14%), without limiting the charging requirements of individual EVs. This is partly due to smart charging, i.e. charging in off-peak hours, and partly due to V2G. This is shown in Figure 6.6 in more detail. The fleet is generally charged at a moderate pace. The charging rate is decreased compared to uncontrolled charging from 16:00, and the fleet starts to feed electricity back into the in the absolute peak (from 18:00 to 21:00). The difference between the peak residual load and the optimized P_{grid} is larger than the amount of power the fleet discharges; hence, this reflects power that is requested from the grid in case of uncontrolled charging, but that can be postponed to off-peak hours.

6.4.2 Capacity Value Ratio of PV, community battery and EV on transmission level

In table 6.3, our approximations for the CVR of the various distributed resources are reported. We will discuss each configuration in sections 6.4.2.1 and 6.4.2.2.

6.4.2.1 CVR of PV and Storage in the Netherlands, 2018

Figure 6.7 illustrates the average CVR per day of PV and batteries for different levels of peak capacity. Note that for visual purposes one day is one data point in

Figure 6.5: Operation of community battery with optimized algorithm on summer day and winter day. Graph a) reflects the load and PV generation, b) shows the residual load in red and the optimized residual load in green when power of the battery (in black) is used and c) shows the accompanying SOC of the battery.

Table 6.3: Approximation of capacity value ratio of the different distributed resources and algorithms at peak capacity of 1.5 GW.

Configuration	Capacity value ratio
PV only	0.6%
PV + Battery (Uncontrolled)	2.6%
PV + Battery (Optimized, PV-charged)	25.0%
PV + Battery (Optimized, grid-charged)	47.0%
EV (Smart charging)	78.5%
EV (V2G)	9.0%

Figure 6.6: Battery operation with V2G. Graph a) reflects the load (including uncontrolled charging load) and PV generation, b) shows the residual load in red and the optimized residual load in green when power of the EV battery (in black) is used and c) shows the accumulated energy charged in the EV battery fleet.

Figure 6.7: Boxplots of average CVR per day of batteries with various algorithms. Peak capacity relates to the upper 0.5 to 4 GW of residual load, which is equivalent to the upper 2.7% to 22% of residual load.

this figure, also when there are multiple peak hours on that day. This figure shows the trend with increasing amount of peak capacity or peak hours, whereas table 6.3 gives a better approximation of the CVR because all peak hours are equally weighted. In general, the PV only scenario and the uncontrolled battery have relatively low CVRs; 0.6% for PV only and 2.6% for PV with uncontrolled battery. The optimization algorithms on the other hand result in substantially higher CVRs, with 25.0% for the PV-charged battery and 47.0% for the grid-charged battery. The uncontrolled battery can increase the CVR of PV in some hours. The CVR of PV and the uncontrolled battery increase when looking at a larger range of the peak capacity, because in those cases more hours with solar irradiation are included; the CVR is zero when focusing on the peak 500 MW only.

The optimization algorithms reverse this trend. They show very high CVRs when focusing on 0.5 GW to 1 GW. The CVRs decrease when the peak capacity range is enlarged; when there are more consecutive peak hours, batteries need to distribute the stored energy over these hours. This can be seen in the battery operation illustrated in Figure 6.8; if only PV-generated electricity is used, the battery can only supply electricity for one hour. Given that there are five peak hours on this day, the PV-charged battery has a CVR of $\sim 10\%$ on this day. The grid-charged battery can have a CVR of almost 100%, because on this specific day there was a morning and an evening peak and the battery could recharge in between. However, also days exist with more consecutive peak hours, resulting in lower CVRs of the Optimized algorithm on those days.

Figure 6.8: Demonstration of battery operation of the optimized batteries (PV-charged and grid-charged). Binary variable S_t is shown in the upper graph in blue ("Peak Hour").

We also compared the results of the Optimized algorithm with a battery that is not coupled with PV but instead exclusively operates to maximize the CVR. The difference between these batteries is that the PV-coupled battery is forced to accommodate surplus PV-generated electricity (see eq. 6.8), because of the prioritization of self-consumption, whereas the stand-alone battery can still feed into the grid in these hours. The results for the categories of 0.5 GW to 3 GW are identical. Only in the category 4 GW, the PV-coupled battery has a slightly lower average CVR. This means it seldom occurs that there is a PV surplus and a peak in residual load simultaneously. This is in line with the results found for the CVR of PV. This provides strong support for the attractiveness of using a battery both for self-consumption and for providing capacity in peak hours.

6.4.2.2 CVR of EVs in the Netherlands, 2018

In Figure 6.9, the CVRs of smart charging and V2G are illustrated. Note that the "capacity" of smart charging is its load in case of uncontrolled charging. The CVR for smart charging is thus not capacity value in a strict sense, but rather reflects the part of the demand that can be shifted from peak load hours. As per ENTSO-E definition, explicit demand-response can be considered in the supply curve [77]. For V2G, the CVR reflects the part of the entire EV fleet's (i.e. also non-connected EVs) discharging power that can be exported to the grid in peak residual load hours.

Most EV charging in the studied area that occurred in peak hours can be postponed to off-peak hours. The average CVR of smart charging in the peak 1.5 GW system capacity is 78.7%. This indicates that charging of EVs requires some, but not much additional capacity to retain the same system reliability, if this is taken as an objective in charging optimization. For larger amounts of peak hours, the CVR of smart charging becomes somewhat lower; when there are many consecutive peak load hours it is more often inevitable to charge the EV in peak hours. The contribution of V2G is moderate with on average 8.9% in the 1.5 GW peak capacity. If all vehicles in the Netherlands would be EVs, this relates to a capacity value of 8.3 GW. In the context of a phase-out of coal-fired power plants, it is worthwhile to study the CVR of V2G in the peak 4.0 GW instead of peak 1.5 GW as done in the previous paragraph, as 4.0 GW relates to the current coal-fired generation capacity. On average, EVs can provide a CVR of 5.2% in the peak 4.0 GW of residual load. This CVR relates a capacity value of 4.8 GW if all 8.5 million passenger vehicles in the Netherlands would be EVs. Hence, these results indicate that all current coal-fired power plants could be phased-out without losing system reliability, if all EVs were used for this purpose. Evidently, there are some

Figure 6.9: Contribution of smart charging and V2G for various amounts of peak load hours associated with the peak capacity displayed on the x-axis. Peak capacity relates to the upper 0.5 to 4 GW of residual load, which is equivalent to the upper 2.7% to 22% of residual load.

considerations with this notion: e.g. perfect foresight of EV charging needs is needed, as well as acceptance of EV owners that their EV battery is used for this purpose. However, it does illustrate the large potential EVs have to contribute to system reliability in the context of a phase-out of conventional power plants.

Figure 6.10 illustrates the operation of smart charging of EVs and of V2G. It shows charging in peak hours can be postponed; the charging power of EVs in the peak hours is approximately zero. When V2G is applied, EVs charge more before the peak load, and part of this charged energy can be fed back into the grid during peak hours. The community becomes even a net contributor in these hours as the graph of P_{grid} becomes negative in these hours.

6.4.3 Uncertainty analyses

6.4.3.1 Future loads: CVRs in case of electrification heat and transport sector

In accordance with the ENTSO-E's proposal for determining CVRs [77], future load profiles have been constructed to study the CVRs in scenarios of electrification of heat and transport. Values for additional demand due to electrification of heat and transport in the Netherlands, 18 and 25 TWh/year, respectively, were taken from Zappa et al. [20]. In order to obtain a rough future EV load profile, arrival time

Figure 6.10: Demonstration of EV smart charging and V2G operation. Binary variable S_t is shown in the upper graph in blue.

data of public charging were taken from open source data [300]; in line with the charging data of this study, it was assumed that EVs charge in two hours. The heat profile G1A, which is a typical heat profile for residential sector, for 2018 from NEDU [299] was used as a base profile. Ambient temperature data from [301] were used to scale the temperature-dependent (i.e. space heating) profile, using a base temperature of 15 degrees Celsius [302]. The natural gas profile was translated to a heat pump profile based on heat pump coefficient of performance values taken from [303] and ratio temperature-dependent and temperature independent (i.e. hot water use) heat from [304]. Evidently, this uncertainty analysis should be treated rather indicative, as scenario building was not the main purpose of this study.

Table 6.4 provides the CVRs for three future load scenarios: electrification of a) heat, b) transport and c) heat and transport. The target capacity was set equivalent to 1.5 GW, which was 8.2% of peak residual load in 2018 (but more when additional load is added). In general, electrification of heat and transport lead to higher CVRs for duration-limited storage, including V2G. Somewhat surprisingly,

Table 6.4: Approximation of capacity value ratio for three future load scenarios: electrification of a) heat, b) transport and c) heat and transport. For comparison with current load, see Table 6.3.

Configuration	CVR		
	Scenario: electrification of		
	Heat	Transport	Heat and transport
PV only	2.6%	0.3%	0.9%
PV + Battery (Uncontrolled)	0.4%	1.0%	0.6%
PV + Opt. Battery (PV-charged)	43.9%	45.1%	59.6%
PV + Opt. Battery (grid-charged)	67.0%	70.8%	80.2%
EV (Smart Charging)	93.1%	94.1%	84.3%
EV (V2G)	12.6%	15.3%	18.8%

the electrification of transport leads to higher values of CVR for V2G: an increase from 8.9% to 15.3%. This is in contrast to what is known from the penetration of renewables, where the CVR decreases with increasing penetration. An explanation can be found in a change of the shape of the residual LDC of the Netherlands. Without the electrification of heat and transport, this profile is relatively flat, because of a large share of electricity demand by industry. This results in days of high load in which many consecutive peak load hours occur, which is not ideal for the CVR of duration-limited storage. The large additional load of 25 TWh for transport (an increase in electricity demand of 18.8%) occurs for a large part in the evening hours, whereas the electrification of 18 TWh of heat occurs in winter morning and evening hours. This results in a less flat LDC, and in fewer days with many consecutive peak hours. Also notable is the higher CVR of PV in case of electrification of heat, which increases to 2.6%. This is due to more peak hours occurring in the morning, when PV is generating electricity.

6.4.3.2 Historical loads: CVRs of batteries in different years

In accordance with ENTSO-E's proposal [77], we have studied multiple years to determine the robustness of the found CVRs. Figure 6.11 illustrates the analysis of the batteries performed with the residual load and solar irradiation of 2016 and 2017. From these graphs, and also by comparing with Figure 6.7 we can see that the CVR of PV has decreased somewhat over the years. This is due to the recent rapid increase in installed capacity of PV in the Netherlands, which has an impact on the residual load; with lower amounts of installed capacity of PV, chances are higher on a peak residual load hour with high solar irradiation and vice versa. This is in line with general findings that capacity values of VRES decrease with a deeper penetration of VRES [283]–[286]. For the optimization algorithms, results are quite robust over the years; batteries are less sensitive for a deeper penetration

Figure 6.11: Capacity Value Ratio for PV only, for uncontrolled batteries and for optimized batteries (PV-charged and grid-charged). Assumed discharge time of batteries is 1.5 hours.

of batteries, because their charging/discharging power is to a very large extent controllable. In this case, they are more sensitive to the steepness of the load duration curve. A very steep peak in the load duration curve leads to fewer peak hours; batteries perform better when there are not many consecutive peak hours.

6.4.3.3 Impact of discharge time on CVRs batteries

Figure 6.12 illustrates the impact of discharge time on the CVR of the community battery. It is evident that discharge time has a large impact on the CVR. The CVR increases in a non-linear fashion with increasing discharge time. In other words, larger batteries can have a higher contribution to supply the peak residual load, but the incremental benefits of increasing storage size diminish with increasing discharge time. For example, for the optimized PV-charged battery, it is notable that increasing the battery above 2.5 hours of discharge time does not make sense from a capacity value perspective with the assumed PV sizes; PV-generated electricity is the limiting factor.

These results can be compared with previous studies, i.e. [81], [291]; this is shown in Table 6.5. Our results correspond well with a study performed for the United Kingdom [291], although we report a lower CVR for higher discharge times. For California, Sioshansi et al. [81] report somewhat lower values for the CVR than our results; hence, our results are between the other studies on this topic. As has been stressed before, the CVR of technologies are strongly influenced by

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Table 6.5: Impact of discharge time on capacity value ratio - comparison different studies.

Discharge time	Sioshansi et al. [81]	National Grid [291]	This study
0.5 hour	-	17.9%	21.1%
1.0 hour	36.3%	36.4%	36.1%
1.5 hour	-	52.3%	47.0%
2.0 hour	49.8%	64.8%	55.1%
2.5 hour	-	75.5%	63.3%
3.0 hour	-	82.0%	69.4%
3.5 hour	-	85.7%	75.1%
4.0 hour	66.8%	-	80.7%

Figure 6.12: Impact of discharge time on CVR of community battery. Assumed peak load is 1.5 GW, which relates to the upper 8.2% of absolute residual load.

the geographical locations. This comparison indicates that this is less the case for batteries than for VRES technologies.

6.4.3.4 Impact access to energy at arrival on CVR EVs

In this study, it was assumed that energy from an EV battery at arrival above an SOC of 50% could be used for V2G. Figure 6.13 illustrates the impact of changing this assumption to 20% or 80%. It is apparent that this impact is large. In general, the higher the minimum SOC the lower the CVR, while absolute values of CVR decrease with higher target capacity. For example, when EV owners would accept their EV would be used for providing capacity to the grid until an SOC of 20%, the

Figure 6.13: Impact of Assumed V2G SOC limit on Capacity Value Ratio of V2G. Energy in EV batteries could be used for V2G until a minimum SOC of 20%, 50% and 80%, respectively. Peak capacity relates to the upper 0.5 to 4 GW of residual load, which is equivalent to the upper 2.7% to 22% of residual load.

CVR in case of a target capacity of 1.5 GW increases from 8.9% to 10.5%, while still satisfying the eventual charging requirements. However, when only energy in excess of an SOC of 80% can be used, the CVR decreases to 5.3%. The impact is more pronounced when studying higher target capacities, because in case of multiple consecutive peak hours, directly using EVs when they connect, which often occurs during peak hours, has substantial impact.

6.5 Discussion

In this section, we reflect on the presented results and provide various considerations and recommendations on determining the CVR for distributed resources.

6.5.1 Large range of CVRs

The results indicate a substantial impact of batteries and V2G to deliver electricity at peak residual load hours, and also a high potential of load shifting of EV charging to off-peak hours. However, it is also evident that a large variation between days exist. Days with multiple consecutive hours of peak load are accompanied with lower CVRs of batteries. It is thus important to stress that a) the reserve margin should consist of multiple technologies, spreading the risk in case of stress events,

and b) PV coupled with batteries and EVs can have a substantial contribution in the first stage of the phase-out of conventional power plants, but other solutions should be present in a deeper phase-out of conventional power plants.

6.5.2 Approximation method versus reliability-based methods

We have found that the CVRs of our approximation method are in line with previously reported CVRs by the reliability-based methods of [81], [291]. If this finding is robust, this dramatically decreases the computational time and data requirements when performing analyses on CVRs. However, it is important to consider that three different power systems are compared; we recommend more comparative research on this topic. Furthermore, our estimates should evidently not be used as a full replacement of the reliability-based methods. The specific residual load profile differs per country as it is based on e.g. the load profile, installed capacity of VRES, weather fluctuations and common outages. TSOs will still use reliability-based methods; ENTSO-E has already provided guidelines on this [77]. This ensures reliable results for determining resource adequacy. However, some of the requirements make analysis on factors influencing the CVR of technologies and algorithms troublesome: Monte Carlo analyses require many unit commitment and economic dispatch model runs to ensure statistical reliability, the models are required to run 10 years into the future, the models are required to include, among others, uncertainty in random outages and various weather conditions. This makes it a very reliable method to determine the full system's resource adequacy, but less adequate to determine the capacity value of individual technologies let alone algorithms within technologies. Here, the approximation method has value in several aspects. It provides the possibility to make fast comparisons and indications of a wide range of technologies and algorithms, for different (future) load profiles. Furthermore, it can show which parameters are important in determining the CVR of a technology and algorithms. Results of the approximation methods could be used as input for reliability-based methods.

6.5.3 Future residual load

We have demonstrated the potential impact electrification of heat and transport on the CVR of the various distributed resources. Our results give an indication, but will differ when different future residual load scenarios are used. As stressed before, the future load scenarios implemented here were rather simplistic. For example, future profiles may be very different as a result of different market incentives that are present. Also, it should be noted that while the CVR of EVs might increase with the electrification of heat and transport, this should be weighed against

a potential additional capacity needed to accommodate charging of EVs. The results of the distribution level optimization give some indication here, showing the electrification of EVs can lead to a decrease in the peak residual load, if this is an objective and V2G is applied.

The increased deployment of variable renewable energy sources will also change the residual load, as we have already seen to some extent in section 6.4.3.2. CVRs of renewable electricity generation technologies are not constant. In general, the more VRES technology is deployed, the lower its CVR will be, if the technology is not combined with a storage technology. Hence, an important recommendation is to perform more scenario analyses with changing residual loads, and also to periodically update calculations on current CVRs. Also, different weather scenarios should be considered.

6.5.4 Impact specific algorithms

The algorithms that are developed have a large impact on the CVR of flexibility resources. These technologies will probably not be focused on maximizing CVR, as flexibility resources can have a variety of purposes. In this study, we addressed this by combining storage with PV systems by ensuring that providing capacity with the community battery does not hamper self-consumption of PV-generated electricity. Therefore, our results can be interpreted as the potential of providing capacity, on top of a default operation of a community battery. Or the other way around: when batteries are used for capacity value, e.g. by TSOs, they can also be used for other purposes like supporting self-consumption.

At the same time, there could also be other, competing objectives when using the flexibility of these technologies. For example, the technologies might be used for market optimizations or minimizing emissions [198]. In that case, CVRs of these technologies can be substantially lower than reported here. From a policy perspective, we recommend to determine the value of contributing to the resource adequacy for flexible resources. Incentive programs can be designed accordingly, which could help steering flexible resource operators to allocate their resources to contribute to the resource adequacy.

6.5.5 Impact of discharge time and energy EV at arrival

By convention, the CVR is determined by dividing the average capacity in peak hours by the power capacity of a technology. This metric may not be the most suitable one in case of storage technologies. In this context, the discharge of a battery is key (or its inverse, the C-rate). Intrinsically, the CVR approaches 1 when the C-rate approaches zero: a very high energy-to-power-ratio ensures a

high probability the full power capacity of a battery can be used during the peak hours. Thus, the metric CVR has a bias towards batteries with low C-rates/high discharge times. We addressed this in this study by varying the discharge time. An important recommendation therefore is to always take both the energy and the power capacity of a storage technology into account when determining and using its CVR. Alternatively, storage technologies could be assessed by a different metric, e.g. with the unit h^{-1} , or the CVR could be corrected using the discharge time. More analysis on the impact of the discharge time can be found in [291].

An important assumption for determining the CVR of V2G, is whether the energy that is stored in the EV at arrival can be used for V2G. In this study, we assumed that if an EV would arrive with an SOC above 50%, the EV could be discharged until 50% to contribute to the peak hours. In section 6.4.3.4 we have demonstrated the large impact of changing this assumption to 20% or 80%. Given the importance of this metric, we recommend to perform survey analysis under EV owners to determine whether, and under which circumstances, they are open to grant some of their EV battery capacity to maintain the overall system reliability. Still, there are also some practical considerations. From the historical data, it is relatively straightforward to determine the energy capacity of the battery, e.g. by taking the maximum charged energy in one transaction. However, in reality it is complicated to determine the SOC of a battery in general, and an EV battery specifically. One approach is to measure the open circuit voltage of the battery. However, this is influenced by many factors and is also highly specific for the type of EV. The most realistic approach is to have communication between the EV and the charging point operator, as reliable information about the battery SOC is present in the battery or battery management system. This information exchange then could also include the minimum SOC an EV owner requires for future trips and the expected departure time.

6.6 Concluding remarks

This study addressed the contribution of distributed resources (PV, community batteries and EVs) to the system resource adequacy and resulted in recommendations regarding critical parameters. As flexible resources are currently being considered in the reserve margin of power system, we have provided handholds of important factors that should be considered in this analysis. Compared to conventional power plants, the flexible resources of batteries and EVs have the advantage that they can be used for various purposes, thereby being less prone to the "missing money" problem, and moreover have lower greenhouse gas emissions. We have shown that the capacity value of PV can be substantially increased when coupled with

storage, without hampering self-consumption of PV. This suggests that PV, coupled with batteries, can play a significant role in contributing to resource adequacy in the context of the phase-out of fossil-fueled power plants, in particular in the first stages of this phase-out. However, it should be noted that batteries have limitations when they are required to supply larger parts of the load. Regarding EV charging, we have demonstrated that EV charging load can be shifted away from peak periods to a very large extent. V2G can play an important role in providing capacity at peak hours, especially when a large part of the passenger vehicles are EVs.

Given the central role of resource adequacy in the EU's Clean Energy package, we recommend to determine the economic value of the CVRs of distributed resources. Future research could aim to determine what incentives are required to ensure distributed resources are used to contribute to the resource adequacy (e.g. via capacity mechanisms). However, currently distributed resources cannot be used for system balancing and be considered for the resource adequacy at the same time as per ENTSO-E's methodology proposal. An open question is the trade-off between these two, and whether it is possible to also find synergies.

7 Synthesis and conclusions

7.1 Research context

In the pursuit of mitigating the adverse effects of anthropogenic climate change, governments across the world have been developing policies to stimulate low-carbon technologies [4], [5]. This, conjointly with technological advances leading to sharp cost reduction in the manufacturing process, has led to exponential growth of installed PV capacity worldwide [16], [17]. Scholars modelling future power systems expect a further increase of PV capacity in the range of 50-100 times by 2050 [18], [19]. This leads to scientific and industrial efforts to integrate high shares of PV capacity into the power system. Batteries are often mentioned as a potential means to support integration of PV power to the grid, because of their ability to match supply with demand and various ancillary services they can deliver to the power system. Besides addressing technical issues, also social issues must be addressed for massive deployment of PV which is why the EU has repeatedly stated the importance of citizen engagement [29], [30].

These developments underline the rationale for the research presented in this thesis. A bottom-up approach was taken, modelling power flows in energy communities, at the distribution level. In this approach, the value of PV systems coupled with batteries (both stationary and in EVs) was studied from an environmental, economic and technical perspective.

7.2 Answers to the research questions

The main research has been broken down into three research questions, addressing the environmental, economic and technical benefits of PV systems coupled with batteries. In this section we provide the answers to these questions by combining results from various chapters.

7.2.1 Environmental benefits

The environmental benefits have been addressed by focusing on the GHG emission reductions that PV coupled with batteries can achieve, using the following research question:

Q1. What is the greenhouse gas reduction potential of PV systems coupled with batteries?

Figure 7.1 illustrates the absolute GHG emission reduction potential of deploying one system of a technology (on the left) and the relative impact of optimizing charging and discharging schedules of the batteries (on the right). In **Chapter 2** it

Figure 7.1: GHG impact of different technologies and optimizations. On the left, the absolute GHG emission reduction of deploying one functional unit of the specified technology is shown. One functional unit entails 3.2 kWp for the PV system (average of the Netherlands), 3.4 kWh for the stationary battery size (optimal size determined in Chapter 5) and one EV driving 13,000 km per year (average of Dutch passenger vehicles) compared to an ICE vehicle driving the same distance. On the right, the relative GHG emission reduction of optimization is illustrated as a result of emission optimization in Chapter 3 and 4, as compared to uncontrolled charging.

was shown that, when taking the full life cycle into account, every kWp of installed PV capacity reduces the GHG emissions of energy communities across Europe by 6% to 13%. The impact of PV technology is moderated by the country-specific solar irradiation, but even more so by the country-specific (hourly) generation mix. Despite having the lowest solar irradiation of the eight European countries under study, the Netherlands exhibits the second-highest GHG emission reduction in absolute numbers; one PV system of 3.2 kWp results in a reduction of 1.55 tCO_{2eq}. Driven by replacing electricity with high carbon intensity (i.e. high generation emission factors), the optimal-sized PV systems reduce the energy-related emissions on community level by 44%.

As shown in **Chapter 2**, the transition from ICE vehicles to EVs saves 46% to 72% of transport-related GHG emissions by passenger vehicles across Europe. Within an energy community (see Chapter 2 for elaboration on energy communities) in the Netherlands, an EV would have 64% less emissions than an ICE vehicle. This reduction is much higher than previously established values, which is due to the high amount of PV capacity in our energy community. This ensures that EVs are

often charged with electricity with low emission factors, and shows the importance of combining the electrification of transport with the deployment of clean energy technologies like PV.

Stationary batteries result in a small increase of GHG emissions. This is due to the emissions associated with the manufacturing of the battery, and the losses that occur when converting electrical energy to chemical energy and vice versa. This shows a clear rationale to optimize the charging process of stationary batteries in order to reduce emissions. This was demonstrated in **Chapter 3**, where it was shown that minimizing emissions can lead to a reduction of 57.2% in emissions compared to a situation with an uncontrolled battery (see Figure 7.1, right). The same framework was applied to EVs as presented in **Chapter 4**, where it was shown that the emissions related to charging of EVs can be decreased by 23.6% compared to uncontrolled charging. V2G technology exhibits the highest relative reduction in emissions by 67.3%. Interestingly, this reduction potential is even higher compared to a the stationary battery, despite being more constrained due to the driver's charging requirements. This can be explained by the C-rates of the stationary battery versus the V2G technology. The C-rate of the stationary battery was 0.4, whereas the EVs could charge and discharge with 22 kW. Given the average charging volume of 17.9 kWh, this could be translated to a C-rate of 1.2. Hence, EVs can meet their charging demand more often in an hour with low emission factors.

7.2.2 Economic benefits

Regarding the potential economic benefits of the investigated technologies, economic optimization was performed both in the investment phase as well as in the operational phase. The research question addressed was:

Q2. What is an economically optimal way to combine PV systems and batteries?

Regarding the investment decisions, the impact of PV self-consumption benefits on the business case of investing in a home battery by PV owners was studied in **Chapter 5**. It was shown that retrofitting could be a positive business case, given a battery investment cost of 234 €/kWh and self-consumption benefits of 16 €/ct/kWh; this would lead to an average optimal battery size of 3.4 kWh for the 58 PV owners in this study. However, costs for small-scale stationary batteries is currently (early 2020) substantially higher, whereas the self-consumption benefits in the Netherlands are zero. In Germany, where self-consumption is incentivized, 40% of PV systems that are installed are coupled with batteries. With the gradual

abolishment of the net metering scheme from 2023 onwards in the Netherlands, self-consumption benefits are estimated at 17 € ct/kWh, which would make batteries more financially attractive. However, with the current battery prices, this would only lead to a positive net present value of battery investment for PV owners with very high surplus PV electricity generation.

Energy arbitrage can lead to additional economic benefits for batteries. In **Chapter 3**, it was shown that optimizing the charging and discharging process of a community battery can lead to savings in electricity costs of 28.8%. These benefits are on top of any self-consumption benefits, as the battery was constrained to prioritize accommodating PV-generated electricity. In charging EVs, compared to uncontrolled charging, 22.7% of the electricity costs can be saved when charging is scheduled in hours of low electricity prices - as shown in **Chapter 4**. In case of V2G, electricity costs can decrease by 32.4%. Higher price volatility leads to higher benefits for flexible resources.

7.2.3 Trade-off between economic and environmental objectives

Next to studying research questions 1 and 2 in isolation, it is important to show the trade-off between economic and environmental objectives in optimization, as some battery/EV owners could prefer the former, some the latter, and some a mix of both. For this purpose, a multi-objective optimization framework was developed to provide insights in these trade-offs. This framework was applied to a community battery in **Chapter 3** and applied to EVs in **Chapter 4**. It was shown that compared to an uncontrolled charging process, cost minimization increases emissions by 49% for the community battery, by 26% for smart charging, and by 31% for V2G.

In the multi-objective optimization, the cost-optimal result and the costs associated with the emission-optimal result can be used as extremes for a division in equally spaced bins. These bins can be imposed as a cost constraint, also known as the ϵ -constraint, in subsequent emission minimizations; in this way, different weights can be assigned to costs and emissions. Figure 7.2 (left) illustrates the CO₂ abatement cost range when altering the cost minimization towards an emission minimization. CO₂ abatement costs are calculated by dividing the increase in costs when shifting from cost minimization towards a partly emission-based optimization, by the decrease in emissions. The lower end of the range entails the CO₂ abatement costs for a minimization with the highest weight on costs, whereas the higher end of the range entails the CO₂ abatement costs of a full emission minimization. For all investigated technologies, GHG emissions can be mitigated at relatively attractive prices, especially when compared to the price of 75\$/tCO_{2eq} needed in 2030 according to the International Monetary Fund [305] and the potential

Figure 7.2: CO₂ abatement costs range in multi-objective optimizations (left). Relative cost and emission reduction of “balanced” optimization, compared to uncontrolled charging (right).

price of 273 \$/tCO_{2eq} in the last stages of low RCP pathways if GHG mitigation is postponed [306]. Figure 7.2 (right) illustrates the results of a balanced schedule. A balanced schedule is defined as the average between the minimal costs and the costs associated with emission minimization, or the middle bin in the ϵ -constraint. These costs are lower than the costs associated with uncontrolled charging, but moreover, at these costs high emission reductions can be achieved compared to uncontrolled charging: 29.7% for the stationary battery, 15.9% for smart charging and 50.8% for V2G. As stressed before, the numbers for V2G are rather high because of the relatively high C-rate.

7.2.4 Technical benefits

The technical benefits were investigated in terms of the potential contribution of PV systems coupled with batteries to peak demand reduction at different levels of the grid, by addressing the following research question:

Q3. What is the capacity PV systems coupled with batteries can provide at different levels of the grid?

In **Chapters 5 and 6**, it was found that PV hardly contributes to the absolute electricity peak demand reduction at both the distribution level and the transmission level. However, when coupled with batteries, PV-generated electricity can be

injected to the grid during peak demand hours. In **Chapter 5**, peak demand reduction was studied at the distribution level with a very high time resolution of 10 seconds. For a community with 79 households, of which 58 were equipped with a battery that was optimally sized for PV self-consumption, the peak demand of the community can be reduced by 5.7% for an uncontrolled battery, 22% for a battery that is pre-charged using simple heuristics (charging at constant rates during winter nights), and 51% in an optimal case. In **Chapter 6**, a similar study was performed for a community of 340 households, with 510 kWp installed PV capacity and a community battery of 428 kWh, but with the time resolution of one hour. It was shown that the peak power extracted from the grid was reduced by 30%. Differences between these studies can be explained by the differences in relative sizes of the battery (on average 2.5 kWh per household in the former study versus on average 1.2 kWh per household in the latter) and the difference in time resolution. In case of an average EV ownership rate of 0.4 EVs per household, uncontrolled EV charging would increase the peak demand by 72%, whereas smart charging would increase the peak demand by only 9% compared to a situation with no EVs - when minimization of peak residual load is set as an objective. Despite the large additional demand due to charging EVs, applying V2G can even decrease the peak residual load of the community by 14%.

At the transmission level, the Capacity Value Ratio (CVR) was determined for PV, stationary batteries and EVs in **Chapter 6**. The CVR is the ratio between the expected output of a technology during the peak residual load hours at the transmission level, and its capacity. Four charging algorithms were developed and tested in a comparative manner for stationary batteries: uncontrolled charging, delayed discharging, charging optimized with PV self-consumption constraint, and charging optimized without PV self-consumption constraint. The delayed discharging entailed only using PV-generated electricity to charge the battery, whereas in the optimized algorithms batteries could also be charged from the grid. The CVR of PV is estimated to be 0.6% which can be increased when coupling a battery with the PV system to 2.6%, 25% or 47% for the uncontrolled, delayed discharging and optimized algorithms, respectively. Imposing the self-consumption constraint for the optimized battery did not decrease the CVR compared to the situation without the constraint, which illustrates the synergy between using a battery for both PV self-consumption and contributing to resource adequacy.

7.2.5 Answer to the main research question

The insights gained by answering the three research sub-questions provide the basis for answering the main research question:

What benefits can be obtained from PV systems coupled with batteries?

In this thesis it has been shown that coupling PV systems with batteries can be beneficial in terms of environmental, economic and technical aspects. Increasing self-consumption of PV-generated electricity was combined with various other purposes. In this way, substantial GHG emission reductions can be obtained by deploying a battery, on top of the GHG emission reductions already obtained from deploying PV systems only. Batteries that are deployed to increase self-consumption of PV-generated electricity can also result in reduction of costs and emissions associated with electricity consumption: multi-objective optimization of community battery charging can simultaneously decrease electricity purchase cost by 9.5% and emissions by 29.7%. The transition from ICE vehicles to EVs is associated with GHG emission reductions by itself; this reduction can be amplified by coupling the charging of EVs with the deployment of PV systems and by applying algorithms such as those developed in this research. The decrease in emissions can be accompanied by a decrease in costs, compared to uncontrolled charging. For smart charging of EVs, electricity cost can be decreased by 17.9% while simultaneously saving 15.9% of GHG emissions. When V2G is applied, even 50.8% of emissions can be saved while still also decreasing cost by 13.9%.

PV systems coupled with batteries can also contribute to the resource adequacy of the power system, which is an important finding in the context of phasing out coal-fired power generation. PV systems coupled with batteries can have a considerable capacity value of 25% of the battery's capacity when they are charged with PV-generated electricity or 47% when charging from the grid is allowed. On the distribution system level, batteries can decrease a community peak residual load by up to 50%.

Since these findings are based on specific case studies, a wide variety of sensitivity analyses was performed to increase the generalizability of the results. This thesis thus provides quantitative analysis to substantiate the value of coupling PV with stationary and mobile batteries, while showing the importance of developing optimal scheduling techniques to go hand in hand with deploying batteries and EVs to achieve maximum benefits.

7.3 Recommendations

7.3.1 Recommendations for future research and practical usage

Power systems are highly country-specific. Historically, this is attributed to a large extent to the country-specific available natural resources - e.g. natural gas in the

Netherlands and lignite in Germany. With the deployment of VRES, differences between countries will continue to exist as countries differ due to variations in weather patterns and potential for specific renewable technologies - although similarities will also arise in the deployment of information and communication technologies and interconnections. Climatic patterns also cause the electricity demand profiles to vary per country, e.g. the heating and cooling demand. Therefore, a first research recommendation is to **perform more comparative research between countries** on the GHG emission reduction potential and capacity value of various technologies. To aid this, in this thesis generic frameworks have been developed that can be applied to specific circumstance. In Chapter 2 the impacts of PV systems, batteries, EVs and heat pumps for eight European countries as technologies supporting the energy transition was shown. This research can be extended to include more European countries, but also countries from other continents. This would provide to valuable insights on how effective country-specific roadmaps for the energy transition can be optimized for every country or continent. In Chapter 6 the capacity value of PV and battery technologies was studied for the Dutch power system. For power systems of other countries, different results may be expected. Moreover, it is not established yet what the most appropriate method for resource adequacy assessment methodologies would be [77] - a research effort is still needed here.

In this research, a multi-objective framework optimizing both costs and emissions was developed and applied for a community battery and an EV fleet as discussed in Chapter 3 and 4, respectively. A recommendation for practical applications is for retailers and/or aggregators to adopt such a framework, and thereby **provide consumers with options to choose a package that fits their individual preference towards cost or emission benefits**. It is recommended to present the different options in such a manner that is understandable for the non-specialized consumer, thereby also increasing awareness. In this context, it is also important to take battery degradation into account. This can be a concern, especially for EV owners. Our research has shown that benefits, both from emission and cost perspective, can outweigh the losses associated with battery degradation.

An upcoming challenge is how to practically facilitate a further deployment of PV systems and the electrification of heat and transport systems. This research has shown that much is possible, also within the current LV-grid capacity limits. However, this is relatively simply achieved in computer models, but can be a big challenge in practice. Much coordination and communication is needed between grid operators and the operators of flexible resources. In this context, GOPACS (grid operators platform for congestion solutions) is a promising development [307]. On this platform, grid operators determine where congestion can be expected and

issue a market message to market parties connected in this area. These market parties can subsequently place an order to prevent the congestion, whereas the system also ensures to balance this elsewhere to maintain the system balance. Further efforts in these areas are recommended, as well as mutual learning between different countries and methodologies.

7.3.2 Policy recommendations

This research has shown that with a further decrease in battery manufacturing costs, stimulating self-consumption of PV-generated electricity might result in a positive business case for coupling batteries with PV systems. However, using a battery solely for increasing self-consumption does not lead to positive system impacts. Deploying batteries without properly managing the charging process can even increase GHG emissions, as explained in **Chapter 2**, and this thus hardly contributes to peak feed-in reduction or peak demand reduction, as shown in **Chapter 5** and **Chapter 6**. Current policies make economic optimization on the day-ahead market a possibility. However, this can also lead to increased stress on the grid, when all EVs and/or stationary batteries respond to the same signals in a similar way, and with the present merit order this will increase GHG emissions as shown in **Chapter 3** and **Chapter 4**. At the same time, in **Chapters 3 - 6** it was demonstrated how increasing PV self-consumption can be combined with substantial reductions in GHG emissions and peak residual loads. Hence, stimulating self-consumption of PV-generated electricity alone is not enough; additional policies are needed. In the end, the provided incentives, most probably financial, will define to a large extent in which way flexible resource are used. Firm policies should be in place to ensure flexible resources would decrease emissions or provide capacity to contribute to resource adequacy. The earlier these policies are enabled, the more positive impact flexible resources can already have, which can also result in increased public acceptance of energy transition technologies.

A specific political issue in the Netherlands, and other countries in Europe, is the phase-out of coal-fired power plants. There are two general approaches to phase-out coal-fired power plants: increase the CO₂ price, or a forced closure. A CO₂ price of 30 €/CO_{2eq} can approximately equal the marginal costs of coal- and gas-fired power plants, but as shown in **Appendix A**, this does not mean that new coal-fired power plants are pushed out of the merit order. For this, much higher CO₂ prices are needed than the current EU Emissions Trading System price of 20 €/t; it should be in the range of 75 €/tCO_{2eq}. However, any increase in the CO₂ price makes the trade-off between costs and emissions less severe, and as shown in Figure 7.2, also a lower increase could steer flexible resources to foster a

decrease of emissions. The direct closure of coal-fired power plants evidently has more impact. A concern could be that this could hamper the resource adequacy of the power system, especially given the expected electrification of heat and transport systems. This research has addressed this concern and has shown that EV charging can largely be postponed outside the peak demand hours, and additionally, stationary batteries and EVs can contribute considerably to the resource adequacy, which decreases the need for conventional power plants as backup. In fact, EVs collectively may function as backup capacity. Also here, it is recommended to design the policies on the short term, whether it is a substantial increase of the CO₂ price or a forced closure of coal-fired power plants; technologies to replace these plants are already available, and climate models have extensively shown the advantages and the need of acting fast.

Policy can also support the decrease of GHG emission in an indirect manner. In this context, it is recommended to provide more transparency in relation to marginal emission profiles. In this research, marginal emission profiles were constructed based on day-ahead electricity prices, which comes with certain uncertainties regarding the accuracy of these profiles. More accurate marginal emission profiles can only be constructed if each balance responsible party publishes the CO₂ intensity of their scheduled generation based on the unit commitment of their power plants. Given the large emission reduction potential of EV charging and/or community battery charging, it is recommended for countries or regions to publish realtime marginal emission factors to facilitate adoption of emission-based charging optimization. These emission factors should be published in such manner that market-sensitive information of electricity generating companies is not revealed.

7.4 Epilogue

Keeping the global temperature increase well below 2°C above pre-industrial levels and pursuing additional measures for limiting the increase to 1.5°C. This presents one of the greatest, if not the greatest, intellectual and societal challenges of our time - with much at stake. To tackle this challenge, input and combined effort from a wide variety of disciplines is required. Natural scientists and engineers are needed for the development and deployment of low-carbon systems. Mathematicians and computer scientists are needed for accurately forecasting electricity supply and demand. Social scientists and politicians are needed to ensure public support. Legal and regulatory experts and philosophers are needed to safeguard energy justice and equity issues. I hope to have provided a small contribution.

A On the Use of Average versus Marginal Emission Factors

This chapter is based on the publication:

W.L. Schram, I. Lampropoulos, T.A. Alskaif, and W.G.J.H.M. van Sark. 2019. "On the Use of Average versus Marginal Emission Factors," in *8th International Conference on Smart Cities and Green ICT Systems (SMARTGREENS)*, pp. 187–193. DOI: 10.5220/0007765701870193

Abstract

In this appendix, we propose using marginal emission factors instead of average emission factors for determining the impact of adding variable renewable electricity to the generation mix. Average emission factors assume constant emissions over time, which does not reflect reality. Therefore, they cannot be used for e.g. accurately determining the mitigated CO₂ emissions by renewables, or for scheduling shiftable loads in order to have the lowest CO₂ emissions. To solve this, we provide a method to construct the marginal emission profiles via the merit order and demonstrate the method by composing these for the case of the Netherlands. Using this method, we re-evaluate the CO₂ impact in 2014 of photovoltaic-generated electricity to be 0.42 Mt – compared to 0.36 Mt using the average emission factor - and for wind-generated electricity to be 3.6 Mt instead of 2.9 Mt CO₂ (an increase of 14.3% and 24.2%, respectively). Furthermore, we show the impact of CO₂ price on the merit order and show that even high CO₂ prices of 50 to 75 €/tCO₂ are not sufficient to phase-out new coal-fired power plants.

A.1 Introduction

In this chapter, marginal emission profiles are developed. These emission profiles were used in Chapter 3 and Chapter 4.

Two options to mitigate greenhouse gas (GHG) emissions are to add variable renewable electricity to the electricity mix, or to decrease electricity demand through energy conservation measures. There are two main methods to determine the impact of such measures on the CO₂ emissions of a country. Mostly, an average emission factor (AEF) is used to estimate the emissions of the replaced electricity generation. This makes the implicit assumption that a decrease in conventional electricity generation, such as from coal- and gas-fired power plants, is evenly distributed over all generation facilities. However, this is not in line with the functioning of electricity markets, since in practice a decrease in requested supply results in decreased electricity generation of facilities operating at the margins.

The AEF is defined as the total direct CO₂ emissions of the electricity generation sector, divided by the total electricity generation over a certain period – usually one year [308]. The concept of marginal emission factors (MEF) focuses on the notion that renewably-generated electricity replaces the electricity generated by the price-setting power plants of a specific settlement period used in the market, e.g. 1-hour or 15-minutes trading interval [309]. This is generally seen as a superior method over the use of AEFs, because the latter disconnects the actual contribution to CO₂ emissions and the abatement scenario by implicitly assuming constant CO₂ intensity [137].

Several studies have shown that the use of MEFs leads to increased accuracy of estimations of CO₂ savings. In England and Wales the use of the AEF led to an underestimation of CO₂ savings when determining the impact of energy efficiency measures [129]. Similar results were obtained for the case of California [130]. In addition, the environmental impact of increased wind power generation in Great Britain could be estimated more accurately by using MEFs [131]. In general, AEFs are lower than MEFs and therefore result in underestimation of CO₂ savings [310].

The contribution of this chapter is threefold. First, we provide a straightforward method of designing marginal emission profiles. Second, we survey and report the data of Dutch generation facilities. We also show the actual CO₂ mitigation based on the marginal emission factors, and compare it with the average emission factor, which has not been done before for the Netherlands. Third, we show the impact of CO₂ price on the merit order, hereby offering guidance for policy makers in determining options to meet CO₂ emission targets.

A.2 Methods

To compose marginal emission profiles, first the merit order needs to be constructed. This is the electricity generation mix sorted from lowest to highest marginal operating costs (i.e. the costs of increasing generation by one unit of energy, in this case MWh).

Marginal costs MC (in €/MWh) of facility f is the sum of the fuel costs, the emission costs and the variable operating costs [311], and thus can be determined as follows:

$$MC_f = \frac{FP_f + EF_f * CP}{\eta_f} + VOC_f \quad (A.1)$$

where FP denotes the price of fuel (in €/MWh_t), η is the conversion efficiency, EF is emission factor of the fuel (in tCO₂/MWh_t), CP denotes the EU Emission Trading System (ETS) CO₂ price (in €/tCO₂), and VOC is the Variable Operational Costs (in €/MWh). We follow IPCC (2006) and focus on CO₂ for GHG emissions in power generation. The marginal emissions ME (in tCO₂/MWh) of facility f are determined as follows:

$$ME_f = \frac{EF_f}{\eta_f} \quad (A.2)$$

Subsequently, there are two options for constructing a marginal emission profile. First, one can compose a generation mix based on the electricity demand in a specified time period, and take the marginal emissions of the price-setting facility.

Second, one can take the day-ahead market (DAM) clearing prices, determine from this which facility was operating at the margin. Then, the emissions of this facility can be taken for the marginal emission profile. The latter is more accurate, as it reflects what historically happened. The former is more suitable when looking at future scenarios.

For constructing the merit order and marginal emission profiles, the following assumptions had to be made:

- To determine the marginal operating facility, we assumed that the facility with marginal costs closest to the spot price was the marginal operating facility.
- All facilities were assumed to operate at their maximum efficiency; efficiency losses of operating at partial load were not considered.
- There are several methods to allocate CO₂ emissions in the case of combined heat and power production [312]. Here we chose to allocate CO₂ emissions to power generation.
- Co-firing of biomass in coal-fired power plants was not included.
- The marginal operating facility was assumed to be located in the investigated country.
- No assumptions about future scenarios were made.
- Bid strategies of retailers were not considered.
- Upstream emissions were not considered.

In the following section, the proposed method is elucidated by applying it on a case study for the Netherlands.

A.3 Results

A.3.1 Merit order and marginal emissions Netherlands

To construct the marginal emission profile, various data were required as input. First, the generation portfolio of the Netherlands was established, using the databases of ENTSO-E [226]. For every facility, the installed capacity and the efficiency were determined. Table A.1 shows all these values and the accompanying sources. Because of data availability, we chose 2014 as base year for obtaining data. Fuel price for coal was based on data from Statistics Netherlands; on average the

Figure A.1: Merit order based on marginal costs (left y-axis, green) and marginal emissions (right y-axis, red) of the facilities operating in 2014 (see Table A.1). Each marker represents a power plant; the distance on the x-axis between two markers reflects the size of the facility.

price of coal was 9.1 €/MWh_t for 2014 [313] and of natural gas prices 24.3 €/MWh_t [314]. VOC was assumed to be 1.2 €/MWh for gas-fired power plants, and 3.0 €/MWh for coal-fired power plants [315]. For 2014, CP was assumed constant at the average of 6.9 €/tCO_2 [316]. The EF of bituminous coal and natural gas were determined to be $0.341 \text{ tCO}_2/\text{MWh}_t$ and $0.204 \text{ tCO}_2/\text{MWh}_t$, respectively [317]. Velsen-24 was a special case; a peak-load facility that uses a mixture of blast furnace gas from nearby steel production and natural gas. Following the position of the Dutch government, we attribute an EF of 1.25 times the EF of natural gas for this [318]. Figure A.1 shows the resulting merit order and accompanying marginal emissions.

Table A.1 lists the main characteristics for all Dutch centralized thermal power plants, their installed capacity, efficiency and the resulting MC and ME. Figure A.1 shows the merit order, with for every individual facility the accompanying marginal emissions. At around 4.5 GW of installed capacity, we see the substantial gap of around 13 €/MWh between the most expensive coal-fired power plant, and the cheapest gas-fired power plant. These coal-fired power plants have much higher marginal emissions: around $850 \text{ tCO}_2/\text{MWh}$, compared to around $350 \text{ tCO}_2/\text{MWh}$ for gas-fired power plants.

Figure A.2 illustrates the marginal emission profile of a randomly chosen day,

Figure A.2: Marginal costs and emissions on 11-01-2018.

i.e. 11 January 2018. DAM-prices are taken from [319] and CO₂ price was 9.28 €/t CO₂ [316]. During most of the day, gas-fired power plants operate at the margin, while during the night coal-fired power plants operate at the margin. This shows that scheduling demand to optimize on costs mainly leads to increased electricity generation by coal-fired power plants, and thus to increased emissions.

When applied to the Netherlands in 2014, we end up with an average MEF of 629 kg/MWh (standard deviation of 278 kg/MWh), compared with an AEF of 503 kg/MWh. Our results are in line with the official Dutch statistics, where only the total yearly MEF is provided; an MEF of 636 kg/MWh [320]. We applied the marginal emission profile to determine the mitigated CO₂ emissions in the Netherlands in 2014 by wind- and PV-generated electricity, assuming these are linearly dependent on wind speed and solar irradiation, respectively [301], [321].

This results in an updated CO₂ impact of wind from 2.9 Mt CO₂ when using the AEF to 3.6 Mt CO₂ when using MEFs (+24.2%) and from 0.36 Mt CO₂ to 0.42 Mt CO₂ (+14.3%). From this, one can also conclude that compared to PV, wind is producing more during hours when coal-fired power plants are operating at the margin, e.g. at night.

A.3.2 Impact of CO₂ price

Figure A.3 shows the merit order of all Dutch thermal power plants for various CO₂ prices. A CO₂ price of 25 €/tCO₂ does not lead to changes in the merit order,

Figure A.3: Impact CO₂ price on merit order of all Dutch thermal power plants. See Table A.1 for overview power plants.

apart for the higher prices (Figure A.3b). The break-even price between the most efficient coal-fired power plants (46-47%) and the most efficient gas-fired power plants lies around 50 €/tCO₂, as can be seen in Figure A.3c. With this price, the old coal-fired power plants become more expensive than many gas-fired power plants, whereas the new coal-fired power plants, which went in operation in 2015 and 2016, remain base load. This only changes when prices are increased to 75 €/tCO₂ (Figure A.3d). Hence, stating one CO₂ price that is needed for a shift from coal to gas is too simplistic; it is depending on the entire generating mix, and the relative age of the different facilities.

This varies from country to country, providing a strong argument for national policies for CO₂ taxes on top of the European level policies. Furthermore, this shows that even high CO₂ prices are not able to push all coal-fired power plants out of the merit order, despite their higher emissions. Either very high CO₂ prices (from 100 euro per tonne), or additional measures are needed if policy makers decide these emissions should be decreased.

A.4 Concluding remarks

In this chapter, we presented a method for designing marginal emission profiles for a specific country based on its generation merit order and applied this for the case study of the Netherlands. The value of this approach can be understood from two perspectives. From a bottom-up perspective, consumers may reconsider the scheduling of their electricity demand. The operation of shiftable loads, such as EVs, wet appliances and stationary storage devices can be scheduled considering the minimization of CO₂ emissions, in addition to cost, if the demand can be shifted to periods with cleaner periods. This can be from coal to gas in the nearby future, but also in a more distant future from periods with fossil-fuel based power plants operating at the margin to periods where renewables are operating at the margin. From a top-down perspective, the approach might help to better determine the impact of implementing renewables in the generation mix, and for determining adequate CO₂ prices to enforce a shift from coal to gas.

Table A.1: Overview and characteristics of all thermal power plants in the Netherlands, using a CO₂ price of 7 €/t CO₂.

Facility Name	Main fuel	Installed capacity (MW)	In Operation	Decommissioned	Efficiency	Marginal costs (€/MWh)	Marginal emissions (kg CO ₂ /MWh)	Source
Centrale Maasvlakte	Coal	1.070	2016		47.0%	27.0	728	[322]
Eemshaven-centrale	Coal	1.560	2015		46.0%	27.5	743	[322]
Engie Centrale Rotterdam 11	Coal	730	2015		46.0%	27.5	743	[322]
Amer Bio WKC	Coal	600	1994		40.0%	31.2	852	[322]

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Centrale Hemweg	Coal	630	1994	2020	40.0%	31.2	852	[322]
Maasvlakte-2	Coal	520	1974	2017	39.0%	31.9	874	[322]
Maasvlakte-1	Coal	520	1973	2017	38.0%	32.7	897	[322]
Gelderland-13	Coal	602	1982	2015	38.0%	32.7	897	[322]
Amer-8	Coal	645	1981	2016	37.0%	33.5	921	[322]
Diemen-34	Gas	435	2012		59.0%	43.9	345	[323]
Centrale Hemweg (gas)	Gas	435	2012		59.0%	43.9	345	[323]
Sloecentrale-10	Gas	432	2010		58.7%	44.1	347	[324]
Sloecentrale-20	Gas	432	2010		58.7%	44.1	347	[324]
Maxima-centrale FL5	Gas	439	2010		58.5%	44.3	348	[325]
Maxima-centrale FL4	Gas	438	2010		58.5%	44.3	348	[325]
Magnum Eemshaven 10	Gas	440	2013		58.0%	44.6	351	[323]
Magnum Eemshaven 20	Gas	440	2013		58.0%	44.6	351	[323]
Magnum Eemshaven 30	Gas	440	2013		58.0%	44.6	351	[323]
Moerdijk-2	Gas	426	2014		58.0%	44.6	351	[326]
Enecogen	Gas	870	2011		58.0%	44.6	351	[325]
Maasstroom Energie	Gas	427	2010		58.0%	44.6	351	[327]
Maasbracht-C (Claus)	Gas	1.275	2012	2014 ¹	56.0%	46.2	364	[328]
Rijnmond Energie	Gas	820	2004		56.0%	46.2	364	[329]
Pergen-1	Gas	260	2007		56.0%	46.2	364	[330]

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A. ON THE USE OF AVERAGE VERSUS MARGINAL EMISSION FACTORS

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Eemscentrale EC4	Gas	341	1996		55.0%	47.0	370	[331]
Eemscentrale EC5	Gas	341	1996		55.0%	47.0	370	[331]
Eemscentrale EC6	Gas	341	1997		55.0%	47.0	370	[331]
Eemscentrale EC7	Gas	341	1997		55.0%	47.0	370	[331]
Eemscentrale EC3	Gas	341	1996		53.0%	48.7	384	[331]
Energiecentrale Den Haag	Gas	95	1906		52.0%	49.6	392	[332]
Diemen-33	Gas	266	1995		51.0%	50.6	400	[333]
Lage Weide	Gas	248	1996		45.0%	57.2	453	[334]
Eemscentrale EC2o	Gas	695	1978		45.0%	57.2	453	[331]
Merwede-12	Gas	225	1990		45.0%	57.2	453	[334]
Centrale Bergum CB1o ²	Gas	332	1975		43.0%	59.8	474	[329]
Centrale Bergum CB2o ^h	Gas	332	1976		43.0%	59.8	474	[329]
Centrale RoCa ^h	Gas	220	1997		42.0%	61.2	485	[329]
Centrale Swentibold ^h	Gas	230	2000		42.0%	61.2	485	[329]
Merwede-11 ^h	Gas	103	1985		41.0%	62.6	497	[329]
Velsen-24	BF- Gas ³	459	1975		35.0%	74.2	728	[329]

² Estimation based on average similar plants

³ Blast furnace gas mixed with natural gas. Based on emission factor natural gas times 1.25 (Afman and Wielders, 2014)

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About the author

Wouter Schram was born in Zoetermeer, the Netherlands, on 12 October 1988. He obtained a Bachelor of Science degree in Psychology at the University of Groningen in 2012. Also, he studied Science & Innovation Management at Utrecht University, from which he graduated in 2013. In the same year, he started the master program Energy Science at Utrecht University. He did his internship at Ecofys in Berlin on science-based benchmarking of the EU Emissions Trading System. In a consultancy project executed for GDF Suez (now Engie), he started to focus on batteries as a possible commercial product in case of net metering abolishment. He wrote his master thesis entitled *Batteries - the missing piece?* on this matter as well.

After obtaining his Master of Science degree in 2015, Wouter started a PhD at the Copernicus Institute of Sustainable Development in 2016. In his PhD, he investigated the coupling of photovoltaics with batteries (standalone batteries as well as electric vehicle batteries). He was situated as a guest researcher at the Austrian Institute of Technology in Vienna in the second half of 2018. He gave oral presentations at three international conferences, was main author of three peer-reviewed journal publications and two peer-reviewed conference publications, as well as co-author of five journal publications and three conference publications. After his PhD, he will stay active as a researcher at the Copernicus Institute, switching his focus toward regional energy transition strategies.

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