Doctoral theses at NTNU, 2024:231

Kjersti Berg

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Member benefits and grid impact under various regulatory frameworks

NTNU
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Doctoral thesis
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ISBN 978-82-326-8054-2 (printed ver.)
ISBN 978-82-326-8053-5 (electronic ver.)
ISSN 1503-8181 (printed ver.)
ISSN 2703-8084 (electronic ver.)

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PRINTED IN
NORWAY
NO - 1598

NORDIC SWAN ECOLABEL
Printed matter
2041 0731

Printed by Skipnes Kommunikasjon AS

Preface

The presented research was carried out at the Department of Electric Power Engineering in the Electricity Markets and Systems Planning group at the Norwegian University of Science and Technology (NTNU). The main supervisor was Hossein Farahmand. Magnus Korpås (NTNU) and Merkebu Zenebe Degefa (SINTEF Energy Research) were co-supervisors.

The research was conducted between June 2021 and March 2024, mainly situated in Trondheim, Norway. I also had a three-month research stay during spring 2023 at Universitat Politècnica de Catalunya (UPC), Barcelona, Spain. The work has been done within the research project FINE (Flexible Integration of Local Energy Communities into the Norwegian Electricity Distribution grid), which is associated with FME CINELDI. The aim of the FINE project is to investigate how local energy communities can be flexibly integrated into the Norwegian power grid [1].

This thesis is a paper-collection, consisting of published or submitted conference and journal articles. The thesis provides a context for the different works, summarises the articles, and presents the main conclusions.

Acknowledgements

Doing research is both rewarding and challenging. It is amazing to be able to invest all your time into a topic that you find interesting, constantly learning and developing. But it can also be hard to pave the way for a PhD and find a direction for your research. In those moments, it is crucial to have good friends and colleagues around you, and I am happy to say that I have plenty of those.

First, I wish to thank my supervisor Hossein Farahmand for guiding me and my research, and for our talks on other life aspects as well. I would also like to thank my co-supervisors, Magnus Korpås and Merkebu Z. Degefa, for valuable discussions and for being available when needed. It has been very valuable to do my PhD work within a research project, ensuring that the work performed is relevant to others. I especially want to thank Henning Taxt, the FINE project manager, for your support throughout this journey.

I have been lucky to collaborate closely with many other talented researchers along the way: Alejandro Hernandez-Matheus, Eduard Bullich-Massagué, Henning Taxt, Ida Fuchs, Karen Byskov Lindberg, Markus Löschenbrand, Marthe Fogstad Dynge, Mònica Aragüés-Peñalba, Rubi Rana, Sigurd Bjarghov, Sverre Stefanussen Foslie and Vemund H. Lenes. Thank you all for enlightening discussions, feedback, and sharing your knowledge with me. I also want to thank the EMESP group, as well as other colleagues I've met at lunch or playing football, for great discussions and a great work environment. You all inspire me to do better research! A special mention to the corner offices, and especially my office mates Aurora Foslie Flataker, Sigurd Bjarghov and Mari Haugen. I also had a great time at UPC, where I want to thank Alejandro Hernandez-Matheus for being a supportive colleague and friend. Writing this thesis was a lot easier with feedback from Sverre Stefanussen Foslie, Marthe Fogstad Dynge and Sigurd Bjarghov, and the use of Christian Øyn Naversen's thesis template. Thank you all! Finally, I want to thank my colleagues at SINTEF Energy Research for valuable discussions and support, and for providing me with a workplace when my office was not waterproof.

When doing research, the brain does not switch off when you leave work. You carry your work around with you while cooking dinner, hiking, having a beer or playing football. I am grateful to have lovely friends and family that help me take my mind off work and always support me. Thank you all for being there for me. Finally, I want to thank Krister for the unwavering support and love I get every day. I feel very lucky to have you in my life.

Summary

Due to global warming, there is a need to electrify fossil fuel processes and increase the amount of renewable energy. A way to include citizens in this green shift is by making it easier to invest in renewable technology and share electricity locally. This can be done through the formation of energy communities, whose purpose is to provide environmental, economic or social community benefits for its members or to the local area. Energy communities can therefore have different goals, such as cost savings, CO_2 emission reduction or increased locally produced renewable energy.

Although energy communities might prove to bring economic and social benefits for the members, it is not clear how they will impact the distribution grid where they are located. The distribution grid is a crucial part of reaching our climate goals, since we need more electrification and distributed renewable energy production. Furthermore, the regulation for energy communities has not yet been fully developed in European countries. To ensure that the new regulations give the right incentives and do not induce stress on the grid, there is a need to investigate how the energy communities impact it. Proposed regulatory frameworks such as collective self-consumption or local collective grid tariffs might reduce the costs for the members but could potentially increase system costs.

The aim of this thesis is to investigate the member benefits of forming local energy communities, and how they will impact the distribution grid, under various regulatory frameworks. This is done by formulating optimisation models for minimising energy community costs when subject to different price signals. Further, how different cases impact the grid, particularly the peak demand, is investigated. The optimisation models in this research cover both operation and investment problems for various technologies present in the energy community — PV generation, battery storage, thermal storage and shiftable loads; various members – residential, commercial and industrial; volumetric and capacity-based grid tariffs; and two regulatory frameworks — local collective grid tariff and collective self-consumption.

The findings of this PhD research give valuable insights for different stakeholders, which can further be used to develop country-specific regulations for energy communities. The regulator can observe how local collective grid tariffs and collective self-consumption impact the peak load of energy communities and how this relates to cost reduction under different grid tariffs. The most interesting finding, in that sense, is that capacity-based grid tariffs do not always lead to peak demand reduction. Members of energy communities, or other end-users considering forming them, can observe that battery energy storage systems are for the most part too expensive and that thermal energy storage should be prioritised if cost reduction is the most important motivation, and a part of the demand

is thermal. Although expensive, battery systems can be valuable if the energy community wants to reduce CO_2 emissions and increase self-consumption. Smart control of shiftable loads such as domestic hot water tanks and space heating are also flexibility resources that should be investigated before investing in battery energy storage systems. Distribution system operators and regulators should note that local collective grid tariffs can be an effective tool to reduce peak demand in the grid if combined with a capacity-based grid tariff. Energy communities are a flexible resource that can both create and solve problems in the grid, depending on which assets are present and which price signals they respond to. On a larger scale, the increased knowledge about energy communities can contribute to facilitating the integration of renewable energy resources and electrification as a means to reach our climate goals in a socio-economic way.

Contents

1 Introduction

This chapter first provides a motivation for the PhD project. Next, the research gaps addressed in the work are elaborated, followed by a presentation of the research questions and the scope of the work. Subsequently, the publications that constitute the thesis are listed along with publications that have been published through the PhD research but are excluded from the thesis. Finally, the outline of the thesis is presented.

1.1 Motivation

Due to global warming, there is a need to electrify fossil fuel processes and increase the amount of renewable energy. A way to include citizens in this green shift is by making it easier to invest in renewable technology and share electricity locally. This can be done through the formation of energy communities, whose purpose is to provide environmental, economic or social community benefits for its members or the local area [2,3]. Energy communities can therefore have different goals, such as cost savings, CO_2 emission reduction or increased locally produced renewable energy [4].

Since energy communities mostly consist of end-users, they will for the most part be situated in the distribution grid. The distribution grid is a crucial part in reaching our climate goals, since we need more electrification and distributed renewable energy production [5,6]. The grid is, however, already at its capacity limit in many places due to intensive electrification [7]. Increased electrification and distributed energy resources such as photovoltaic (PV) generation may lead to several problems in the grid, such as increased losses, congestion, breaches of voltage limits and power quality problems [8–12]. Upgrading the grid is costly and takes a long time; therefore, it is important to reduce the stress on the grid as much as possible. Energy communities might, in the worst case, incur extra costs on the system [13], for instance, by increasing peak demand [14].

Energy communities are also a potential resource in the grid, since it is a way of organising several customers with flexible resources [15]. If the community has a community manager, this would also lead to the distribution system operator (DSO) only having one actor to communicate with. Aggregating and organising flexible resources in the distribution grid can help relieve the grid of capacity or voltage problems [16,17], which again can defer grid upgrades that take long to execute [18].

Regulatory frameworks for energy communities encompass a set of guidelines and policies designed to govern the establishment, operation, and interaction of collective energy initiatives. They are, however, not in place in most European countries. To ensure that the new regulations on energy communities give the right incentives, there is a need to investigate how they impact the grid. Each EU member country is responsible for forming a regulation of energy communities. Several countries have started with collective self-consumption schemes, and other countries are investigating local grid tariffs [19]. To ensure a good future regulation of energy communities, different cases must be analysed. This will shed light on how the framework can reward energy community operation that does not impose new challenges on the grid, or even relieves the grid of problems.

1.2 Research gaps

There are two main gaps that this research aims to address. The first is related to energy community modelling. Most energy community studies have focused on households and not included other members such as commercial buildings or industrial consumers [20, 21]. Energy communities can consist of several customer types, which is important to consider both in terms of member benefits and grid impact. The distribution of economic benefits among members is also a topic that requires further investigation [20]. Furthermore, most research on energy communities focuses on PV and battery systems [20]. Although the costs of battery systems are decreasing, they are still expensive and might not be profitable to invest in. It is therefore crucial also to investigate other flexibility assets, such as thermal energy storage and shiftable loads. Many studies also neglect cyclic battery degradation when modelling battery systems in optimisation models [4], leading to aggressive battery charging and discharging when responding to price signals. Such operation of the battery system might lead to severe ageing, reducing its lifetime significantly [22]. This is not necessarily captured in simple models, which restrict upper and lower limits of state-of-charge, thus, more detailed models for cyclic battery degradation should be considered when including batteries in optimisation models.

Depending on the country investigated, energy communities will also have very different characteristics, in terms of solar irradiance, load profiles, spot prices and CO_2 emissions. Many energy community studies are performed for countries that already have a significant number of communities [20]. There is, however, still a need to investigate various countries in order to give valuable input on how the regulation of energy communities can lead to different results depending on the country.

The second research gap is related to the distribution grid impact of energy communities. Until now, most research on energy communities has focused on societal participation in a community and benefits for members through reduced costs. Thus, the grid impact has been neglected [4], and studies on the synergies between energy communities and grid services are limited [20]. Although energy communities might bring economic and social benefits for their members, it is not known how they will impact the distribution grids where they are located. Energy communities can potentially collaborate with the DSO, but not many studies have investigated this topic [4]. Community storage might be a valuable asset in distribution grids with voltage problems [23], but there is a need to understand how much the DSO should remunerate the energy community for providing such a service, since it leads to non-optimal battery operation.

When optimising energy community operation with the objective to minimise costs, all price signals play an important part. Hence, the assumptions made regarding regulatory frameworks will heavily impact the results. Given that the regulation is in many countries immature [24], it is important to investigate proposed regulatory frameworks in order to understand how, i.e., grid tariffs, virtual metering and collective tariffs change the operation of flexible assets, and thereby the impact on the distribution grid. Also, since forming energy communities often leads to cost savings for the members, it should be clear what these cost savings stem from in order to understand whether they come from a reduction in wholesale market costs, taxes or grid tariff costs.

1.3 Research questions

This PhD work addresses the research gaps within the topic of interaction between local energy communities and distribution grids. The main aim is to investigate the member benefits of forming local energy communities, and how they will impact the distribution grid under various regulatory frameworks. This is achieved by answering three main research questions:

RQ1 What are the member benefits of forming energy communities?

- a How are operational costs, self-consumption and CO_2 emissions impacted by PV generation, flexible assets and members in the energy community across different regions?
- b What is the economic feasibility of an energy community investing in batteries and thermal storage, and how do these energy storage systems interact?
- c What is the impact of including cyclic battery degradation in energy community optimisation?
- d How can costs be distributed between members in an energy community?

RQ2 How will energy communities impact the distribution grid?

- a How is the grid exchange impacted by PV generation, flexible resources and members in the energy community across different regions?
- b Does a capacity-based grid tariff always lead to a lower peak demand, compared to the volumetric grid tariff? What is the largest impact on cost savings?
- c How can energy communities cooperate with the DSO to solve voltage problems, and how much should the energy community be remunerated for this service?

RQ3 What are the benefits and challenges of local collective grid tariffs and collective self-consumption as regulatory frameworks?

1.4 Scope of research

The optimisation models described in this thesis aim to optimise energy community operation and investment, and therefore distribution grid planning is considered out of the scope. The optimisation models are deterministic and assume perfect foresight, and sensitivity analyses have been performed to investigate the uncertainty of the results. All cases are run for one year, to quantify annual costs and grid exchange. This makes it possible to investigate the seasonal variations of PV generation and load, which is quite significant in Norway. The data used in the case studies are of hourly resolution, leading to hourly results from the optimisation models, and more dynamic results for, i.e., energy storage operation being out of scope.

Since this PhD work is a part of the FINE project, which aims to investigate the integration of local energy communities in Norway, the data used are mainly for Norwegian case studies. Two case studies are based on real measurements from customers: a housing cooperation and an industrial consumer. One case study in Spain is also included to investigate how different geographical areas, with other conditions for spot market prices, solar irradiance and load profiles, impact the results. All case studies have focused on *local* energy communities, with a limited geographical span, to be able to quantify the impact they might have on the distribution grid.

Grid tariffs are the charges imposed by the DSO for using the electrical grid, and they play a crucial role in shaping the economic viability of energy communities. In this work, both volumetric and capacity-based tariffs are used. The volumetric tariff used in this work is flat, or depends on the season and hour of the day. The capacity-based tariff[1] used in this work is based on the measured monthly peak and is either stepwise or linear.

In this work, optimisation is for the most part assumed to be collaborative, meaning that the optimisation is solved centrally, and a community manager is envisioned to optimise the use of common assets. When a local collective grid tariff is assumed, all members collaborate to reach the best outcome for the energy community as a whole, and the costs will be redistributed among the members afterwards. Local electricity markets, peer-to-peer trading and game theory have not been investigated in this work.

1.5 List of publications

The following papers constitute this thesis and can be found in the appendix.

I. A. Hernandez-Matheus, M. Löschenbrand, K. Berg, I. Fuchs, M. Aragüés-Peñalba, E. Bullich-Massagué, and A. Sumper, “A systematic review of machine learning techniques related to local energy communities,” *Renewable and Sustainable Energy Reviews*, vol. 170, p. 112651, Dec. 2022. `http://dx.doi.org/10.1016/j.rser.2022.112651`

II. K. Berg, S. Bjarghov, R. Rana, and H. Farahmand, “The impact of degradation on the investment and operation of a community battery for multiple services,” in *2022 18th International Conference on the European Energy Market (EEM)*, Sep. 2022, pp. 1–8. `http://dx.doi.org/10.1109/EEM54602.2022.9921037`

III. K. Berg, R. Rana, H. Taxt, and M. F. Dynge, “Economic assessment and grid impact of different sharing keys in collective self-consumption,” **Submitted**

[1] Also called demand charges or measured capacity

to conference.

IV. K. Berg, V. H. Lenes, and K. B. Lindberg, "Optimal control of domestic hot water tanks in a housing cooperative - benefits for the grid," in *2023 IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*, Oct. 2023, pp. 1–5. `http://dx.doi.org/10.1109/ISGTEUROPE56780.2023.10407406`

V. K. Berg, S. S. Foslie, and H. Farahmand, "Industrial energy communities: Energy storage investment, grid impact and cost distribution," **Under review**.

VI. K. Berg, A. Hernandez-Matheus, M. Aragüés Peñalba, E. Bullich-Massagué, and H. Farahmand, "Load configuration impact on energy community and distribution grid: Quantifying costs, emissions and grid exchange," *Applied Energy*, vol. 363, p. 123060, Jun. 2024. `http://dx.doi.org/10.1016/j.apenergy.2024.123060`

VII. K. Berg, R. Rana, and H. Farahmand, "Quantifying the benefits of shared battery in a DSO-energy community cooperation," *Applied Energy*, vol. 343, p. 121105, Aug. 2023. `http://dx.doi.org/10.1016/j.apenergy.2023.121105`

The following papers have been published during the PhD, but are not included in the thesis due to minor contributions or their being outside the scope of the thesis:

- R. Rana, K. Berg, M. Z. Degefa, and M. Löschenbrand, "Modelling and simulation approaches for local energy community integrated distribution networks," *IEEE Access*, vol. 10, pp. 3775–3789, Jan. 2022. `http://dx.doi.org/10.1109/ACCESS.2022.3140237`
- K. Berg and M. Löschenbrand, "A data set of a Norwegian energy community," *Data in Brief*, vol. 40, p. 107683, Feb. 2022. `http://dx.doi.org/10.1016/j.dib.2021.107683`
- M. F. Dynge, K. Berg, S. Bjarghov, and Ü. Cali, "Local electricity market pricing mechanisms' impact on welfare distribution, privacy and transparency," *Applied Energy*, vol. 341, p. 121112, Jul. 2023. `http://dx.doi.org/10.1016/j.apenergy.2023.121112`
- A. Hernandez-Matheus, K. Berg, V. Gadelha, M. Aragüés-Peñalba, E. Bullich-Massagué, and S. Galceran-Arellano, "Congestion forecast framework based on probabilistic power flow and machine learning for smart distribution grids," *International Journal of Electrical Power & Energy Systems*, vol. 156, p. 109695, Feb. 2024. `http://dx.doi.org/10.1016/j.ijepes.2023.109695`

1.6 Structure of thesis

This thesis is structured as follows. Chapter 2 provides a background for local energy communities in the distribution grid. Chapter 3 describes the papers that constitute the thesis, and their contributions with regard to the research questions. Finally, Chapter 4 gives concluding remarks and suggestions for future work. All publications are printed at the end of the thesis.

2 Background

Before investigating the research questions, a background on energy communities and their impact on the distribution grid is given in this chapter. First, the concept of local energy communities is presented to give context to the benefits that the members may receive from participating. Next, to understand the impact local energy communities might have on the distribution grid, various regulatory frameworks are presented along with an explanation of the DSO's need for flexibility.

2.1 Local energy communities

This section first provides the European definitions for energy communities. Next, the current status of energy communities is given, highlighting the members and assets that are typically present, and the motivation for members to form energy communities. Finally, the general approach for the energy community optimisation models is presented.

2.1.1 Energy community definitions

The EU has issued two directives with official definitions for energy communities: 'Renewable Energy Community' (REC) [2] and 'Citizen Energy Community' (CEC) [3]. These definitions are listed in Table 2.1. Member states must revise national laws to comply with the EU rules, and therefore, they must develop national-level definitions for citizen and renewable energy communities. The differences between the two definitions were investigated in [25], where the authors highlighted that renewable energy communities have certain characteristics that are not present in citizen energy communities, such as a specific geographical scope owing to the required proximity to renewable energy projects. Also, unlike the renewable energy community, a citizen energy community is technology-neutral and can therefore incorporate both renewable and conventional sources of electrical energy. In the general discussion, however, there is little or no differentiation made between the two definitions, where the term *energy communities* is mostly used [17, 26].

A uniform definition of an energy community does not exist in the literature, and it is up to each member country to define their own national laws from the EU directives. An energy community can therefore mean different things, depending on the context and country. The term *local* energy community is not used in any directive, but is mostly used to highlight an emphasis on the geographical limitation of the community.

Table 2.1: Comparison of definitions of Renewable and Citizen energy community

Topic	Renewable energy community [2]	Citizen energy community [3]
Participation, control and members	"which, in accordance with the applicable national law, is based on open and voluntary participation, is autonomous, and is effectively controlled by shareholders or members that are located in the proximity of the renewable energy projects that are owned and developed by that legal entity"	"is based on voluntary and open participation and is effectively controlled by members or shareholders that are natural persons, local authorities, including municipalities, or small enterprises"
	"the shareholders or members of which are natural persons, SMEs [small and medium-sized enterprises] or local authorities, including municipalities"	"may engage in generation, including from renewable sources, distribution, supply, consumption, aggregation, energy storage, energy efficiency services or charging services for electric vehicles or provide other energy services to its members or shareholders"
Purpose	"the primary purpose of which is to provide environmental, economic or social community benefits for its shareholders or members or for the local areas where it operates, rather than financial profits"	"has for its primary purpose to provide environmental, economic, or social community benefits to its members or shareholders or to the local areas where it operates rather than to generate financial profits"

2.1.2 Current status: members and assets

As seen in the energy community definitions, members can be natural persons, small and medium-sized enterprises or local authorities. This comprises, i.e., single houses, apartment blocks, municipality buildings, smaller industry facilities or commercial buildings. Therefore, the members will have different electricity consumption, investment capabilities and goals. Furthermore, different energy generation and storage assets are used in different countries, as reported by [27]. In Austria, Switzerland and Italy, hydropower plants and biomass district heating plants are common, while Sweden and Finland have many energy communities with biomass district heating. Most of Germany, Spain and France use solar energy. Wind energy is also commonly used in the Netherlands and Denmark. The authors of [27] also found that the technology in the energy community is connected with the size of the community: i.e., biomass/biogas district heating communities and wind communities require larger investments, and therefore also have more members. In [25], solar and wind technology were found to be the most commonly used in energy community projects, followed by biomass and biogas.

Research has for the most part focused on PV and battery systems, while wind, electric vehicles and biomass are rarely considered [20]. Costs of both PV systems and batteries have declined significantly over the last years, and lithium-ion battery costs are projected to keep declining until 2030 [28]. Lithium-ion batteries can, however, age quickly due to cyclic degradation, and therefore the operation of the batteries will affect the lifetime and costs [29]. In addition to energy storage, smart control of loads is also an important flexibility resource in energy communities [30]. Shifting existing loads can be more economic than investing in new technology such as energy storage, although it does require a home energy management system. Examples of shiftable/flexible loads at the residential level are space heating, domestic hot water tanks or heating, ventilation and air conditioning systems [15]. The residential load is, however, highly stochastic, as it depends on the behaviour and habits of the residents. Industrial and commercial consumers might have more predictable load, and more to gain from shifting loads with high peaks. It is, however, often important that their processes are not interfered with, as this could cause them to lose profit. Industrial consumers with thermal processes may also benefit from investing in thermal energy storage as a flexible resource.

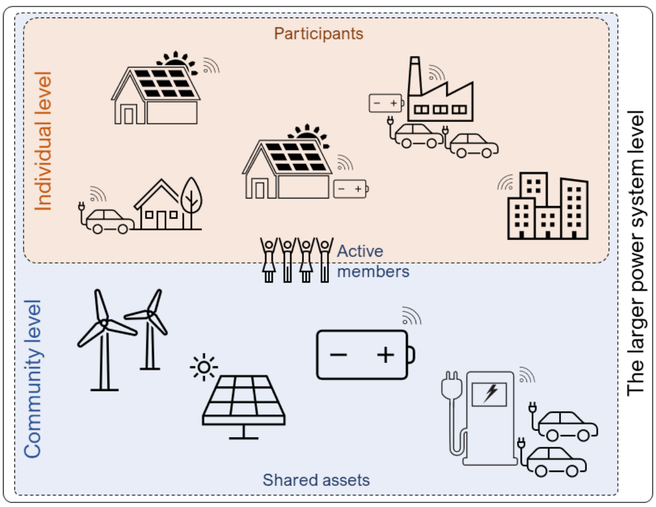


Figure 2.1: Visualisation of a local energy community, from [31].

An important part of energy communities are the shared assets. On the community level, members can jointly invest in shared generation such as PV panels and wind turbines, or flexible loads like shared electric vehicle chargers. Energy storage, such as battery energy storage systems or thermal storage systems, can be used to, for instance, increase the self-consumption of locally produced electricity [14].

Joint investments are more economical due to economies of scale [28, 32], and several studies have shown that community batteries are more economic than individual batteries placed at each member's location [23, 33, 34]. In addition to these shared assets, each member might have invested in individual assets such as electric vehicles, rooftop PV generation, energy storages or home energy management systems for shiftable loads. Figure 2.1 shows a visualisation of a local energy community, with an individual level and a community level, situated in the larger power system.

Ref. [27] found that there are nearly 4,000 energy communities in Europe today. They can take any form of legal entity, where the majority are cooperatives, community interest companies[1] or non-profit organisations [27]. An energy community can be structured in many ways, being controlled centrally or distributed, operating assets collaboratively or through local electricity markets [20, 36]. Depending on the structure, other stakeholders can be aggregators, supervisors, community managers, local market operators, etc. [20]. Figure 2.2 shows an illustration of a collaborative energy community that is optimised centrally, where a community manager controls the shared assets and distributes the costs and savings between the members.

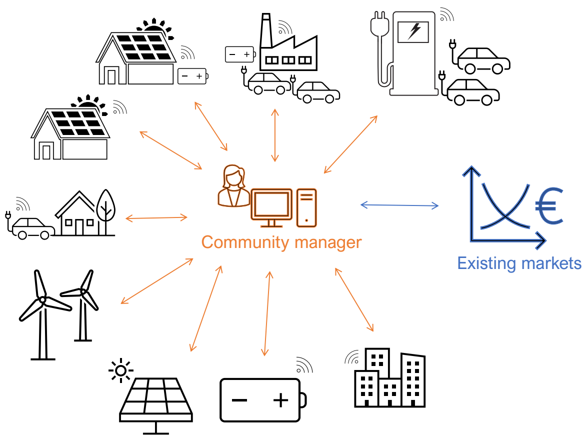


Figure 2.2: Central optimisation of collaborative energy community with a community manager, from [37].

The motivation of the members to create an energy community can vary. It can, for instance, be to reduce costs, increase the self-consumption of local production or reduce CO_2 emissions from consumed electricity [4, 20]. The review of energy community projects in [25] showed that the most common drive was the motivation to invest in renewable energy, and that financial motives were important but did

[1]From [35]: "A Community Interest Company (CIC) is a limited company, with special additional features, created for the use of people who want to conduct a business or other activity for community benefit, and not purely for private advantage."

not necessarily exclude other social and environmental motivations. A review of energy communities in the Nordic countries [17] pointed out that the energy mix in a country affects the motives behind joining, since energy communities that form in countries with a high share of renewable energy will contribute less to the energy transition. The goal of the members will affect the investment and operation decisions made by the energy community. I.e., if the goal is to increase self-consumption, a larger energy storage is needed than if the goal is to reduce costs. To reduce costs, it might be more profitable to only install renewable generation, at the drawback of being less self-sufficient in periods of low production.

2.1.3 Modelling of energy community optimisation

In this PhD research, the optimisation problems are modelled from the energy community perspective, with various members and assets in the various papers. This subsection aims to give a short description of the modelling. The general form of the optimisation models used in the work is given in (2.1)-(2.7), where the items in blue indicate that they are not included in all papers.

$$\text{Minimise energy community investment and operational costs} \tag{2.1}$$

$$\text{Such that the following constraints are fulfilled:}$$

$$\text{Energy balance} \tag{2.2}$$

$$\text{Capacity-based grid tariff} \tag{2.3}$$

$$\text{Battery operation} \tag{2.4}$$

$$\text{Battery degradation} \tag{2.5}$$

$$\text{Thermal storage operation} \tag{2.6}$$

$$\text{Load shifting} \tag{2.7}$$

All optimisation models minimise the energy community operational costs over the course of one year. Investment problems include the annualised investment costs of the assets considered. The operational costs comprise wholesale market costs, grid costs (volumetric and/or capacity-based), taxes, battery degradation costs and load shifting discomfort costs. The energy balance always includes grid import, grid export, PV generation and load, and whether energy storage charge/discharge and upwards/downwards load shifting are included depends on the optimisation problem. The grid tariffs are either volumetric or capacity based. The capacity-based tariffs are modelled with constraints that keep track of the monthly highest peak. In some cases, this tariff is stepwise, where binary variables are used to keep track of which step the highest monthly peak falls within. The battery degradation model is a linear model that splits the battery into segments and keeps track of how many segments the battery discharges through [38]. This discharge is multiplied with a degradation cost in the objective function, where the cost increases with the number of segments. The degradation cost is calculated from the future replacement cost and the cycle depth stress function of the battery. The thermal storage systems modelled are hot water tanks, assumed to have perfect stratification, meaning that the tank holds a uniform temperature [39]. The load shifting model is a general model that assumes that a certain percentage of the load can be shifted in each timestep [40]. The energy shifted up and down must be equal throughout the day. It is further assumed that this shifting is associated with a discomfort cost, which is added to the objective function.

2.2 Energy communities' impact on the distribution grid

Energy communities will for the most part be situated in the distribution grid, and their impact on the distribution grid will, in addition to the assets and members, depend on the regulatory framework. This section first gives an overview of regulatory frameworks, before elaborating why energy communities with flexible resources can be potential cooperation partners for the DSO. Finally, the modelling approach for the grid interaction is described.

2.2.1 Regulatory frameworks

The cost optimal decisions for an energy community are heavily dependent on the regulatory framework. The regulatory framework decides how the grid tariffs are designed, whether virtual sharing of electricity is allowed, and how members are metered (individually/aggregated). This again impacts which generation and flexibility assets are economical to invest in, as well as their operation.

Grid tariffs

Grid tariffs are charged to grid users by the DSO to recover the costs of operation and investment in distribution grids. The key principle of grid tariffs is to be cost-reflective, meaning that they should accurately reflect the costs associated with the generation, transmission, and distribution of electricity to the end-consumers. Additionally, regulators should strive for the tariffs to achieve cost recovery, and be non-discriminatory, transparent, predictable and simple [41]. Grid tariffs can be formed in many different ways, but generally often consist of an energy component, a power component and a fixed component [41]. Traditionally, smaller customers have had volumetric grid tariffs because of a lack of metered data, while larger customers such as industries or commercial end-users have had capacity-based grid tariffs [41, 42]. With the roll-out of an advanced metering infrastructure, capacity-based tariffs are also easier to implement for residential consumers. The form and level of household electricity tariffs today differ greatly among different European countries (some have high network charges, while others have high taxes) [43].

In addition to the grid tariff, consumers pay energy costs dependent on the wholesale market and taxes.

Virtual sharing

The core of energy communities is the wish to share electricity, where the focus is often on sharing locally produced electricity. It should, however, be noted that as per the definition of Citizen energy communities, members do not necessarily need to share generation, but can share, i.e., load and energy storage. One way to share electricity is to build physical lines between the customers, and some energy communities can be formed as microgrids, where they build their own grid which they own and operate [44]. This is not allowed in all countries, and depends on the rules on concessions for electricity grids [17]. I.e., in Germany, actors other than DSOs can apply for concessions, and several energy communities manage their own grid [17]. This is, however, expensive, and unnecessary if there already exists a distribution grid that can be used to transfer this electricity. It also requires knowledge and technical competence, something energy community members do not necessarily hold. A more efficient way is to use the collective distribution grid, which is operated and maintained by the DSO [17]. Therefore, *virtual sharing* is the dominant solution in the regulatory frameworks proposed, where sharing of electricity is purely virtual and has no connection to the physical flow. The question remaining is how the energy community should be metered for the use of the distribution grid while sharing electricity virtually.

Current status of regulation

As stated in [24], the European countries have very different regulations on energy communities and collective self-consumption, and the level of maturity of the regulations differ considerably. Figure 2.3 shows three different regulations: business as usual, collective self-consumption and local collective tariff. In the *business as usual* case, renewable energy generation is connected to the grid as a producer. The revenues from selling energy to the wholesale market can then be divided between the members of the community afterwards. To incentivise renewable energy production, and the local consumption of this, several countries have created regulations for *collective self-consumption*. In collective self-consumption, each member receives a virtual generation share from a shared renewable generation asset, and therefore a new virtual demand. This virtual demand can be used to calculate both energy charges and network charges, depending on the regulation. Collective self-consumption is often relevant for consumers/prosumers located in the same building or multi-apartment block [24]. Other countries are investigating local tariffs as a way to create incentives for energy communities. A *local collective tariff* means that the community is considered as one customer, with one metering point[2]. Wholesale purchase and grid exchange is decided from the aggregated import/export in that point. Costs/revenues must be redistributed among members afterwards, for instance, by the use of Shapley value[3] or on the basis of the electricity consumed [46].

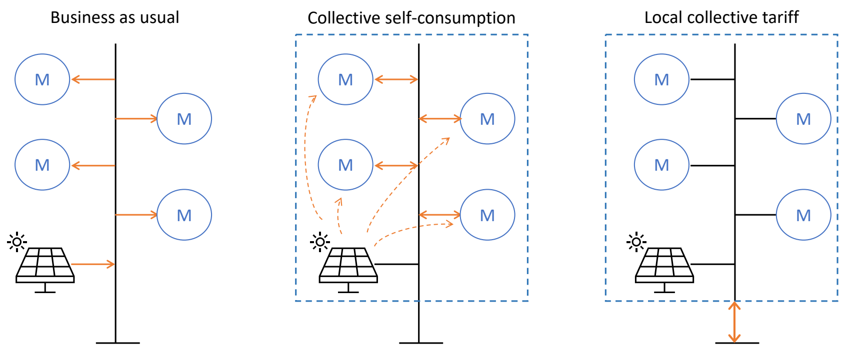


Figure 2.3: Examples of regulatory frameworks for PV generation in an energy community. Orange lines indicate where metering happens, blue dashed lines indicate the members.

The definitions of energy communities do not state a geographical boundary. However, if the energy community is rewarded for reducing local grid impact, it must be limited geographically. Some countries have specified geographical boundaries [19]. For example, in Slovenia, the community is limited to the same low-voltage transformer. In Belgium (Wallonia), local perimeters are used, which are defined on a case-by-case basis. Other states base it on spatial limitations from distances or administrative structures.

An overview of the regulatory status for collective self-consumption and energy communities of European countries is given in [19]. Austria, Belgium (Wallonia) and Italy are developing local tariffs specifically for renewable energy communities. France, Portugal and Spain are allowing collective self-consumption initiatives to

[2]It does not necessarily need to be a physical connection point, as in a microgrid [44].

[3]The Shapley value is a concept from cooperative game theory, where the payoffs are distributed among players in a coalitional game [45].

use the public grid and receive specific tariffs. Ref. [17] investigated regulatory frameworks in the Nordics, and found that in Finland, it is possible to create cross-property energy communities if they are connected to the grid via single connection points. Denmark has investigated local collective tariffing, enabling tariffs tailored by the respective community's contributions to the collective grid [47]. The study resulted in a new regulation, which entered into force in 2023 [17]. In Norway, a collective self-consumption scheme entered into force in October 2023 [48], where customers situated on the same property are allowed to share up to 1 MW of renewable energy production virtually. The Norwegian regulator has also proposed a sharing scheme of up to 5 MW where the generation can be shared virtually with customers situated on the same property or on neighbouring properties, as long as the customer has a tariff that reflects the marginal losses [49].

The goals of an energy community may not necessarily align with what is beneficial for the grid, and in the worst case, the energy community may incur extra costs on the system [13]. Ref. [14] showed that if they are not given proper incentives, they will significantly increase the electricity import from the electricity grid, and thus increase the grid capacity needed. As a general rule, any savings in network charges should reflect a value for the grid [13]. If energy communities receive a reduction in network charges (through, i.e., local collective tariffs), they should at least not impose new challenges on the grid. Since local, collective tariffs aggregate several customers' demands, it is expected that the members will experience a cost decrease from the aggregation of load alone. Ref. [50] therefore argues that such aggregated tariffs should be increased in level to avoid shifting costs over to other customers. Ref. [24] states that the motivation for developing local grid tariffs for energy communities is to ensure a cost-reflective grid tariff where they pay for their actual contribution towards network costs. In Belgium (Wallonia and Flanders), a cost-benefit analysis must be performed that investigates the impact of energy communities on the distribution network, including avoided investments, and based on this, specific tariff reductions may be applied [19]. A key challenge is to balance the cost reduction with the grid impact. As stated in [25]: "[...]the expected benefits of reduced grid fees due to the reduction in power flows from the main grid may only be beneficial for the members of the community. The reason is that such savings may transform into costs for customers elsewhere in the system, meaning that real-cost efficiency for the overall system is not achieved".

2.2.2 Cooperation between energy communities and DSO

The grid is dimensioned for the peak load, which often occurs in winter for countries with low temperatures due to high heating demands [8, 51]. Grid investments in equipment, such as lines and transformers, are costly and ultimately need to be covered by the end-users. In grids where congestions occur in only a few hours over the year, due to high peak loads, utilisation of flexible resources can be a cost-effective alternative, at least to defer the grid investment [30]. Energy communities with flexible resources could therefore be valuable flexibility assets for the DSO [14]. Designing a good regulatory framework might lead to the energy communities reducing peak demand in the grid, implicitly, by responding to the grid tariff price signals. They can also provide flexibility to the DSO explicitly, by direct communication.

As pointed out in [25], energy communities may reduce network losses, reduce or postpone network investments [14], and offer flexibility services and reliability. However, to unlock the flexibility, [52] highlights that "(...) it is a necessary precondition that flexibility is incentivised, for example via network tariffs, and that DSOs are obliged to consider flexibility sources as an alternative to grid expansions." In other words, for energy community flexibility to be utilised in the grid operation, incentives are required for both the energy communities and the DSO.

2.2.3 Modelling of grid interaction

In this PhD research, the grid interaction is either modelled passively, where the energy community only responds to price signals from the wholesale market and grid tariff, or actively, where the DSO collaborates with the community. In the passive interaction, the grid is represented by import and export variables, and the operation of assets depends on the wholesale market price, grid tariffs, taxes and costs of operating assets, if relevant. When the energy community is assumed to have a local, collective grid tariff, all load and generation are summarised and the optimisation model minimises the total, aggregated cost. Under collective self-consumption, on the other hand, each member optimises its costs individually.

Active interaction with the DSO is modelled by including the linear DistFlow equations made for radial distribution grids [53] in the optimisation model. When the community battery is used to improve the voltage, a constraint is added to keep the voltage above a certain limit. The cost difference between an optimal operation of the community battery, and the operation when this voltage constraint is added, is assumed to be the (minimum) remuneration from the DSO to the energy community.

3 Paper contributions and main findings

This chapter provides a summary of all publications, which can be seen in Figure 3.1 together with the research questions. Paper I is left out of the figure, since this is a review article. RQ1 and RQ3 are answered by Papers II-VII, while RQ2 is answered by Papers III-VII. In the following sections, the main contributions from each paper are highlighted before the research questions are answered and discussed.

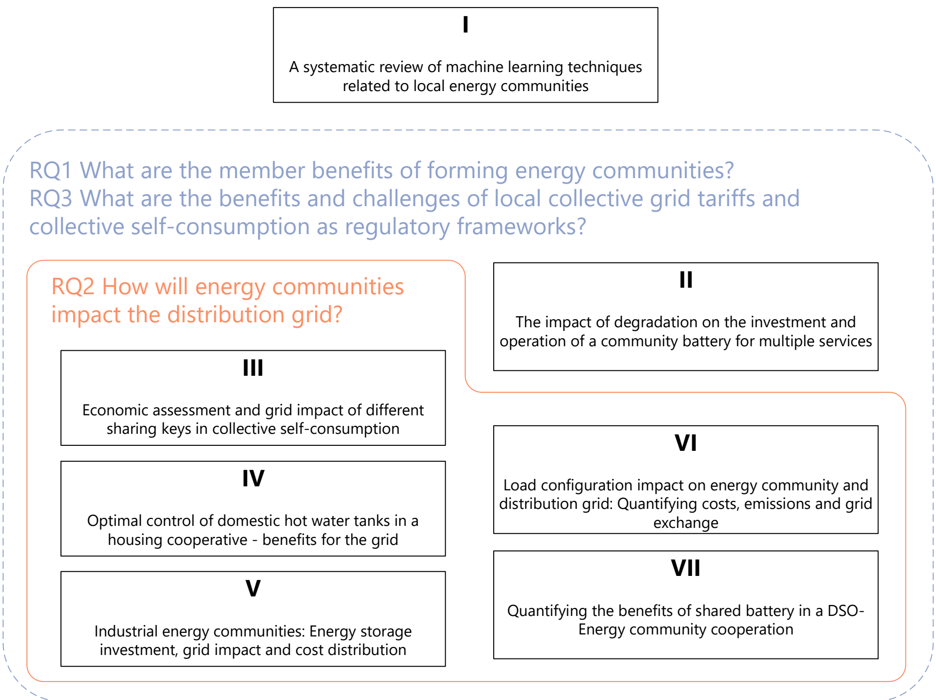


Figure 3.1: Mapping articles and research questions

3.1 Contributions of the papers

Table 3.1 shows an overview of the papers presented in the thesis. The papers differ in terms of optimisation problem type, members in the community, flexible resources in the community, grid tariff and regulatory framework.

Table 3.1: Overview of papers

	Problem		Members			Flexible resource			Grid tariff		Regulatory framework	
Paper	Investment	Operation	Residential	Commercial	Industrial	Battery storage	Thermal storage	Shiftable loads	Volumetric	Capacity	CSC[3]	Local tariff
II	✓		✓			✓				✓		✓
III		✓	✓					✓		✓	✓	
IV		✓	✓[1]				✓			✓		✓
V	✓		✓[2]	✓[2]	✓	✓	✓			✓		✓
VI		✓	✓	✓		✓		✓	✓			✓
VII		✓	✓			✓			✓			✓

[1]Apartment blocks
[2]Urban area with commercial and residential loads
[3]Collective self-consumption

3.1.1 Paper I: A systematic review of machine learning techniques related to local energy communities

Paper I is a literature review of machine learning techniques related to local energy communities. The main contributions of the article are the following:

- Conceptualisation of local energy communities from a European perspective.
- Extensive review of state-of-the-art machine learning literature associated with local energy communities.
- Detailed applications of machine learning methods within local energy communities.
- Evaluation of and the future outlook on machine learning methods utilised in local energy communities.

I contributed to the first part of the paper, where an overview of 25 existing energy community projects was presented. We also presented a definition of a local energy community, highlighting geographical locality, joint ownership of assets, active members, the presence of smart communication to enable interaction between members and community managers, and the possibility of financial transactions between members.

There were large differences in the energy community projects. Certain projects were organised in collectives through citizen engagement, others were registered as companies owned by local citizens. The number of members varied greatly, from three to 56,000 members. The stakeholders consisted of citizens, municipalities, technology providers, DSOs, universities, local businesses, energy generation companies and housing associations. The typical generation technologies in the reviewed projects were PV panels, wind turbines, small-scale hydropower plants, and thermal energy systems for heat production, typically through combined heat and power generation, or geothermal and solar heating. Energy storage for back-up or other grid services was realised through either diesel generators or battery energy storage systems. These assets were observed both at the individual level or as shared assets in the community. The motivation of the projects was to increase renewable energy production, consume renewable energy that was produced locally and increase self-sufficiency.

3.1.2 Paper II: The impact of degradation on the investment and operation of a community battery for multiple services

The aim of **Paper II** was to investigate how battery degradation impacts the investment and operation of a community battery that performs multiple services in an energy community, under two different tariff schemes – volumetric and capacity-based[1]. The main contributions of the work are as follows:

- Optimisation models for investment in and the operation of shared PV generation and battery assets in an energy community, including cyclic degradation cost.
- Evaluation of how battery operation and degradation are impacted by two different grid tariff schemes: volumetric and capacity-based.
- Evaluation of how the battery performs multiple services (self-consumption, peak shaving, energy arbitrage) for the energy community when degradation cost is included.

For this case study, the objective was to find the optimal investment of a shared PV

[1] Called *energy tariff (ET)* and *demand charges (DC)* in the paper.

Table 3.2: Optimisation results

	Volumetric	Volumetric w/ deg.	Capacity	Capacity w/ deg.
Battery capacity [kWh]	6.8	6.8	7.0	7.0
PV capacity [kWp]	25.4	24.9	0	0
Max. import [kWh/h]	35	35	35	35
Max. export [kWh/h]	10.0	8.0	0	0
Lifetime [y][b]	6.3	12.1	6.0	12.2

[b]lifetime is here calculated from the cycle lifetime of the battery, which is 2000 cycles at full discharge [38].

and battery system for an energy community with 10 households, when the energy community had a restriction on grid import. Cases were run for volumetric and capacity-based tariffs, with and without degradation cost included in the objective function. As Table 3.2 shows, the resulting battery sizes were approximately equal for each case, since the main reason for installing the battery was to meet the import restriction. The model did not find it profitable to invest in a PV system when we had a capacity-based grid tariff.

When including degradation cost in the objective function, the battery assessed whether the revenues from the service outweighed the degradation cost of the battery cycle. Under a capacity-based grid tariff, it was profitable to do peak shaving. Under a volumetric grid tariff, the battery gained value mainly through self-consumption and spot price arbitrage when the price was high, despite the degradation costs. The lifetime of the battery was significantly shortened when degradation cost was not included in the objective function, highlighting the need to include cyclic degradation in models that investigate the profitability in investment and operational problems with batteries.

3.1.3 Paper III: Economic assessment and grid impact of different sharing keys in collective self-consumption

The aim of **Paper III** was to investigate how the collective self-consumption (CSC) scheme in Norway will impact the members of the energy community and the distribution grid. The main contributions are as follows:

- Investigation of how the collective self-consumption scheme in Norway, including two static sharing keys, affects the cost distribution in the energy community.
- Quantification of how the collective self-consumption scheme impacts the distribution grid when each member optimises costs with shiftable loads. The

optimisation model includes a general load shifting model and a formulation for a stepwise capacity-based grid tariff.

This case consisted of 423 households with a shared PV system of 1 MWp. Table 3.3 shows the annual costs for all cases. In No CSC-E, there was no collective self-consumption; PV production was assumed to have its own meter and all production was directly fed to the grid. The revenue from feed-in was then divided equally between the members of the energy community. The remaining cases have collective self-consumption, where PV production was virtually subtracted from the load, depending on the sharing key. For an equal key (case E), the total costs were reduced mainly due to a reduction in spot market cost, grid energy cost and taxes. Comparing the two sharing keys, the yearly consumption key (case YC) led to lower spot market costs, taxes and energy revenues. When the households were flexible (case YC-flex), the costs were even lower, since the shiftable loads increased the self-consumption of PV generation for each household, and each household could optimise against spot price and grid tariffs. The total costs were then reduced by 16% compared to the reference case without PV generation, and by 9% compared to the case without collective self-consumption.

Table 3.3: Total operational cost for energy community, split into different cost components [k€]

Cost component	Ref.	No CSC-E	E	YC	YC-flex
Spot market cost	394	394	355	350	339
Grid energy cost	79	79	68	67	66
Taxes	208	208	184	180	177
Energy revenue	0	-66	-23	-17	-14
Grid capacity cost	115	115	113	113	100
Total	796	731	698	693	668

Table 3.4 shows the annual physical grid exchange at the point of common coupling (PCC) of the energy community. The values of cases No CSC-E, E and YC are the same, since the load and PV generation are exactly the same. For these cases, the maximum import remains unchanged compared to the reference case, since the PV generation is low in winter. However, the maximum import increased by 9.6% when the households were flexible (due to each household individually optimising against spot price variations). Comparing this with the reduction in grid related costs, it seems likely that the collective self-consumption scheme, with the stepwise capacity-based grid tariffs, will lead to grid costs being shifted over to end-users outside of the energy community.

Table 3.4: Summary of annual grid exchange and self-consumption rate (SCR) at PCC

Case	Sum imp. [MWh]	Sum exp. [MWh]	Max. imp. [MWh/h]	Max. exp. [MWh/h]	SCR [%]
Ref.	5,065	0	1.35	-	-
No CSC-E, E, YC	4,269	173	1.35	0.51	82
YC-flex	4,240	144	1.48	0.47	85

3.1.4 Paper IV: Optimal control of domestic hot water tanks in a housing cooperative - benefits for the grid

The aim of **Paper IV** was to quantify the benefit that electric domestic hot water tanks can give to a housing cooperative and the distribution grid by optimising the operation of the hot water tanks. We also investigated how a local collective grid tariff[2] will impact the costs for the housing cooperative and the grid exchange. The main contributions are as follows:

- Linear optimisation model for a housing cooperative, with PV generation and electric vehicle charging, including shared thermal energy storage heated by heat pumps and electric heating element.
- Quantification of reduced costs and grid exchange when operating domestic hot water tanks optimally.
- Quantification of the differences in electricity costs and grid exchange when optimising each apartment block in the energy community individually or centrally.

The case studied in the paper is a housing cooperative in Norway, located north-east of Oslo. Housing cooperatives fulfil many of the criteria of being an energy community: they are legal entities that often share costs for investments and maintenance of properties; they often have common assets; and they are controlled by their members. The housing cooperative in this paper consists of six apartment blocks, each with a shared domestic hot water tank for the residents. There is also a common garage with electric vehicle charging and PV generation. The apartment blocks do not have PV generation today, but this was added with simulated data.

The total imported power to the energy community for the three cases can be seen in Figure 3.2, showing a base (B) case with no optimal control of the domestic hot water tanks, individual (I) optimisation of each domestic hot water tank for each

[2] Called *aggregated net metering* in the paper.

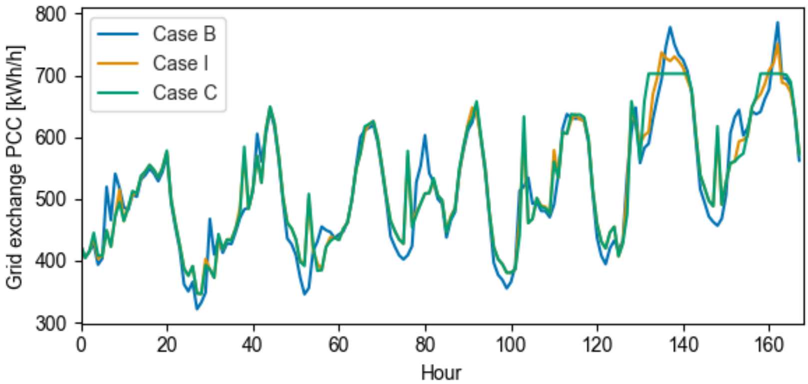


Figure 3.2: Grid import to EC (at PCC) for all cases, week 1

apartment block, and central (C) optimisation of all domestic hot water tanks. Peak import was highest in the base case (786 kWh/h). In Case I, individual optimisation led to a peak import of 751 kWh/h for the energy community, which is a reduction of 4.4% compared to Case B. In Case C, the peak import was lowered to 703 kWh/h, when the energy community optimised all electricity consumption and domestic hot water tanks together, including the electric vehicle charging in the garage. Compared to Case B, this was a reduction in peak import of 10.6%.

The local collective grid tariff led to a 2.6% cost reduction for the energy community, compared to the base case. Sensitivity analysis showed that PV generation had no impact on peak demand, while the capacity-based grid tariff was the main reason for the peak demand reduction.

3.1.5 Paper V: Industrial energy communities: Energy storage investment, grid impact and cost distribution

Paper V investigated the economic viability of an industrial consumer participating in an energy community with local collective tariff[3]. The contributions of this paper are as follows:

- Investigation of a storage investment decision of community electrical and thermal energy storage for an energy community with an industrial consumer and an urban area with PV generation.
- Optimisation model of an industrial consumer participating in an energy

[3]Called *aggregated net metering* in the paper.

community. The case study includes real, hourly measurements for one year from the industrial consumer and the distribution grid.
- Study of the incentives for the industrial consumer to participate in the energy community by assessing equitable methods for distributing costs.

The results showed that in an industrial energy community with thermal demand, thermal storage was the most favourable storage option, due to lower investment costs than a battery system. Furthermore, we found that optimising the storage sizes for the whole energy community led to a cost reduction of 1.8%, while the maximum import was reduced by 5%, compared to the reference case. The optimal thermal storage size when optimising for the energy community was 16% higher than the optimal thermal storage size when optimising for the industrial consumer alone. It was not economically viable to invest in a battery system for either of the cases.

The sensitivity analysis (Figure 3.3) showed that battery system investment costs must decline significantly for it to be a competitive option compared to thermal storage. The model only invested in a battery system when the investment cost was 150 €/kWh or lower. Therefore, in industrial energy communities with thermal demand, these results support the conclusion that thermal storage should be invested in where possible before considering investing in battery systems.

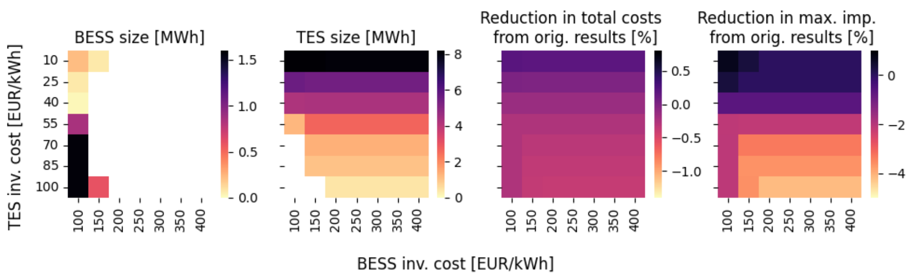


Figure 3.3: Heatmap of battery system (BESS) size, thermal storage (TES) size, reduction in total costs and reduction in maximum import to the energy community as function of thermal storage and battery system investment costs. White colour means no storage investment.

Table 3.5 shows that the cost distribution method heavily impacted whether it was economically attractive for the industry consumer to join the energy community. Originally, the operating costs were 1,030 k€ and 3,009 k€ for the industry consumer and the urban area load, respectively. The costs for the industrial consumer increased if flat energy pricing or non-coincident peak methods were used. Using the coincident peak method, the industry was rewarded for lowering its individual peak (using storage) when the system peak was occurring. The downside was that the urban area experienced increased costs compared to the reference case, since it was not rewarded for what the storage systems were doing as they were placed at the industry consumer's location. Only the Shapley value method reduced costs for both the industrial consumer and the urban area. The drawback of this method is that the cost for the industry consumer and the urban area, if they did not join the energy community, needs to be known, while the other methods only rely on smart meter data.

Table 3.5: Redistribution of operating costs [k€]

Method	Industry	Urban area
Flat energy pricing	1,039	2,929
Coincident peak	513	3,454
Non-coincident peak	1,037	2,931
Shapley value	979	2,989

3.1.6 Paper VI: Load configuration impact on energy community and distribution grid: Quantifying costs, emissions and grid exchange

The aim of **Paper VI** was to investigate the energy community benefits and grid impact for different member configurations. The main contributions of this article are as follows:

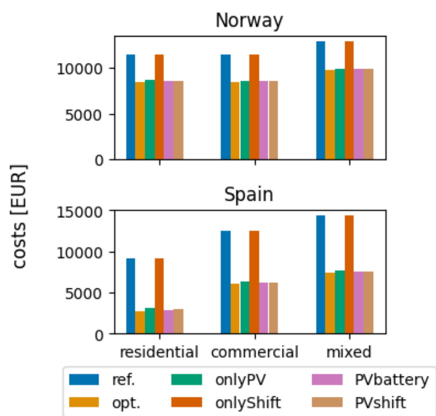
- Investigation of energy communities with three different load configurations: residential, commercial and mixed. Grid impact is quantified through maximum import to and export from the energy community.
- Insight into the use of different flexible resources in the energy community, and the interaction among technologies — PV, community battery, and shiftable loads — by systematically excluding each one from the optimisation.
- Comprehensive comparison of the aforementioned grid impact with the energy community benefits of costs, self-consumption and CO_2 emissions for all load configurations.
- Case studies are run for two countries, Norway and Spain, to gain insight into how the seasonal variations in load and PV generation impact the results.

Table 3.6 shows a summary of the energy community benefits and grid impact for the different load configurations, where each result is given a score of low, medium or high depending on the percentage change from the reference case. As the table clearly shows, the Spanish energy communities have a much better outcome in terms of cost reduction, emissions reduction and grid impact. Residential energy communities had a superior outcome in terms of cost reduction and emissions

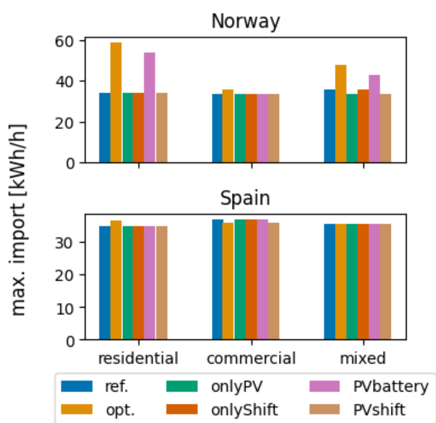
Table 3.6: Summary of optimisation results per load configuration

	Energy community benefit			Grid benefit	
Norway	SCR	Cost	Emissions	Max. export	Max. import
Residential	Low	Low	Low	Low	Low
Commercial	High	Low	Low	Medium	Medium
Mixed	Medium	Low	Low	Medium	Low
Spain	SCR	Cost	Emissions	Max. export	Max. import
Residential	Low	High	High	Low	Medium
Commercial	High	Medium	Medium	Medium	High
Mixed	High	Medium	Medium	High	High

reduction. In Norway, the commercial load configuration obtains the best result, both in terms of energy community benefit and grid impact. This is mainly due to a high self-consumption rate, and relatively low grid impact. The Norwegian residential and mixed energy community led to higher maximum import because of battery charging. Residential loads were the least grid-friendly for both countries, due to a lower correlation between load and PV generation than the other load configurations.



(a) Total operating cost.



(b) Maximum import.

Figure 3.4: Comparison for all cases, where technologies have been systematically excluded (i.e., case PVbattery does not include load shifting).

PV generation was the main driver for reducing costs for both countries and all load configurations (see Figure 3.4a). The flexibility resources, shiftable loads and battery system, only led to a marginal further reduction of costs when combined with PV generation. Considering the high investment cost of battery system technologies, these results indicate that the operational cost reduction achieved through batteries is not significant enough to justify their adoption within the energy community, if the motivation is to reduce costs. Appendix A shows additional plots of the sensitivity analysis, which were not included in the paper. The figures show that the residential loads had the highest maximum export and the lowest self-consumption rate for all technology combinations. Figure 3.4b shows the maximum import when excluding technologies. We see that batteries heavily increase the maximum import in residential and mixed Norwegian energy communities. This impact cannot be seen for the Spanish energy communities.

3.1.7 Paper VII: Quantifying the benefits of shared battery in a DSO-energy community cooperation

The primary objective of **Paper VII** was to quantify the benefits of using community-owned battery storage for an energy community and a DSO. The electricity and degradation costs for the energy community were estimated by running an optimisation model with and without voltage constraints. The main contributions of this paper include:

- A linear optimisation model that minimises the electricity and degradation costs for an energy community. The optimisation model includes linear battery degradation equations, which ensures that degradation costs are accounted for while maintaining a low complexity of the optimisation problem. The case studies show how the community-owned battery is used differently when voltage constraints are considered.
- Quantification of how much the DSO should remunerate the energy community for the voltage service.

Figure 3.5 shows the voltages at the energy community bus (16) and the neighbouring bus (17) for three cases, where in the first two cases, the energy community optimises for itself without considering voltage constraints. In EC no deg., battery degradation cost is not included in the objective function, while in EC it is included. In EC+DSO, both degradation cost and voltage constraints are included. We can observe that when the degradation cost is not included (upper graph), the battery is often charging at the same time as the voltage is below the limit. This occurs less when the degradation cost is included (middle graph), indicating that many of the voltage problems in the upper graph are caused by the battery. There are, however, also many hours where the voltage is below 0.92 pu and the battery is not charging. Finally, the lower graph shows how the battery operation is changed to keep the voltages within the voltage limit. Hence, the battery operation affected both the voltage of the energy community bus and the neighbouring bus. The battery caused some voltage problems due to spot price arbitrage, mostly in the bus where the energy community was connected. This result is of importance for customers who are connected to the same bus as

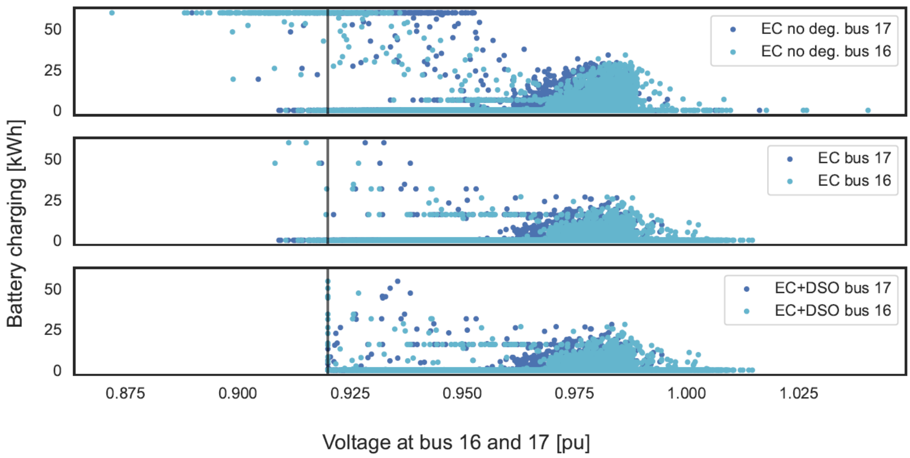


Figure 3.5: Battery charging vs. voltages for cases EC no deg., EC and EC+DSO.

an energy community, as the community might actually create voltage problems for itself and other customers connected to the same bus. Furthermore, we found that a battery-friendly operation was also a grid-friendly operation, since the voltage violations decreased when the degradation model was included in the optimisation.

Moreover, our results showed that the cost difference for the energy community, and thereby the remuneration needed from the DSO, was very low. It amounted to 15 € per year, which equals 0.12%. The sensitivity analysis showed a range of 9-21 € in remuneration per year, where the battery replacement cost was the most sensitive parameter. The sensitivity analysis also showed that increasing the PV size did not reduce voltage violations and that it had little impact on the remuneration from the DSO. Also, for lower battery sizes, the battery system was not able to provide the service to the DSO at all hours. The degradation cost had a major part in the remuneration from the DSO. If battery degradation cost would not be considered, the energy community would be remunerated less than their real cost of providing this service.

3.2 RQ1 What are the member benefits of forming energy communities?

a) How are operational costs, self-consumption and CO_2 emission impacted by PV generation, flexible assets and members in the energy community across different regions?

The different papers included the following assets: rooftop PV panels, battery energy storage, thermal energy storage and shiftable loads.

Regarding operational cost reduction, a general finding from all papers is that PV generation was the main cost driver. It is, however, not necessarily profitable to invest in PV systems in regions with low solar irradiation. In **Paper II**, the optimisation model did not invest in PV generation when the grid tariff was capacity-based, since the PV generation did not contribute enough to reduce the monthly peak demand. The data used in this paper was, however, for Mid-Norway, where the solar irradiance is quite low. With respect to flexibility resources, it was found that existing domestic hot water tanks in, i.e., apartment blocks (**Paper IV**) is a low-hanging fruit. However, this requires smart control of the hot water tanks. Furthermore, it was shown that battery systems do not lead to significant cost reductions, compared to the investment cost needed, in Norwegian cases. Load shifting, on the other hand, was shown to give a similar operational cost reduction to batteries in **Paper VI**.

Self-consumption was increased in the energy communities with batteries. **Paper VI** also showed that shiftable loads led to an approximate equal self-consumption rate as batteries for commercial and mixed loads. Here, the batteries were sized to ensure a certain self-consumption, while the load shifting percentage was assumed to be 20%. For residential loads, the battery gave a higher self-consumption rate than load shifting for both Norwegian and Spanish energy communities.

In terms of CO_2 emissions, **Paper VI** showed that PV generation was the main driver for emission reduction. Battery systems only led to slightly lower CO_2 emissions in Norwegian energy communities, compared to only having PV generation. Shiftable loads were a good alternative to battery systems, as they obtained almost equal reduction in CO_2 emissions when combined with PV generation. The results for Spanish energy communities also showed similar results for battery and load shifting together with PV generation.

When comparing flexible resources, it should be noted that the shiftable loads were modelled through a general load shifting model, which assumes that it is possible to shift 20% of the load in each hour. This shiftable load can be, i.e., domestic hot water tanks or space heating. The load shifted up and down must be equal throughout the day, and it is assumed that this load is shifted with a discomfort cost, which is added to the objective function. In addition to this, the houses would also require some smart control/home energy management system, a cost which has not been included. When comparing shiftable loads and batteries, they are very different in terms of predictability/stochasticity. The battery is there for the sole purpose of charging and discharging when it is optimal. The domestic hot water tanks and space heating are highly dependent on the behaviour of the residents. Therefore, in actual operation, there would need to be good forecasts for these optimisation schedules to work.

Paper VI showed that various member configurations in Norwegian energy communities (residential, commercial and mixed loads) had a similar operational cost reduction (25%) and CO_2 emission reduction (24%). In the Spanish energy communities, there was significantly more to gain both in terms of operational cost reduction and emission reduction, where residential loads obtained a 70% cost reduction and a 64% emissions reduction. In Norway, the commercial loads had the highest self-consumption, since the load corresponded better with PV generation. In Spain, the mixed loads had the highest self-consumption. A better correlation between PV generation and load also led to a smaller battery need, which in turn reduces the investment costs for the energy community.

b) What is the economic feasibility of an energy community investing in batteries and thermal storage, and how do these energy storage systems interact?

According to **Paper V**, it was more profitable to invest in thermal storage than battery storage, and the sensitivity analysis showed that battery storage costs would need to decline significantly for it to be competitive when there is an option to install a thermal energy storage. To install a thermal storage, the presence of some thermal demand is required, i.e., something that the thermal storage can be used for. Therefore, a combination of the two storage systems might prove to be the optimal solution, depending on the energy community's demand.

In the investment problem in **Paper II**, costs did not decide the battery size, as the battery was installed to avoid breaching the grid limit. Without the grid restriction, the model did not deem it profitable to invest in a battery system. Hence, community batteries in Norway are only profitable for residential loads if they serve an additional purpose other than minimising costs (in this case, to keep the load within a certain limit).

c) What is the impact of cyclic battery degradation in energy community optimisation?

When cyclic battery degradation models were used, the optimal battery operation changed drastically, and the battery lifetime was approx. halved (in **Paper II**). Also in **Paper VII**, we saw that including a degradation model had a large impact on the battery operation, and whether the model found it profitable to do spot price arbitrage. In this study, the grid tariff was volumetric, leading the model to place more emphasis on the spot price variations. Batteries that optimise based on spot price, without any restriction on battery health, react to nearly all variations in spot price and therefore age faster.

d) How can costs be distributed between members in an energy community?

In **Paper III**, we investigated sharing PV generation through two static sharing keys: one equal and one yearly consumption-based. The individual cost reduction heavily depended on the PV sharing key used. The equal sharing key favoured houses with low energy consumption, while the yearly consumption-based sharing key favoured houses with high yearly consumption. Which one is best depends on the definition of fairness: does the energy community want the cost distribution to be *equitable* (you get as per what you bring), or *equal* (everyone gets the same). This should also be seen in connection with the contribution to the investment cost of the PV systems.

In **Paper V**, the total costs were reduced when the industrial consumer formed an energy community with the urban area. When redistributing these costs, we saw that the only method that led to a decrease in costs for both the industrial consumer and the urban area was the Shapley value. Redistributing costs based on other methods, such as peak load or yearly consumption, gave an increase in costs for one of the participants, and proved to be a poor way of redistributing the costs when a local collective grid tariff is assumed. This is because one actor can end up being punished for increasing its individual peak, although it reduces the aggregated energy community peak.

To summarise, it is evident that the sharing key and method for the redistribution of costs has a great impact on the economy of the members. Although the main motivation to join an energy community might be non-economical, the members should experience the cost distribution to be fair, as it will be difficult to recruit members if they are worse off economically. The redistribution could be directly connected to the investment cost of the assets; however, this would exclude households with a low-income. It is therefore important that the social aspects of the energy community are also considered in this question.

3.3 RQ2 How will energy communities impact the distribution grid?

a) How is the grid exchange impacted by PV generation, flexible assets and members in the energy community across different regions?

All these case studies included PV generation as the renewable generation technology. A general finding, across all articles, is that PV generation alone does not contribute to reduced peak demand. Although case dependent, and input dependent, it should also be noted that none of the case studies found a very high peak export from the PV generation. This is especially true for the case study in **Paper IV**, where we looked at apartment blocks, since the roof area will always be low compared to the load.

Flexible households led to a 9% increase in maximum import in **Paper III**. This happened because each house was shifting load individually within their capacity-based tariff step, and all responded to a low spot price the same hour. When load shifting was used in **Paper VI**, the peak load was unchanged.

In **Paper IV**, we saw that the optimisation of hot water tanks led to lower peak demand. The central optimisation of all domestic hot water tanks in the apartment blocks gave a decrease in peak import of 10.6%, compared to the base case, and also a small reduction in peak export. In **Paper V**, the investment in thermal energy storage led to the peak demand of the industrial energy community being reduced by 5.1%, mainly due to the incentive from the capacity-based grid tariff. Interestingly, the peak demand at the transformer level was reduced by 3.1% when the industrial consumer was optimising alone. Therefore, the grid already had some benefit from the storage investment without a local collective grid tariff.

In **Paper VI**, the battery created new peaks when the spot price was low because of a volumetric grid tariff. For Norwegian energy communities, we saw that the maximum import increased significantly because of the battery operation responding to spot price variations. Interestingly, this was not the case for the Spanish energy communities. **Paper VII** found that the community battery created more undervoltage problems, because the energy community had a volumetric grid tariff and spot price was the dominant price signal in the optimisation. We found that a battery-friendly operation was more grid-friendly, because when the battery degradation model was included, it reduced the amount of undervoltage problems due to the optimisation model being more restrictive on charging. From these results, it became evident that the way degradation is taken into account has a large impact on how community battery systems impact the grid.

To summarise, it seems that it is the grid tariff that has the highest impact on the grid exchange, not the technology itself.

In **Paper VI**, we compared residential, commercial and mixed energy communities. To begin with, they were all scaled to meet the same peak load, for comparison purposes. The load profiles correlated differently with the PV generation. The residential loads had the lowest correlation between PV generation and demand, and therefore they required the largest battery to ensure a certain level of self-consumption. As already discussed, batteries under volumetric grid tariffs in Norway mainly respond to spot price variations, and therefore lead to high peaks when spot price is low. The low correlation between load and PV generation also led to the residential loads having the highest maximum export.

b) Does a capacity-based grid tariff always lead to a lower peak demand, compared to the volumetric grid tariff? What is the largest impact on cost savings?

As previously discussed, a volumetric grid tariff leads to the flexible resources targeting low spot price hours, while a capacity-based tariff dominates the spot market cost and incentivises lower peak demand. One exception was shown in **Paper III**, when a stepwise capacity-based grid tariff was used in collective self-consumption. The steps in the tariff leave room for spot price arbitrage, which might lead to new load spikes when each member is optimising individually.

The other papers with capacity-based grid tariffs always showed that energy communities led to a lower peak demand, because a local collective grid tariff was assumed, leading to an incentive to lower aggregate demand. If the future spot prices increase in level and variability/fluctuation, a relevant question is what happens if the spot price becomes more dominant than the capacity-based grid tariff? Sensitivity analysis on spot market prices in **Paper V**, where we have a capacity-based grid tariff, showed that a higher spot price level (multiplied with 5) decreased the maximum import, because the increased spot prices made it profitable to invest in a larger storage, which then could be used to lower the peak even further. However, this did not occur for all sensitivities of spot price levels. For instance, the maximum import did not decrease when the spot price level was multiplied with 3. This analysis showed the complexity of the constant trade-off between the different costs in the objective function: the energy storage investment cost, the spot price and energy grid tariff costs, the monthly peak grid tariff cost and the remuneration from the feed-in. In **Paper VII**, which had a volumetric grid tariff, we saw that an increased spot price led to more voltage violations due to it being even more profitable to do arbitrage, and therefore the battery charged/discharged more heavily.

Both in **Paper III** and **Paper IV**, the different cost components were reported.

In **Paper III**, the cost reduction stemmed from a reduction in spot market cost, grid energy cost, taxes and grid capacity cost. In **Paper IV**, the total costs were mainly reduced due to a reduction in capacity-based grid tariff costs. As discussed in RQ2, the peak load was reduced in **Paper IV**, while the peak load increased in **Paper III**. Hence, there is not always a connection between the grid cost reduction and the peak load reduction. As discussed in Chapter 2, this could lead to energy communities shifting costs over to other grid customers. These findings are supported by [14], where the authors found that net metering of taxes and grid tariffs increase self-consumption but do not affect the peak import of electricity.

c) How can energy communities cooperate with the DSO to solve voltage problems, and how much should the energy community be remunerated for this service?

As already discussed, energy communities can resolve grid problems implicitly by reducing peak import. This is especially true when we assume a local collective that is capacity-based, since this gives incentive to reduce the aggregate peak load.

Paper VII showed how an energy community could resolve grid problems explicitly. We investigated how it could cooperate with the DSO by providing voltage support when the voltage went below a limit. In some hours, the battery was resolving a problem, while in other hours it was merely avoiding creating a problem. This is also connected to how the battery degradation was accounted for in the optimisation model: if degradation was not considered, the battery created more voltage problems.

When the battery was used to improve the voltage in the distribution grid, the remuneration needed was found to be quite low (at the most 21€ in the sensitivity analysis). The actual remuneration would be higher than this, as this only represents the cost difference observed by the energy community when buying electricity at non-optimal times and the degradation cost from changing the battery operation. In any case, if energy communities invest in community batteries, it seems like a good option to rent this battery out to the DSO in hours of need. The practicalities around this would need to be sorted, as there would need to be a forecast of load, and perhaps the DSO would like to reserve the battery for a day or more to be sure that it is available when needed. However, the sensitivity analysis showed that the battery size must be considered, so that it is large enough to maintain the voltage within the standard range. Given the existing high investment costs for batteries, a joint investment between the energy community and the DSO emerges as a potential solution. In this proposed model, the energy community would invest in the energy capacity they need, while the DSO would bear the cost of the additional energy capacity necessary for improving the grid voltage.

3.4 RQ3 What are the benefits and challenges of local collective grid tariffs and collective self-consumption as regulatory frameworks?

A local collective grid tariff means that all members get one common tariff, which means that the energy community is incentivised to reduce their common load. The cost reduction stems from a reduction in taxes, grid tariff and spot market cost. As seen in RQ2, in a collective self-consumption scheme, each household optimises individually (non-collaborative), and therefore does not necessarily reduce their aggregate load, even if a capacity-based grid tariff is used. A similar finding was presented in [54], where it was shown that individual tariffs have a reduced capability to reduce peak load, since each member optimises individually.

The challenge with local collective grid tariffs is that the costs savings need to be redistributed among the members after optimisation. **Paper V** investigated this and found that the way the costs are redistributed heavily impacts the profitability for members to join the community. Depending on the cost distribution method, some members could benefit way more than others, and the energy community would therefore need to decide what they perceive as a fair distribution. Furthermore, a local collective grid tariff does not necessarily resolve grid problems if the spot market price gives a stronger price signal than the grid tariff. A collective grid tariff also requires that all members of the energy community cooperate, which might be difficult to organise in practise. The benefit of a local collective grid tariff is that it gives an incentive to install community storage for peak demand reduction, especially if the community has a capacity-based grid tariff. The collective self-consumption scheme studied in **Paper III** showed that the individual members did not have an incentive to lower aggregated peak demand.

In **Paper IV**, we compared a central optimisation of several apartment blocks, with individual optimisation for each apartment block. This can be a view of how the aggregation, and local collective grid tariff, plays out. When we optimised for the whole energy community, the peak demand was reduced by 10%, whereas when we optimised individually, it was reduced by 4%. One main reason for this higher reduction in peak demand is that when we optimise centrally, all parts of the energy community can be included. In this case, this was the common garage with electric vehicle charging and PV generation. When we optimised each apartment block individually, the garage had no way of contributing to the whole community, as it was metered separately. When optimised centrally, the hot water tanks could adjust their operation to the garage's electric vehicle charging and PV generation.

3.5 Further discussion and main takeaways

The results from this PhD work must be seen in light of *optimal* investment and operational decisions. Energy communities with professional actors (industry consumers and commercial businesses) are expected to have a higher focus on cost minimisation and technology to ensure optimal scheduling of assets, in part because it requires technical competence to understand why, i.e., a battery should be operated in a certain way. Energy communities with residential members might be less likely to focus on this, where the aim might be less driven by cost minimisation, and more by the social and environmental aspects of providing themselves and their neighbours with renewable energy. Regardless of the motivation, if the assets used in energy communities are programmed to do what is considered to be cost optimal, and they operate automatically, this PhD work shows that the regulatory frameworks, i.e., the price signals, have a great influence on how this in the end impacts the distribution grid.

The findings in this PhD research have implications for various stakeholders: energy community members, regulators and DSOs. For the members, it is evident that not all technologies are profitable to invest in. It is crucial to agree on what the motivation for forming the energy community is, before the technology is decided. If cost reduction is important, then PV generation together with existing hot water tanks has been shown to be a good solution. Smart control of shiftable loads in buildings is also a low-hanging fruit. If self-consumption, or self-sufficiency, is important, then battery energy storage systems are more reliable and robust than shiftable loads. Members of energy communities, or other end-users considering forming them, can observe that battery energy storage systems are currently too expensive. Thermal energy storage should therefore be prioritised if cost reduction is an important motivation. If the energy community wants to reduce CO_2 emissions and increase self-consumption, battery systems can be valuable assets. Smart control of shiftable loads such as domestic hot water tanks and space heating are also flexibility resources that should be considered before investing in expensive battery energy storage systems. Note that there are other technologies that have not been addressed in this research, such as smart control of electric vehicle chargers or seasonal storage.

For the DSO, the main takeaway is that grid tariffs send an important price signal to energy communities, and that communities can be a powerful way to aggregate customers and reduce peak demand, if given the right price signals. Local collective grid tariffs can be an effective tool to reduce peak demand in the grid if combined with a capacity-based grid tariff. Furthermore, energy communities are a flexible resource that can both create and solve problems in the grid, depending on which assets are present and which price signals they respond to. DSOs that want to defer grid investments can investigate further how to collaborate with energy communities to reduce voltage problems.

Regulators can observe how local collective grid tariffs and collective self-consumption impacts the peak load at energy communities and how this relates to the cost reduction, under different grid tariffs. The most interesting finding, in that sense, is that capacity-based grid tariffs do not always lead to peak demand reduction. This could mean that collective self-consumption will shift grid costs over to other customers in the grid. In this regard, local collective grid tariffs seem like a better alternative for the grid, but further investigation is needed. It should, for instance, be clarified to which extent the local collective grid tariff gives a reduction in network charges and taxes.

4 Conclusion

The aim of this thesis was to investigate the member benefits of forming local energy communities, and how they will impact the distribution grid, under various regulatory frameworks. This was done by formulating optimisation models for minimising energy community costs when subject to different price signals. Further, it was investigated how different cases impact the energy community benefits and the grid, in particular peak demand. The optimisation models in this paper collection cover both operational and investment problems, for various technologies present in the energy community – PV generation, battery storage, thermal storage and shiftable loads, various members – residential, commercial and industrial, volumetric and capacity-based grid tariffs, and two regulatory frameworks – local collective grid tariff and collective self-consumption.

4.1 Concluding remarks

With respect to how aggregated energy community benefits are impacted by different technologies and members under different grid tariffs, it has been shown that batteries in Norwegian residential energy communities can contribute with increased self-consumption and reduced CO_2 emissions. Batteries can become profitable in industrial energy communities with PV generation and a capacity-based grid tariff, if investment costs continue to decline, but they are for the most part out-competed by thermal storage. Optimising the operation of existing domestic thermal storage is a low-hanging fruit for energy communities that wish to reduce costs. Household flexibility through shiftable loads lead to cost reductions and increased self-consumption in residential energy communities, and should be the first means of flexibility before considering battery systems.

We also investigated how energy communities will impact grid exchange when they minimise their operating costs. The collective self-consumption scheme led to a cost reduction, but an increase in peak import, because each household optimises their peak load individually. When we investigated a local collective grid tariff scheme, there was a contradiction between the cost reduction for the energy community and the peak import when a volumetric tariff was used: the costs declined, but the peak import increased. For a capacity-based grid tariff, there was a correlation between the cost reduction for the energy community and the peak import. Local collective grid tariff schemes, however, can only be in place if regulation allows it and needs further investigation.

It was found that energy communities can solve grid capacity problems implicitly by responding to capacity-based grid tariffs, especially if a local collective grid tariff scheme is allowed. They can also solve grid problems explicitly through improving the voltage in the distribution grid by community batteries, as long as the battery capacity is large enough. This was found to give a marginal rise in operational costs for the energy community, which would need to be covered by the DSO.

The findings in this PhD work give valuable insights for different stakeholders, which can be further used to develop country-specific regulations. The regulator can observe how local collective grid tariffs and collective self-consumption impact the peak load at energy communities and how this relates to the cost reduction, under different grid tariffs. The most interesting finding, in that sense, is that capacity-based grid tariffs do not always lead to peak demand reduction. Members of energy communities, or other end-users considering forming them, can observe that battery energy storage systems are for the most part too expensive and that thermal energy storage should be prioritised if cost reduction is the most important motivation and a part of the demand is thermal. Although expensive, battery systems can be valuable if the energy community wants to reduce CO_2 emissions and increase self-consumption. Smart control of shiftable loads such as domestic hot water tanks and space heating are also flexibility resources that should be investigated before investing in battery energy storage systems. DSOs and regulators should note that local collective grid tariffs can be an effective tool to reduce peak demand in the grid if combined with a capacity-based grid tariff. Energy communities are a flexible resource that can both create and solve problems in the grid, depending on which assets are present and which price signals they respond to.

4.2 Future work

Future work should investigate how to increase revenue streams to the energy community from different grid services, both local flexibility or the participation in frequency markets/ancillary services. This would also require the balancing of the impact on the local distribution grid along with the ancillary service to the transmission grid.

Papers IV and **VII** include electric vehicle charging, but only as a constant load. In reality, the charging power of electric vehicles can be regulated throughout a charging session, and the electric vehicle batteries could also be used as additional energy capacity if needed. Electric vehicles are, however, highly stochastic: we do not know exactly when they will be connected to the charger, and we do not know which state of charge the batteries will have. If the energy community size is large, it is possible to assume that a certain number of vehicles will always be connected to the chargers, but this is more difficult for smaller communities. Other technologies which should be investigated in future studies, in terms of both energy community benefits and grid impact, are seasonal storage and wind generation.

Since energy communities might have different motivations, not only to reduce costs, this could be weighted in multi-objective optimisation. Then each motivation, such as self-consumption or CO_2 reduction, can be modelled with a cost in the objective function, which is weighed together with the actual operational costs.

There are many steps that would need to be made before the optimisation models presented in this work could be used for real-time control of energy communities. This includes having good forecasts for spot price, PV generation and load, in a higher time resolution. When it comes to investments, stochastic models could be used to include several scenarios for prices, load and PV generation.

As this work has shown, the regulatory framework is highly uncertain and impacts the profitability of the energy community and the distribution grid. Therefore, it is important to keep investigating regulatory frameworks for various energy community types, in terms of members and technologies, as well as the impact they might have on the grid planning and network cost distribution.

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Publications

Paper I: A systematic review of machine learning techniques related to local energy communities

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Cite as:
A. Hernandez-Matheus, M. Löschenbrand, K. Berg, I. Fuchs, M. Aragüés-Peñalba, E. Bullich-Massagué, and A. Sumper, "A systematic review of machine learning techniques related to local energy communities," *Renewable and Sustainable Energy Reviews*, vol. 170, p. 112651, Dec. 2022. http://dx.doi.org/10.1016/j.rser.2022.112651

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Renewable and Sustainable Energy Reviews 170 (2022) 112651

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Review article

A systematic review of machine learning techniques related to local energy communities

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ARTICLE INFO

Keywords:
Local energy communities
Machine learning
Energy decentralisation
Energy forecasting
Energy management systems
Energy transactions

ABSTRACT

In recent years, digitalisation has rendered machine learning a key tool for improving processes in several sectors, as in the case of electrical power systems. Machine learning algorithms are data-driven models based on statistical learning theory and employed as a tool to exploit the data generated by the power system and its users. Energy communities are emerging as novel organisations for consumers and prosumers in the distribution grid. These communities may operate differently depending on their objectives and the potential service the community wants to offer to the distribution system operator. This paper presents the conceptualisation of a local energy community on the basis of a review of 25 energy community projects. Furthermore, an extensive literature review of machine learning algorithms for local energy community applications was conducted, and these algorithms were categorised according to forecasting, storage optimisation, energy management systems, power stability and quality, security, and energy transactions. The main algorithms reported in the literature were analysed and classified as supervised, unsupervised, and reinforcement learning algorithms. The findings demonstrate the manner in which supervised learning can provide accurate models for forecasting tasks. Similarly, reinforcement learning presents interesting capabilities in terms of control-related applications.

1. Introduction

Recent technological developments in renewable energy have enabled a shift in the energy generation capacity closer to the consumption. This evolution has led to a decentralisation process that is required for the coordination of generation and demand in electric power systems. A part of this process involves the management of a greater number of active consumers and so-called prosumers, i.e., consumers who also produce electricity in the grid. Consequently, the energy sector is transitioning towards a more decentralised control owing to these prosumers and active consumers, who cooperate for the management and control of storage systems and flexible demand. A resulting framework attempting to solve the challenges associated with this decentralisation is that of local energy communities (LECs) representing local, self-organising entities that operate autonomously or semi-autonomously within an electricity grid [1]. The shift towards a more community-focused approach from a traditionally centralised power system is further amplified by the increasing digitalisation of these systems, for example, in terms of the metering and control of energy. In this context, recently popularised technologies such as distributed ledgers [2], big data applications and artificial intelligence have shown promising results for shaping the future of decentralised power systems [3].

This paper focuses on the recently growing field of machine learning, which is a subcategory of the research field of artificial intelligence. Machine learning is based on the development of computer systems that can learn from data without explicitly following instructions. This learning is achieved via algorithms and statistical models to analyse and draw inferences from the data patterns. In several research fields such as those of medicine and finance, machine learning has been used to solve high-complexity problems. Moreover, community-based power systems are no exception to the advent of machine learning [4]. This study aims to discover a relationship between the operation of LECs and

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https://doi.org/10.1016/j.rser.2022.112651
Received 6 September 2021; Received in revised form 17 May 2022; Accepted 30 May 2022

existing machine learning algorithms on the basis of recent research reported in the literature.

1.1. Research questions and contributions

This study aims to provide a systematic review on the state-of-the-art of machine learning that are applicable for LECs. Towards this end, an in-depth discussion and conceptualisation has been provided to answer the following question: ***'what constitutes as a local energy community?'***; the LEC characteristics have been defined from the perspective of European electricity systems. Following this general conceptualisation, an extensive review was conducted on the basis of the previously derived characteristics of LECs to answer the following question: ***'which machine learning literature is related to local energy communities'***. Eventually, an answer has been presented to the following question: ***'what future trends and conclusions can be drawn from machine learning utilised in local energy communities?'***.

In summary, the contributions of this paper are as follows:

1. A conceptualisation of LECs from a European perspective
2. An extensive review of state-of-the-art machine learning literature associated with LECs
3. Detailed applications of machine learning methods within LECs
4. An evaluation of and the future outlook on machine learning methods that are utilised in LECs

1.2. Outline

This paper is structured as follows: In Section 2, LEC definitions within regulatory frameworks and existing community-based energy projects are presented. Furthermore, the criteria for conceptualising an LEC are explored in detail. In Section 3 a meta-review of the associated literature, aiming to better contextualise the present work with respect to the existing literature reviews, is presented. In Section 4, an initial overview of the different machine learning tasks and techniques are listed. Furthermore, the different practical applications of machine learning in LECs have been analysed, and a structured evaluation of these applications is presented in Section 5. Finally, a summary of the main research findings as well as an outline of current developments, potential trends in the future, and suggestions for further research direction are presented in Section 6.

2. Local energy communities

Although it has been indirectly defined in literature, for example, the general definition within the regulatory framework of the European Union (EU) for energy communities, to the best of the authors' knowledge, no direct definition of LEC has been reported in the relevant literature. To close this research gap, the authors of this study analysed 25 existing community-based energy projects on the basis of two EU regulatory definitions of energy communities. Accordingly, a definition of an LEC is presented in this study. This definition serves as the foundation for the identification of the areas of application for machine learning methods.

2.1. Classification of local energy communities

In the existing literature, an LEC has been perceived mainly as a technical rather than a structural concept. However, the definition of an LEC extends beyond purely technical, social, and organisational aspects [5]. In a study [6], the authors analysed different approaches and terms for the integration of local energy systems into a larger centralised energy system. They investigated community microgrids, virtual power plants, energy hubs, prosumer community groups, community energy systems, and integrated community energy systems. Subsequently, the authors introduced a comprehensive concept for integrated community energy systems, which is similar to the concept of LEC and is presented in Section 2.2. In another study [7], the authors defined 'clean energy communities' as social and organisational structures that are formed to achieve the specific goals of its members, primarily in terms of clean energy production, consumption, supply, and distribution. They analysed the long-term dynamics and possible pathways of the transition from centralised to decentralised systems in the energy sector as well as the co-evolution of energy systems and energy communities. This study aims to explore the manner in which different machine learning techniques can assist in the operation of LECs and optimisation of their local energy systems. As presented in the following sections, the foundation for a framework for LECs has been established on the basis of two different definitions within the EU regulatory framework and analyses of 25 existing community-based energy projects.

2.1.1. Regulatory definitions

As mentioned, the EU has issued two directives with official definitions that are proximate to those of LECs: 'Renewable Energy Community' (REC) [8] and 'Citizen Energy Community' (CEC) [9]. These definitions are listed in Table 1. Member states must revise national laws to comply with the EU rules, and therefore, they must develop national-level definitions for citizen and renewable energy communities.

The specific differences between citizen and renewable energy communities are further explored in detail in the literature [1]. The authors explored renewable energy communities to showcase certain characteristics that are not inherited by the citizen energy communities: a specific geographical scope owing to the required proximity to renewable energy projects, a more restricted membership, i.e., participants cannot join the renewable energy community as their primary economic activity, a need for autonomy from individual participants or stakeholders, and the possibility of grid control by enterprises located in the proximity of the renewable energy project. Furthermore, unlike the renewable energy community, a citizen energy community generally follows technology-neutral policies, and thus, it incorporates both renewable and conventional sources of electrical energy.

2.1.2. Existing energy community projects

A review of functional energy communities in Europe was performed to identify the characteristics of an LEC. The following keywords were used to search for energy community projects (Oct. 2020): 'energy community', 'renewable energy community', 'citizen energy community', 'local energy market', 'electric energy community', 'microgrid', 'renewable energy market', 'local energy system', 'micro energy system', 'zero emission neighbourhood', 'smart neighbourhood', and 'micro markets'. This search resulted in approximately 200 projects, 60 of which were investigated in more detail in this study. For a project to be included in the review, it had to: (a) fit the definitions of citizen and/or renewable energy communities, (b) focus on electrical energy systems, and (c) possess sufficient information regarding the structure, stakeholders, technology, and motivation of the project. By applying these criteria, the initial number of 60 projects was reduced to the 25 projects that are listed in Table 2. The research findings on the structure, stakeholders, technology, and motivation of the 25 projects are detailed herein.

Structure

In terms of composition, an energy community can be distinguished by its physical and organisational structure. The physical structure involves the geographical area and location of the grid as well as the electrical grid topology. In contrast, an energy community's organisational structure can be categorised into seven types, as described in the relevant literature [1]: energy cooperatives, limited partnerships, community trusts and foundations, housing associations, non-profit customer-owned enterprises, public–private partnerships and public

Table 1
Comparison of definitions of renewable and citizen energy community.

Renewable energy community [8]	Citizen energy community [9]
(a) "which, in accordance with the applicable national law, is based on open and voluntary participation, is autonomous, and is effectively controlled by shareholders or members that are located in the proximity of the renewable energy projects that are owned and developed by that legal entity";	(a) "is based on voluntary and open participation and is effectively controlled by members or shareholders that are natural persons, local authorities, including municipalities, or small enterprises";
(b) "the shareholders or members of which are natural persons, SMEs [small and medium-sized enterprises] or local authorities, including municipalities"; and	(b) "has for its primary purpose to provide environmental, economic, or social community benefits to its members or shareholders or to the local areas where it operates rather than to generate financial profits"; and
(c) "the primary purpose of which is to provide environmental, economic or social community benefits for its shareholders or members or for the local areas where it operates, rather than financial profits"	(c) "may engage in generation, including from renewable sources, distribution, supply, consumption, aggregation, energy storage, energy efficiency services or charging services for electric vehicles or provide other energy services to its members or shareholders"

Table 2
Existing energy community projects.

Project	Country	Motivation	Participants
BeauVent [1]	Belgium	Increase renewable energy production	>5000
Courant d'Air [10]	Belgium	Provide renewable energy to consumers	>2000
Ecopower [11]	Belgium	Increase renewable and local energy production	56,000
Svalin Energy Collective [12]	Denmark	Increase renewable and local energy production, reduce climate impact	20 households
Cornwall Local Energy Market [13]	England	Test market-based flexibility provision, reduce climate impact	100 households, 100 businesses
Larsmo Vindkraft Ab [14]	Finland	Increase renewable and local energy production, lower costs	200
Enercoop [15]	France	Increase renewable energy production, lower costs	92,000
Fermes de Figeac [16]	France	Increased income for members	321
Jühnde Bioenergiedorf [17]	Germany	Local solutions for solving climate change	660
Elektrizitätswerke Schönau [18]	Germany	Increase renewable energy production, energy democratisation	185,000
Sprakebüll Village [19]	Germany	Increase renewable energy production, self-sufficiency	247
Wildspoldsried microgrid [20]	Germany	Self-sufficiency with renewable energy, research on microgrids	2500
Aran Islands Energy Cooperative [14]	Ireland	Self-sufficiency with renewable energy, research on microgrids	100 stakeholders
Erris Energy Community [21]	Ireland	Energy efficiency, increase renewable energy production, community aspect	Unspecified
Amelander Energie Coöperatie [22]	Netherlands	Self-sufficiency, increase renewable energy production	286
Brattøra [23]	Norway	Energy efficiency, positive energy block	3 office buildings
Elnett21 [24]	Norway	Reduce fossil fuels in transport and enterprises, avoid grid congestion	Port, airport, businesses
Spoldzielnia Nasza Energia [1]	Poland	Energy independency, lower costs	300
Slupsk pilot [1]	Poland	Energy poverty, reduce air pollution	200 households
Edinburgh Community Solar [25]	Scotland	Reduce climate change, energy poverty, energy security	540
Isle of Eigg [26]	Scotland	Increase renewable energy, lower costs	96
BRF Lyckansberg [27]	Sweden	Local renewable energy production, export surplus electricity	85 apartments
Farmarenergi Eslöv [28]	Sweden	Reduce fossil fuels	9 farmers
Simris Energy System [29]	Sweden	Increase renewable and local energy production, avoid congestion	140 households
Quartierstrom [30]	Switzerland	Local market to balance power from renewable energy	37 households

utility companies. A review of the 25 community projects revealed numerous organisational structures. Certain projects, such as *Svalin* [1] and the *Isle of Eigg* [31] are organised in collectives through citizen engagement with the social aspects of sharing at its core. Other projects were registered as companies owned by local citizens, such as *Amelander* [32] and *Jühnde* [1]. As displayed in Table 2, the number of members in these projects greatly vary, with three members in *Brattøra* [23], and 56,000 members in *Ecopower* [11]. Furthermore, a few of these projects have emerged from scientific research and are not initiated by citizen participants.

In certain studies [32,33], researchers investigated the importance of social and organisational aspects in energy communities. Reportedly, factors such as a shared vision, the level of activity in the community, the type of organisation, and the organisation's affiliations on local, regional, or national levels can significantly influence the success of the energy community.

Stakeholders

Stakeholders in an energy community can either serve as active participants forming the energy community or passive actors with invested interests in the project. Within the 25 aforementioned projects, the stakeholders comprise citizens, municipalities, technology providers, distribution system operators (DSOs), universities, local businesses, energy generation companies, and housing associations. In addition to the aforementioned examples, the relevant literature [34] lists research centres, consultancies, information and communications technology (ICT), telecommunication companies, utilities and engineering service providers, retail companies, transmission system operators (TSOs), industry organisations, real estate developers, energy service providers, public utilities, energy cooperatives, and transport solution companies as potential stakeholders.

Generation, load, storage and flexible resources

For the reviewed projects, the typical generation technologies in energy communities comprise photovoltaic (PV) panels, wind turbines, small-scale hydropower plants, and combined heat and power plants. Additionally, thermal energy systems for heat production are incorporated in most of the reviewed communities, typically through combined heat and power generation, or geothermal and solar heating. Energy storage for back-up or other grid services was realised through either diesel generators or battery-based energy storage systems. These generation and storage technologies can be observed either at the household level or as shared assets in the community. The various types of load sources in these 25 reviewed energy community projects were categorised as households, prosumers, office buildings, industry/farms, and public buildings. The yearly load demands of these categories differ on daily and seasonal scales. Typical flexible resources available within load categories comprise electric vehicles (EVs), heat pumps, and water boilers. Optimal control of these flexible resources and energy storage systems is crucial to minimise the energy costs of the community.

An energy management system will be required by the community to control its flexible resources, through which the community can ultimately decide the period and manner of energy utilisation, thereby lowering the overall energy costs.

Motivation and benefits

The energy community projects, reviewed in this study, address environmental concerns and the related goal of increasing the share of renewable energy, which comprise the core motivation for establishing an energy community. For example, both *BeauVent* [1] and *Sprakebüll* [19] aimed to achieve 100% renewable energy production in the community, whereas *Svalin* [12] aimed to consume renewable energy that was entirely produced locally. Similarly, the common motivation behind energy community projects involves further investment in sustainable energy infrastructure for the community [1]. Furthermore, several projects such as *Amelander* [22], *Aran* [14] and *Wildpoldsried microgrid* [20] have highlighted the importance of self-sufficiency. Such requirements for self-sufficiency may be motivated by economics, security of supply (especially relevant in energy communities, which are microgrids), or a demand for greater transparency regarding the origin of the consumed electricity.

The economic incentives of communities typically lead to reduced wholesale market expenses owing to increased self-consumption of locally produced energy, revenue generation through feed-in of excess power generation, or a reduction in costs to the DSO owing to a lowered peak power consumption (caused by load shifting). Certain energy communities provide balancing and frequency control services to the TSO, such as the *Cornwall Local Energy Market* [13] and *Wildpolsried microgrid* [20].

2.2. Definition of a local energy community

As detailed in Section 2.1, the regulatory definitions and review of existing energy community projects facilitate the establishment of a definition of an LEC. This definition can be achieved by incorporating the five criteria that are fundamental to an energy community, which can be referred to as an LEC:

1. **Locality**: The community should possess a large proportion of local investment and ownership and be managed locally. A community is located within a defined geographical area and is typically connected at the distribution-grid level.
2. **Energy sustainability**: The community or its members fully or partially own the process of renewable energy generation, energy storage, EV chargers, or other relevant assets or infrastructure. These assets and infrastructure are shared by the community; from an energy system perspective, they are established at a single customer location.
3. **Community engagement**: Most of the participants are active members of the community, i.e., they are invested in the energy-related assets and provide flexible demand options. The main objective of the community is not profit-oriented; however, it aims to provide environmental, economic, or social benefits for its members/shareholders and/or the local area where it operates. The community participants may be individuals, small- and medium-sized enterprises, or local authorities, including municipalities.
4. **ICT**: The community possesses ICT infrastructure of varying degrees. Typically, this includes smart meters and communication, control, and energy management systems. Such infrastructure can enable the flexible operation and optimisation of the local system and facilitate interaction with national power systems in the form of transmission grids and wholesale electricity markets.
5. **Transactions**: The community allows for energy-related financial transactions amongst its members. This feature is generally implemented in local energy markets; however, such a feature is not mandatory. The transactions conducted not only consist of local transactions but also include transactions between the community and the national power system, for example, via wholesale electricity markets.

Criteria 1, 2, and 3 are closely related to the definitions of citizen and renewable energy communities. Criterion 4 indicates that an energy community must exercise some degree of ICT technology for the control of assets, communication amongst its members, and data collection. According to Criterion 5, a mechanism is required to share the energy-related costs and benefits amongst the members in the community. Table 3 depicts the relationship between the criteria defined for the applications, which are further detailed in Section 5.

To summarise this definition, an LEC is illustrated in Fig. 1 as a part of the larger power system.

3. Associated literature reviews

On the basis of the definition of an LEC provided in Section 2.2, a recent body of literature reviews associated with the topic has been identified, as listed in Table 4. The associated literature reviews were selected according to their relevance to the topic of LECs by considering the commonalities in the fundamental criteria established in the previous section. The exception to this has been reported in several studies [50–52], which possesses no direct relation but relates tangentially to locality and ICT infrastructure. The associated methods are explored in detail in the following section.

A range of literature reviews specialise in topics related to LEC; however, they do not specifically focus on local applications. Within the topic of forecasting, in a review [35] recurrent neural network models focusing on the specific problem of solar power forecasting were analysed with data from the South Korean power grid. Furthermore, an overview of deep learning in renewable electricity forecasting has been reported [37]. A review [39] specifically focused on time-series drift in terms of flexibility in power system flexibility, whereas another review [40] explored load forecasting from short to long term periods. Most of reviews of energy management systems highlight the topic of locality, except for the review [48] which presents a general view on reinforcement learning and its application in problems concerning power system control, and excluding the review [42] that explores energy storage and EVs. With regard to the protection, stability and quality of power systems, none of the reviews consider locality. In a review [50], methods such as support vector machines, neural networks and genetic algorithms were analysed in the context of fault detection. Moreover, deep learning has been analysed in the context of power quality [51]. Furthermore, the review [52] explores applications of machine learning in reliability assessment and control (specifically on the topics of security assessment, emergency control, preventive control, error measurement and power flow predictions). Most reviews of machine learning in smart grids do not consider locality. The emerging importance of machine learning and autonomous control in power systems has been reported [53]; although the review was not specifically focused on decentralised solutions, the reported topics were strongly related to such solutions. Furthermore, machine learning in smart grids has been analysed with a focus on data and data security [54]. The relevance of artificial intelligence to sustainable energy systems has been investigated in a general context [56]. In a review [55] machine learning in power systems has been investigated with a focus on topics such as forecasting, failure analysis, demand side management, and cyber security. Additionally, a review of the last decade of machine learning in power systems has been established [4].

The remaining related literature reviews focus on the subcategories of the field of machine learning. Reinforcement learning is a core topic in studies that focus on control aspects. The Markov decision process, i.e., the heating and storage of heat in water boilers, has been explored, and Q-learning has been identified as the state-of-the-art for dealing with control in such decision processes [43]. Researches [44]

Table 3
Value matrix criteria—applications.

Application	Locality	Energy sustainability	Community	ICT	Transactions
Forecasting	Generates information for short-term planning of the resources in the LEC	The individual and community assets are optimally managed by having information of future DER and related asset behaviour (such as storage)	Individuals can better coordinate with better prediction on their demand and supply	A condition for data security in forecasting systems	Energy and price forecasting provides operational inputs allowing the LEC to conduct an optimised economic dispatch
Storage optimisation	Enables localised storage as a grid asset, increases self-consumption of local renewable resources in the LEC		Storage assets are coordinated with other assets in the community and investments can be shared	Automated control of the storage system and associated information streams	
Demand response	Decentralised demand response becomes a feasible asset in the power system	Time-flexible demand can increase the consumption of intermittent renewable energy in the community	Demand response can be aggregated and coordinated with other community members	Local assets interact with the larger power grid via wholesale markets. e.g. as virtual power plants	Local assets interact with the larger power grid via wholesale markets, e.g. in form of virtual power plants
Energy management system	Decentralised coordination of resources	More optimal coordination provides more efficient utilisation of renewable energy and lowers emissions	Provides the sense of common welfare and a central coordination point within an LEC	Data storage and monitoring systems constitute the core of an EMS	
Power quality, stability and security	Practices that secure proper functioning and handling of the equipment owned in the LEC	Towards energy sustainability goals, energy generated and dispatched from LEC has to comply with the quality standards of power grids	Akin to centralised power systems, in decentralised systems such as LEC, the grid remains a shared asset	Grid data collection, maintenance and security	-
Energy transactions	Transactions are moved to the local level, consumers and prosumers financially interact with each other within an LEC	Local markets trade mainly local, renewable generation	Transactions within a community lead to higher level of self-consumption	LEC members are able to make better informed decisions about the sourcing of their energy supply; because to information sensitivity, transactions must also be secure	Local markets are integrated into wholesale markets and also have to provide proper supply/demand on balancing and regulating markets

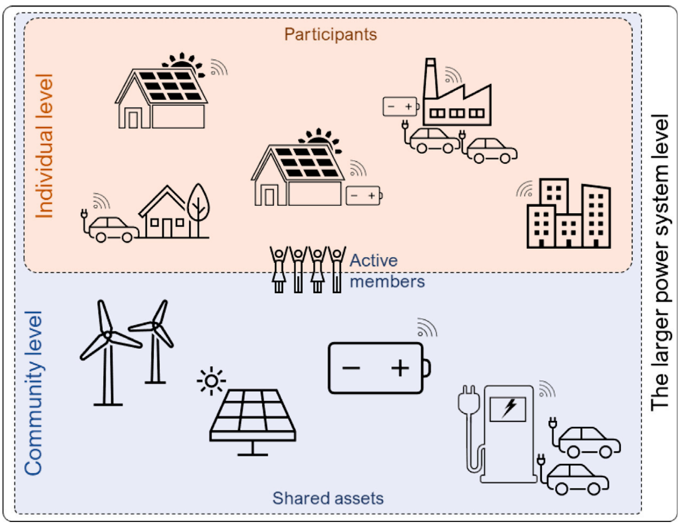

Fig. 1. Visualisation of a local energy community in the larger power system. The local energy community consists of two levels: the community and the individual level. The individual level consists of the participants in the community, such as residential consumers, prosumers, and enterprises. The participants own individual assets such as EVs, PV panels and batteries. Moreover, the ICT infrastructure, such as smart meters and energy management systems, are also incorporated into this system. The community level consists of shared assets, such as community-owned PV panels, wind turbines, batteries and charging stations for EVs.

approached the topic from the perspective of building management and discussed the real-world challenges involved in the implementation of reinforcement-learning frameworks. Similarly, control problems in buildings have been addressed through reinforcement learning, focusing on demand response control [45] and the latter focusing on its practical applications [46]. Another literature review focusing on the

Table 4
Literature reviews on machine learning applied on associated topics.

Source	Year	Topic	Locality	Energy sustainability	Community engagement	ICT	Transactions
Forecasting							
[35]	2019	PV generation forecasting	x	✓	x	x	x
[36]	2019	PV generation forecasting	✓	✓	x	x	x
[37]	2019	Renewable energy forecasting	x	✓	x	x	x
[38]	2019	Load prediction with smart meter data	✓	✓	x	✓	x
[39]	2020	Forecasting of flexible resources	x	✓	x	x	x
[40]	2020	Load forecasting	x	✓	x	x	x
Energy management system							
[41]	2020	Battery state estimation	✓	✓	x	✓	x
[42]	2020	Battery control methods	x	x	✓	x	✓
[43]	2018	Water heater control	✓	x	✓	x	x
[44]	2019	Energy management systems of buildings	✓	✓	✓	x	x
[45]	2021	Energy management of appliances in buildings	✓	x	✓	x	x
[46]	2019	Demand response control	✓	x	✓	x	x
[47]	2020	Demand response	✓	x	✓	x	x
[48]	2019	General control problems in power systems	x	x	✓	x	✓
[49]	2020	EV flexibility	✓	x	✓	x	x
Power system protection, stability and quality							
[50]	2017	Fault detection	~	x	x	~	x
[51]	2019	Power quality analysis	x	x	x	~	x
[52]	2020	Reliability assessment and control	x	x	x	~	x
Machine learning in smart grids							
[53]	2019	Role of machine learning in power systems	x	x	x	✓	x
[54]	2019	Machine learning in smart grids	x	x	x	✓	x
[55]	2020	Machine learning in smart grids	x	✓	✓	✓	x
[4]	2020	Deep learning in smart grids	x	✓	x	✓	✓
[56]	2020	Sustainable development	x	✓	x	x	x
[57]	2020	Distributed smart grids	✓	x	✓	x	x
[*]	–	Local energy communities	✓	✓	✓	✓	✓

* this paper, ✓related, ~ tangentially related.

subcategory of supervised learning has been reported [41], focusing on methods dealing with battery state estimations, namely Markov process- based methodologies such as Kalman filters.

Compared to these sources, literature reviews focusing on local applications and considering multiple subcategories of machine learning focus on specific problems. A review of applications, utilising smart meter data, such as load forecasting and related issues, including screening for energy theft and demand response forecasting, has been reported in the literature [38]. Additionally, solar energy predictions in microgrids have been surveyed [36], and the demand response and associated methods for operation, prediction, and segmentation have been highlighted [47]. Finally, a method for charging demand prediction of electric vehicles have been reported in literature [49].

In terms of the existing literature, a prior research has been reported, which is most relevant to this study [57]. However, the prior research focuses on single assets, especially energy management systems, whereas the present study focuses on energy communities, especially LECs, as an integrative unit. Although these approaches overlap, the research presented herein will dive deeper into specific applications such as agent-based coordination and classification from a communal perspective.

4. Machine learning methods

This section provides a short introduction to machine learning and its main categories as well as the main topics related to LECs, which were revealed in literature review performed in Section 3.

Popularised by a study [58], machine learning algorithms are traditionally classified into three main categories: *(a) Supervised Learning*, *(b) Unsupervised Learning*, and *(c) Reinforcement Learning*. The three categories, with their respective associated algorithms, are illustrate in Fig. 2. The essence of these classifications lies in the interaction of the algorithms with the data and environment. A comprehensive review of these methods and associated concepts have been reported in [59].

Supervised Learning algorithms are supplied with knowledge pertaining to the data in the form of so-called labels and are used to predict new and unknown data labels. This process can occur in the form of tasks such as classification, where labels represent categories, and regression tasks where the labels represent the values to be predicted. In this study, the regression tasks are referred from traditional linear regression, advanced models such as Lasso regression, or Ridge regression to models such as support vector machines, a method that can be fit on nonlinear data sets. In the context of LECs, regression methods are primarily used to predict and forecast of uncertain parameters. This forecast applies to both the demand side (e.g. household loads or utilisation of devices) and the supply side (e.g. available PV capacity) [60,61]. However, classification problems rely on prediction tasks for categorical or qualitative outputs [59]. Consequently, classification methods are generally used in scenarios wherein the problem involves the detection of specific cases in datasets on the basis of historical examples. The main applications of such methods related to LECs comprise fault detection and error classification [62].

Finally, probabilistic tasks refer to methods that consider uncertainty in the data not only to optimise the expected value but also to infer the distribution of such uncertainty. A simple example is provided by the probabilistic form of regression, such as Bayesian regression. Applications of probabilistic methods in LECs include the fitting of stochastic processes or determination of the parameters of distributions for renewable energy installations, household loads, or usage patterns of electric vehicles and electric devices.

Deep learning, commonly referred to as a neural network, can perform any of the aforementioned tasks. These methods employ function approximations consisting of stacks of differentiable linear regression 'layers' and nonlinear 'activation functions'. Hence, neural networks are built with different configurations of layers to solve the problem and handle the nonlinearities of such problems. Such models are widely used in LECs, including neural networks for forecasts [63] and predictions of deep learning models for optimal control [4,64]. A more in-depth discussion on deep learning topics has been reported in [65].

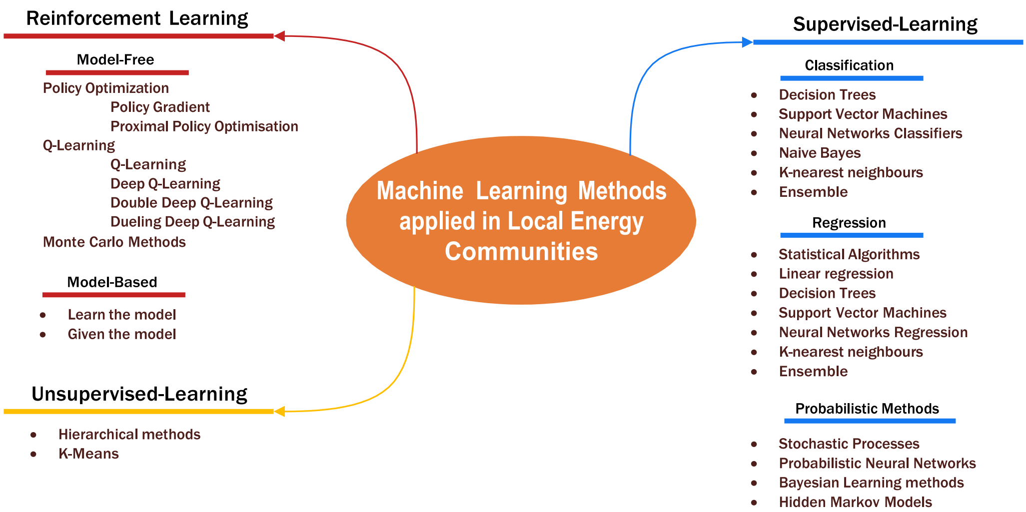

Fig. 2. Machine learning methods and algorithms.

In contrast to supervised learning, unsupervised learning aims to describe associations and patterns between unlabelled input data [59]. Clustering techniques aim to find commonalities in data sets and classify the closest data points as clusters. In the context of LECs, clustering methods are primarily found in applications for load profiling and segmentation.

The last category, reinforcement learning (RL), from the other two categories. It not only passively observes and labels the data but also exerts active control on a given system. A common textbook source for RL algorithm is provided [66]. However, in the traditional literature on electrical engineering, these RL algorithms have also been referred to in the context of optimal control under the name of 'approximate dynamic programming'. Further background information on this topic is currently available [67].

5. Applications in the operation of local energy communities

The literature review presented in Table 4 demonstrates the range of potential applications of machine learning within microgrids, smart grids and other energy communities. However, considering the criteria in the definition of an LEC, as depicted in Section 2, applications such as forecasting, energy management system, power system protection, stability, quality, and optimisation and energy transactions have been selected as a result of a categorisation of the discovered literature associated with the aforementioned topics. The following section presents the analyses and further classification of the studies and models targeted specifically at the aforementioned applications related to LECs.

5.1. Forecasting

Forecasting is the process of predicting a variable in the future by analysing historical data trends. Demand and generation forecasting are of great importance to the system operators of electrical grids. The frequency of occurrence of the algorithms that were used in the reviewed studies for each forecast application is illustrated in Fig. 3.

Forecasting studies are commonly classified to their time horizon prediction: short-term, medium-term, and long-term [57]. However, certain studies approach the problem on a very short-term horizon [61, 68]. The forecasting interval depends on the purpose on the forecast. For daily operation tasks, very short-term and short-term are the required time horizon, whereas for grid planning and investment evaluation, a long-term horizon is preferred [40]. Table 6 shows the machine learning algorithms in the literature review for different forecast tasks classified according to time horizons listed in Table 5.

Table 5
Forecast time horizons.

Forecast horizon	Time interval
Very short-term	1 s to less than 1 h
Short-term	Few minutes to few days
Medium-term	Few days to few months
Long-term	Months, quarters, years

5.1.1. Demand forecasting

The literature on demand forecasting represents the largest share of the recent literature on energy forecasting. This is because of the increased uncertainty in the operation owing to the addition of new actors to the energy system, such as prosumers or new assets, which can act as flexible loads and shift or reduce their consumption during specific periods [48]. An accurate prediction of demand helps to improve the operation of an LEC [97,98]. For LECs with controllable loads, several control strategies rely on an accurate forecasting model [99].

Demand forecasting can be performed at individual, community, or asset level facilitated by the data gathering ability of smart meters and ICT infrastructure. In terms of the asset level, machine learning regression models such as K-nearest neighbours (KNN), decision trees and neural networks (NNs) have been explored to accurately predict the consumption of two machine tools in a factory in a very short-term horizon [68]. A combination of an autoregressive integrated moving average (ARIMA) model with a nonlinear support vector machine (SVM) has been used to predict the electrical consumption of an air conditioner by employing the data retrieved from smart meters [81]. Similarly, [80] compared linear models, linear and nonlinear SVMs, and NNs to predict annual heating and cooling loads in residential spaces in a long-term prediction task; the optimal results were obtained using nonlinear SVMs.

At individual level, researches [73] approached the short-term forecast of the energy consumption of three households in a nanogrid via smart meter data by reviewing several supervised learning algorithms. Refs. [74,76] have discussed on the high volatility and uncertainty of residential load profiles; Long short-term memory neural networks

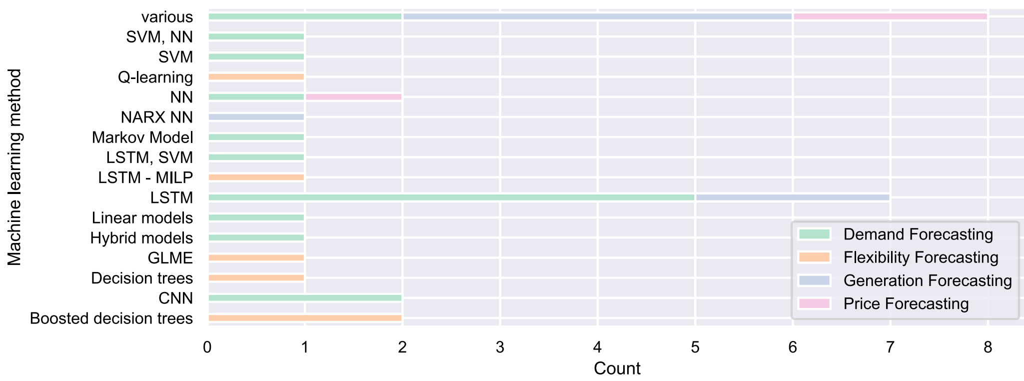

Fig. 3. Machine learning techniques used for forecasting in literature.

Table 6
Machine learning (ML) techniques for forecasting.

Forecast topic	Task	ML Algorithm	Forecast horizon	Year	Source
Demand forecasting	Load curve	SVM	Short term, medium term	2021	[69]
		Hybrid models	Short term, long term	2020	[70]
		CNN	Short term	2019	[71]
		LSTM	Short term	2020	[72]
		Various	Short term	2020	[73]
	Households	Linear models	Short term	2018	[74]
		Various	medium term	2020	[75]
		LSTM, SVM	Short term	2019	[76]
		LSTM	Short term	2018	[77]
	Households and SME	Markov Model	Short term	2019	[78]
	Appliances	LSTM	Short term	2020	[79]
	Residential space heating and cooling loads	CNN	Long term	2020	[80]
	Machine tools	SVM, NN	Very short term	2020	[68]
	Power demand for different facilities	LSTM	Short term, long term	2020	[63]
	AC energy consumption	LSTM	Short term	2019	[81]
	Rural microgrid	NN	Short term	2020	[82]
Renewable energy forecasting	PV generation	LSTM	Short term	2019, 2020	[83,84]
		Various	Short term	2019	[85]
		Various	Various	2019	[61]
	PV generation, wind generation and demand	NARX NN	Short term	2019	[86]
	Wind forecasting	Various	Various	2020	[87]
Flexibility forecasting	Demand side flexibility	LSTM - MILP	Short term	2021	[88]
		Boosted decision trees	Short term, medium term	2020	[89]
		GLME	Medium term	2019	[90]
		Decision trees	–	2021	[91]
	EV charging demand prediction	Boosted decision trees	–	2020	[49]
	EV charging navigation	Q-learning	–	2020	[92]
Price forecasting	Price forecasting Turkish market	Various	Short term	2018	[93]
	Price forecasting Iberian market	NN	Short term	2018	[94]
	Price forecasting EPEX	Various	Short term, long term	2019	[95]
Various	Price, generation, demand	Various	Short term	2021	[96]

(LSTMS) were used to obtain short-term household forecasts, yielding minimal prediction errors.

At community level, load forecasts are usually performed by considering aggregated load. For example, different algorithms have been used to forecast one day-ahead energy consumption in a residential building [77]. The authors first reviewed several single algorithms and subsequently combined these algorithms with an optimisation technique, thereby achieving improved results with the latter technique. Ref. [63] forecasted short-term and long-term energy consumption of different buildings, ranging from a residential to a factory and hospital, and the challenges of each profile have been reported. The authors compare mixed-data sampling method with LSTMs and a combination of both methods, resulting in a more accurate result.

In contrast to deterministic methods, probabilistic methods have been applied in certain studies. These methods extend the capabilities of the deterministic model by quantifying the uncertainty factors in the load forecasting task. As exemplified in [71], the authors trained recurrent neural networks (RNNs) using a probabilistic objective function to forecast the day-ahead load consumption. Probabilistic output prediction provides information on risk and related scenarios for decision making in the operation planning of the energy system [78]. Moreover, a semi-hidden Markov model have been developed to predict short-term consumption of home appliances [79].

5.1.2. Renewable generation forecasting

Most LECs will have renewable energy sources to fulfil their energy needs and sustainability goals. Accordingly, the nature of these energy generation sources results in a significant level of uncertainty in the energy supply [37,100]. An example has been reported [101], wherein multiple methods were reviewed, including nonlinear autoregressive exogenous neural networks (NARX NN), Gaussian process regression, and SVM, to forecast the behaviour of wind generation, PV generation, and demand for households. The authors assessed the inputs needed for each predictive task and highlighted the NARX NN as a robust model for wind and PV generation by conducting a sensitivity analysis. As reported in the literature [96], the results for wind generation forecasts were improved through the incorporation of exogenous information when comparing deterministic and probabilistic methods. Similarly, NARX NNs have been used [102,103] for wind and PV generation.

As mentioned in Section 2.1, PV generation is one of the most popular technologies for the generation of renewable energy in households and communities. Therefore, a number of studies have focused on this particular application. For instance, the statistical and machine learning methods for PV generation forecast have been comparatively analysed [61]. Finally, the authors compared a hybrid combination of two methods and an optimisation theorem, concluding hybrid methods increase the forecasting accuracy by adding benefits of individual methods. The performances of several machine learning algorithms have been analysed to predict the PV generation for a power plant [85]; the importance of input data, such as weather, for the prediction performance has been analysed to predict of PV generation for a power plant. The optimal results were obtained using random forest. RNNs have been extensively explored in the literature for forecast tasks concerning PV generation; for example, LSTMs have been implemented to predict the output power of different PV generation plants for a short-term time horizon [83,84].

5.1.3. Flexibility forecasting

From a prosumer's perspective, flexibility can be defined as the ability to modulate generation/consumption behaviour via an external signal, such as a change in the energy price [104]. Flexibility is a service that can be provided within the LEC at both household and community levels (refer to Fig. 1). Flexibility forecasting is based on load forecasting, considering the available flexibility sources [90]. Accurate flexibility estimation allows the LEC and its participants to generate revenue by selling flexibility to a system operator, such as *Cornwall Local Energy Market* [13]. In accordance with the classification reported in [105], flexible assets can be classified as demand side, supply side, and storage assets. This section focuses on the demand side flexibility and storage.

For flexibility estimation, [88] the economic optimisation of an energy management system has been attempted in an urban microgrid, considering the flexibility of ancillary services. The load consumption forecast was performed using LSTM. Furthermore, mixed integer linear programming (MILP) was used to optimise the energy dispatch in the day-ahead operation of the microgrid with three different types of loads: building, smart homes with and without available PV capacity, and differently clustered loads. In another study [89], the authors forecast the loads' total consumption and flexibility using boosted trees for both day-ahead and week-ahead time horizons in a commercial building. In a study [90], the flexibility was calculated for a single household for one month using generalised linear mixed-effect models (GLMM). The present study also analyses the flexibility at the household asset level.

With the novel vehicle-to-grid (V2G) technology, EV charging stations in the grid serve as a flexible asset. V2G can operate as an available energy storage device, thereby acting as a flexibility source [106]. In addition, they can be considered as a mobile energy storage system [105]. Therefore, they are also subject of study for forecasting flexibility calculations. To this end [49], prediction methods for the EV charging demand during charging sessions have been studied to optimise the management of the electric grid. Models such as linear regression, boosted decision trees, random forest, and SVM were used to predict the charging demand of EVs for flexibility predictions. Ref. [92] proposes a storage optimisation problem for EVs incorporating uncertainty caused by traffic solved by a RL model-free Q-learning algorithm. The use of decision trees has been evaluated for flexibility-based operational planning dispatch in a microgrid system connected to the grid, with storage, renewable generation, critical loads, and an industrial controller [91]. The authors comment on the feasibility of implementing decision tree-based rule programming in a PLC-based controller and highlight its interpretability in the dispatch rules compared to other state-of-the-art alternatives such as NNs.

5.1.4. Electricity price forecasting

Electricity price forecasting is an application for both community and peer-to-peer market-level configurations. A forecast of the energy price at a specific time in the future provides valuable information for handling load consumption and flexibility more efficiently [107]. Moreover, price forecasting helps to create optimised programs to efficiently dispatch the energy within the LEC, by supporting efficient resource scheduling decisions [57]. In this section, although most of the studies focus on centralised energy markets, they are highly relevant for LECs.

Most of the studies on LECs focus on the day-ahead electricity price forecasting. The price forecasting has been analysed in the Turkish day-ahead market using an RNN, and the method was compared with several other NN architectures [93]. The optimal results were obtained using the gated recurrent unit configuration of RNN. The authors highlight the capabilities of this algorithm to capture spikes and volatility. Similarly, scholars [94] implemented a regression technique using NN to predict day-ahead prices in the Iberian electricity market. Additionally, researches [95] approached electricity price forecasting for both day-ahead and a four-week time horizon in EPEX[1] in Germany/Austria. Reportedly, amongst the algorithms tested, the optimal results were achieved using NNs.

5.2. Energy management systems

An optimised energy management system allows efficient energy consumption scheduling through the coordination of the assets in the system, such as PV generation, storage, EVs, and flexible loads via demand response programs. As reported in the existing literature [104,108], an energy management system can be used to process price signals and perform cost-efficient dispatch within a wholesale market framework. Furthermore, the relevant literature indicates that data-driven algorithms support automatic optimisation of energy management systems at both individual and community levels. The distribution of machine learning techniques in the reviewed literature for energy management system is displayed Fig. 4.

5.2.1. Energy management system and control

The majority of the studies focus on the energy management optimisation by data-driven algorithms. As reported in [109], an energy management system has been developed using stochastic processes for an islanded microgrid. Additionally, researches in [110] exposed a method which optimises the power exchanged with the utility through a probabilistic approach using a Gaussian process model and model predictive control for interconnected microgrids. Supervised learning algorithm algorithms were used by researches [111], who presented a multi-agent day-ahead energy management system of a microgrid incorporating various methods from machine learning and operations research. Specifically, it demonstrates the incorporation of forecasting via RNNs and convolutional neural networks (CNNs) into distributed optimisation via the alternate direction method of multipliers. Furthermore, a framework has been introduced to optimise the cost of networked microgrids featuring wind turbine generation, EV charging, and battery storage [112]. The output power of the wind turbines is predicted via SVM and a battery optimisation algorithm is used to find

[1] European Power Exchange SE is an electric power exchange operating in Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Luxembourg, the Netherlands, Norway, Sweden and Switzerland.

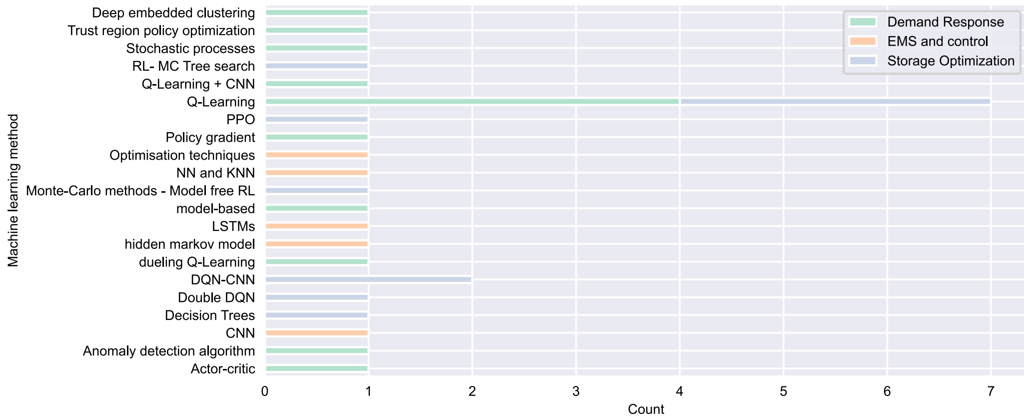

Fig. 4. Machine learning techniques in literature for energy management system.

Table 7
Machine learning (ML) techniques for energy management system and control.

Task	ML Algorithm	Level	Year	Source
Energy management system optimisation	Alternated Method of Multipliers	Microgrid	2019	[111]
	Q-learning	Household	2020	[114]
	MDP, RNN	Microgrid	2019	[115]
	SVM	Microgrid	2021	[112]
	MDP	Microgrid	2021	[116]
	DQN	Microgrid	2020	[117]
	Stochastic processes	Islanded microgrid	2021	[109]
	DQN	Microgrid	2020	[118]
	Linear reward interaction	Islanded microgrid	2020	[119]
Energy management system optimisation —flexible demand	Actor Critic	Microgrid	2020	[120]
Energy management system optimisation —HVACs units	Policy Gradients	Building	2021	[121]
Energy management system optimisation —EVs	Various	Smart grid	2019	[113]
Non-intrusive load monitoring	NN, KNN	Household	2019	[122]
	Hidden Markov model	Household	2019	[123]
	CNN	Household	2019	[124]
Energy share optimisation	DQN	Building	2018	[125]
	Gaussian process	Interconnected microgrids	2021	[110]
Energy data mining	CNN	Household	2019	[126]
	Optimisation techniques	Household	2019	[127]
Topology identification	LSTMs	Household	2020	[128]

the optimal power dispatch for batteries and EVs. Focusing on EVs, researches in [113] reviewed the optimisation of EV charging sessions by considering the vehicle's state of charge with the objective of reducing charging costs. Several machine learning algorithms were tested in this study; the results indicate that deep neural networks provide solutions proximate to the global minimum owing to the complexity of such an algorithm. A literature review of machine learning algorithms for energy management systems and controls for different application levels is presented in Table 7.

For RL approaches, scholars [117,118] used deep Q-learning (DQN) to optimise operation of the elements connected to the EMS. Another model-free approach reported in the literature featured an Actor–critic approach to coordinate flexible demand, generation, and storage in a real-time application [120]. In addition, the utilisation of deterministic policy gradients has been reported for the optimisation of agents comprising heating, ventilation, and air conditioning units [129]. The solution was demonstrated in a case study, suggesting an improvement over classical rule-based policies or discontinuous deep reinforcement learning in the form of Q-learning.

Nonintrusive load monitoring is a technique used to segment the energy consumption into patterns and identify the behind-the-meter loads. In the context of LECs, this method was applied to identify home appliances and consumption patterns. A hidden Markov model approach has been presented to identify individual load sources of various types in a single aggregated load time series, focusing on online (i.e., real-time) applications [123]. Similarly, several machine learning algorithms have been reviewed to perform a non-intrusive load-monitoring task using a home energy management system [122]. As reported in the literature [126,127] sociodemographic information was extrapolated from home energy management systems and smart meter data via clustering techniques, such as KNN, and classifiers, such as SVM.

5.2.2. *Energy storage*

Energy storage systems are used in LECs to balance energy over multiple periods of operation. These assets provide opportunities for the shifting of loads from peak to baseload periods and the integration of intermittent renewable energy [130]. As [131] storage systems may become essential assets in future LEC projects, such assets are crucial for the day-to-day operation of an LEC, focusing on flexibility and energy sources in islanded microgrids. The principle of optimal dispatching is at the core of these operations. The field of machine learning comprises a range of deep reinforcement learning (DRL) methods, which are the prevalent methods applied to energy storage applications, as indicated

Table 8
Machine learning (ML) techniques for energy storage optimisation.

Task	ML Algorithm	Year	Source
Battery dispatch optimisation w/PV	MC Tree search	2020	[133]
	DQN	2016	[134]
	Q-learning	2016	[135]
	PPO	2020	[60]
Battery dispatch optimisation	Decision trees	2020	[100]
	Double DQN	2020	[136]
	Q-learning	2020	[137]
	DQN	2020	[138]
	MC methods	2020	[129]
Transactional charging	Q-learning	2020	[139]

in recent literature. Such DRL methods can be used to develop a control function, represented via a Q-function that can handle large search spaces for dynamic problems such as optimal storage [132]. The algorithms reported in recent literature to address storage optimisation problems in power systems, which are similar to those in LECs, are listed in Table 8.

Q-learning has become a method of reference for research on most battery storage optimisation, as is the case in [137]. Similarly, [138] applied DQN to an islanded microgrid. The authors used a CNN architecture to predict Q-values, arguing the chosen convolutional architecture for its simplicity and good performance. In contrast, [136] used a double-DQN to address the uncertainty in the microgrid system for both grid-connected and islanded modes. The authors highlighted that the chosen method mitigates the overestimation that a single Q-value estimator can generate in the results. In contrast, [129] approached the DSO's optimisation retail pricing strategy problem with a RL Monte-Carlo method in a simulated multi-microgrid system.

Q-learning has also been used to solve the complexity caused by PV generation in the microgrid [134,135]. Other model-free methods, such as the Monte-Carlo tree search algorithm, have been implemented as solutions to reduce the computational burden involved for solving the stochastic dispatch of battery storage during PV generation [133]. Similarly, as reported in the literature [60], a policy gradient method, namely the proximal policy approximation (PPO) has been established. The PPO agent maximises the accumulated net revenue of the system by successfully adapting to the PV uncertainties and market signals. The PPO agent outperformed the other tested algorithms, such as the deep deterministic policy gradient, Actor–critic, and double-DQN algorithms.

5.2.3. Optimal demand response

Demand response is defined, according to the Federal Energy Regulatory Commission, as "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardised" [140]. Accordingly, the demand response can be used as a strategy to manage controllable loads when this is beneficial to the user. Data-driven approaches to optimise demand response strategies have been presented in the literature. The machine learning techniques for demand response applications are listed in Table 9. Similarly, for storage problems, RL is generally used to handle the optimal demand response. Most studies have sought a reduction strategy for energy costs. For instance, Q-learning has been applied to determine the optimal hour-ahead consumption of several appliances, such as time-shifting loads, non-controllable loads, and EVs, considering future electricity prices and PV generation trends [114]. Moreover, as reported in [141], DQN has been used for dynamic control of residential loads. A deterministic policy gradient has been employed for the optimal load schedule [142], whereas in another study [143], an Actor–critic approach was used. In contrast to previous model-free algorithms, researchers [144] applied a model-based adjustment to the traditional Q-learning algorithm, thereby improving the performance over traditional model-free learning.

Pricing models have also been explored for the development of efficient demand response programs. A study [146] aimed to approximate the impact of time-of-use pricing on-demand response via the clustering of smart meter usage data into various profiles, whilst considering the uncertainty. With a similar objective, scholars [147] used stochastic processes to incorporate uncertainty in the pricing demand response to maximise the risk-sensitive revenue derived by the DSO. Another algorithm [149] utilised the time-of-use tariffs to control the demand response within a Markov decision process with binary action spaces. This dynamic operation problem was thereafter solved via deep-duelling Q-learning. For a real-time approach, researchers [150] utilised trust region policy optimisation to address the dynamic scheduling problem of batteries and demand response. The authors demonstrated the superiority of the algorithm compared to the traditional DQN and deep deterministic policy gradient within a practical case study, wherein various residential appliances were considered.

5.3. Power system protection, stability, quality and optimisation

Either when operating in islanded mode or when connected to the grid, LECs may experience stability issues owing to weak interconnection points or insufficient capacity of distribution lines to handle the bilateral power flows from renewable sources of energy generation [153]. Hence, the importance of fast location of faults and post-fault decision making can be supported by intelligent computation programs on the basis of machine learning, leveraging the ICT measurements as the input. In the literature, different approaches to assist power system protection, stability, quality, and optimisation for smart grids and microgrids exist, and these approaches are of great interest for the operation of LECs. This section broaches the literature on LEC system adequacy and security applications, including cybersecurity concerns. Fig. 5 illustrates the occurrence of a particular machine-learning technique in the reviewed literature used for power system protection, stability, quality, and optimisation. The machine learning algorithms for each application are summarised in Table 10.

5.3.1. Protection and fault monitoring

The secure operation of the energy service in the presence of a fault is crucial for the security of the LEC [52]. Thus, identifying these faults is an important task for LEC control systems, and historically, the relevant research have focused on faster and more accurate methods to identify fault events in the grid. This is achieved via historical and real-time measurements as input data for the machine learning algorithms, aiming to increase the likelihood of an appropriate response for the grid's protection control system.

Most studies approach the problem of fault event identification as a supervised classification learning problem via training data-driven algorithms and correlating features given by measurements of a pre-specified type of fault. Researchers [154,159] have applied different ensemble methods, such as random forest and boosting techniques, to classify faults in a microgrid context. Furthermore, the multi-class classification problem of fault detection in PV arrays has been analysed

Table 9
Machine learning (ML) techniques for demand response.

Task	ML Algorithm	Level	Year	Source
Demand response	Actor critic	Household	2018	[143]
	RL model-based	Microgrid	2016	[144]
	Policy gradient		2021	[142]
	DQN	Household	2018	[141]
	Anomaly detection algorithm		2021	[145]
Demand response pricing models	Deep embedded clustering	Household	2019	[146]
	Stochastic processes	Electric utility	2018	[147]
Demand response energy efficiency	Q-learning	Building	2019	[148]
Demand response control considering tariffs	Duelling Q-learning	Smart grid	2020	[149]
Demand response in real time	Trust region policy optimisation	Household	2020	[150]
Decentralised demand control	Q-learning	Household	2015, 2020	[114,151]
	Q-learning	Buildings	2020	[152]

Table 10
Machine learning (ML) techniques for power system protection, stability, quality and optimisation.

Topic	Task	ML Algorithm	Level	Year	Source
Protection and fault monitoring	Fault detection	Boosted decision trees	Smart grid	2020	[154]
		CNN	Smart grid	2020	[155]
		NNs	energy grid	2020	[156]
		NNs, SVM	Microgrid	2020	[157]
		Boosted decision trees	Microgrid	2021	[158]
		Random forest	Microgrid	2020	[159]
		SVM	Smart grid	2019	[160]
	Line fault detection and location	NNs, SVM	Microgrid	2019	[161]
	Fault detection PV arrays	Random forest	Microgrid	2018	[162]
	Fault detection generators	SVM	Microgrid	2020	[163]
	Line fault detection	NNs	Microgrid	2017	[62]
Stability	Harmonic voltage estimation	LSTM	Unbalanced distribution grid	2020	[164]
	Dynamic event detection	NNs, decision trees, K-NN classifiers	Microgrid	2018	[165]
	Load shedding	Duelling deep Q-learning	Islanded microgrid	2021	[166]
Power quality	Power quality disturbances detection	CNN	Microgrid	2020	[167]
	Power quality disturbances	CNN	Microgrid	2020	[167]
	Volt-var control	Actor–Critic	Smart grid	2020	[168]
Optimal power flow	Simulate uncertain variables	Markov processes	Household	2020	[169]
	Wind power integration uncertainty	Bayesian inference	Microgrid	2020	[170]
	Simulate uncertain variables	Bayesian inference	–	2020	[171]
	Simulate decentralised OPF problem	Linear regression	–	2020	[172]
Cyber security	Cyber attack identification	LSTM-LUBE	Microgrid	2021	[173]
		LUBE-MSOS	Microgrid	2021	[174]
		Markov decision process	Smart grid	2018	[175]
		Bayesian networks	Smart grid	2019	[176]
	Electricity theft identification	RNN-GRU	Distribution grid	2020	[177]
	FDI attack detention	Various	Smart grid	2016	[178]

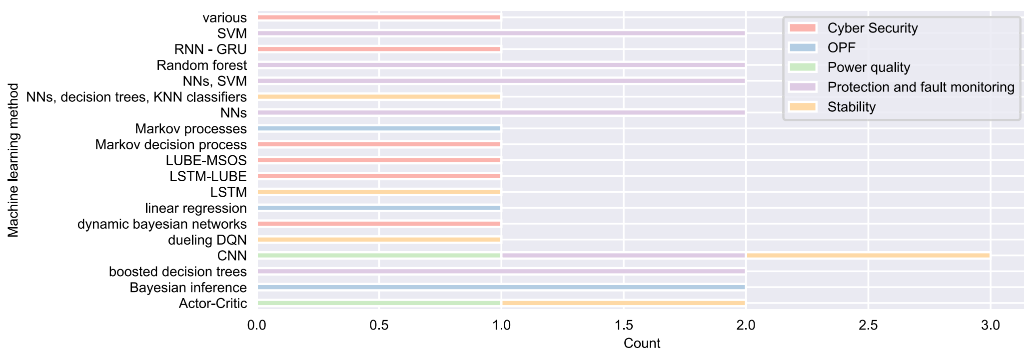

Fig. 5. Machine learning techniques in literature for power system protection, stability, quality, and optimisation.

using a random forest with a majority voting decision on the final ensemble algorithm [162]. Similarly, faults in generators present in a microgrid have been analysed using an SVM [163].

Nonlinear methods have shown the potential to deal with high-complexity classification tasks by determining strong relationships amongst the features extracted from the voltage and current signals.

For instance, a general overview of the fault detection task in microgrids has been provided, whilst focusing on nonlinear classifiers, and a comparative study of NNs and SVMs has been conducted [157]. Scholars [62] proposed a microgrid protection scheme that analyses different classifiers, such as naive Bayes, SVMs, and NNs, highlighting NNs performance over the rest of the classifiers. In a similar context, a microgrid protection scheme has been proposed using line voltage and currents to train the NN to detect faults and an SVM for fault location [161]. In addition, a CNN has been suggested for classifying earth faults and faulty feeders on the basis of signals obtained from smart meters [155]; reportedly, the CNN can detect features in the input dataset and provide accurate results using minimal signal processing techniques.

Researchers [158] have proposed an in-depth analysis of fault current tracing via the decomposition of current signals with wavelet transforms to obtain three-phase line currents and zero-component signals. This paper proposes the utilisation of these signals as the input for optimised decision trees to classify fault types and faulty phases, considering the short detection time and real-time application of the proposed methodology. Moreover, scholars [156] approached fault detection by analysing power signals and proposed applying anomaly detection in the form of NNs classifiers.

5.3.2. Stability

During normal operation of the LEC, grid congestions may arise due to sudden change in generation/consumption and weather events. The ability of the network to maintain voltage magnitudes, voltage angles, and inadequate frequency values is what is referred to as system stability. Therefore, post-fault decision making is another contributing factor in maintaining the grid stability in LECs. The identification of various events has been explored for a microgrid with several sources of energy generation [165]. The explored events include the identification of starting generators, introduction to fault, post-fault stability, operating point, fault clearance, and post-fault transient state. The suggested multi-classifier methods are random forests featuring bagging techniques, NN, and KNN. According to the authors, the further addition of extracted features to the time-series data improved the identification of all events.

Post-fault or preventive measures are required to maintain the grid stability following event detection. In this regard, emergency load shedding under different disturbance scenarios have been addressed as a Markov decision problem, and duelling deep Q-learning has been employed in an islanded microgrid [166].

5.3.3. Power quality

Power quality also refers to the voltage quality. Thus, this parameter is used to analyse the presence of harmonics and the maintenance of operational parameters within the recommended regulations. Power quality issues can interrupt operation, damage equipment, and generate unpredictable behaviour in the controllers. The need for fast methods to detect power-quality issues is increasing because of new energy technologies involving power electronics [51]. Most of the studies associated with LECs present signal analysis of voltage and/or current measurements to classify disturbances in the grid as the main applications of machine learning in this problem.

Accordingly, researchers [167] have proposed a CNN that was trained to identify and classify power quality disturbances from a voltage signal dataset consisting of harmonics, voltage swell, voltage sags, and flicker. In another study, scholars [168] proposed an actor–critic topology to manage the load injections of controllable devices within a microgrid, aiming at decentralised voltage control. Moreover, a method for harmonic state estimation has been reported in the literature [164], which was applied to smart meter data collected within an unbalanced distribution grid. The authors used an LSTM to determine power consumption and finally detected harmonic sources within the grid with a sparse Bayesian learning estimator.

5.3.4. Optimal power flow

To ensure the secure operation of the power system, power flows need to satisfy stability limits, such as voltage limits. The guaranteed optimisation of these power flows ensures the steady-state operation of the system whilst minimising a specific objective function. To this end, the other machine learning applications, which were reported in the literature, focus on the study of the efficient computation of power flows, with data-driven methods serving as an alternative to traditional numerical methods. For example, scholars [172] suggested a mechanism to decentralise the solution of optimal power flows using machine learning by solving several cases under different parameters to build a dataset that allows regression of unsolved optimal points pertaining to the power flow problem.

Similarly, several studies have proposed machine-learning techniques to study probabilistic power flows. In a study [171], variational Bayesian inference was used to approximate probabilistic optimal power flows, thereby addressing wind generation and load uncertainties. Furthermore, the result from a study [170] supports the integration of wind power in a microgrid, considering an AC optimal power flow formulation. This was achieved by incorporating the uncertainty into the balancing equations. The resulting problem was formulated as a stochastic optimisation problem and solved via multi-objective Bayesian learning. In another study [169], the authors utilised Markov processes to simulate uncertain components such as household loads or weather patterns.

5.3.5. Cyber security

Recently, cybersecurity in the context of power systems has become increasingly important owing to the rise of digitalisation and associated risks, such as breaches by third parties. Regardless of the smart infrastructure at both the on-grid and household levels, LECs are not insulated from these risks [179]. In recent studies, data-driven models relying on machine learning have proposed solutions to security challenges on a more local level. Accordingly, the use of power flow equations combined with time-series prediction models has been proposed to identify manipulated meter readings at the distribution grid level [177]. Furthermore, the authors compared traditional models, such as ARIMA, with RNNs. In addition, scholars [173,174] used an LSTM with lower and upper bound estimates (LSTM-LUBE) to detect cyberattacks in microgrids. RL was used in a study [175] to detect cyberattacks in smart grids. The problem was formulated as a model-free partially observable Markov decision problem.

Although the advantages of this method have been demonstrated, the authors remark on the implementation of deep RL as an improvement. Another approach was reported in a study [176], which used dynamic Bayesian networks and a restricted Boltzmann machine to detect unobservable cyberattacks. Furthermore, false data injection detection (FDI) have been formulated as a supervised learning problem [178]. Various classifiers are compared including the KNN, NNs, and SVM algorithms for different grid sizes. AdaBoost and multiple kernel learning were also employed as decision and feature levels; reportedly, these fusion algorithms are less sensitive in terms of grid size.

5.4. Energy transactions

Concerning the transactional activities of energy systems, data-driven algorithms have shown suitability for application in trading programs and as tools to study, analyse, and optimise participant behaviour in local energy markets regardless of the market configuration in the LEC. Emerging blockchain technologies enable trading platforms for LEC participant transactions in peer-to-peer market configurations [104]. The machine learning algorithms reported in the recent literature for energy transaction applications are listed in Table 11.

RL is the architecture chosen for research to generate goal-oriented trading strategies. For example, researchers [180,182] applied

Table 11
Machine learning (ML) techniques for energy transactions.

Task	ML Algorithm	Level	Year	Source
Trading strategies	Q-learning	Microgrid	2017	[180]
	DQN	LEM	2018	[181]
	Q-learning	Distribution grid	2019	[182]
	DQN	Microgrid	2019	[183]
Energy-supply game with economic dispatch and demand response	Q-learning	Smart grid	2017	[184]
Peer-to-peer transactions	Fuzzy Q-learning	Energy community	2019	[185]
Trading strategy, reduce plant schedule	DQN	Microgrid	2019	[186]
Trading strategies real time	DQN	Microgrid	2018	[187]
Blockchain platform	RNN	Smart grid	2021	[188]

Q-learning algorithms to develop efficient trading strategies in local energy markets, aiming to facilitate trading amongst participants and maximising utility for agents in the local energy market. Similarly, scholars [181] sought to model participants' trading behaviour by implementing a DQN algorithm. Furthermore, explored a CNN-DQN incremental RL algorithm has been explored by storing transition samples from training, a so-called experience replay procedure, thereby enabling high data efficiency by reusing the samples [182]. In a study, [186] the authors implemented DRL for energy trading within a microgrid, aiming to optimise the schedule of the virtual power plant, considering the availability of wind power and batteries.

Peer-to-peer market structures are currently being developed using blockchain technology. Blockchain applications for this type of market have been reviewed in detail [104], whilst scholars [188] have explored a blockchain-enabled peer-to-peer energy-trading platform with the integration of machine learning. The development of trading strategies in a peer-to-peer market has been explored in a study [183], which focuses on the development of a trading model for the microgrid market using DQN to overcome the challenges of dealing with uncertain variables, such as renewable generation and load demand, thereby obtaining revenues considering seasonal changes. Furthermore, fuzzy Q-learning has been used to address continuous space-state problems [185], considering a large number of scenarios in an energy trading process.

Researchers [187] generated a bidding strategy to maximise revenues in a microgrid featuring flexible and non-flexible consumption, storage, and solar generation for a real-time trading horizon. The strategy was developed using a DQN algorithm that considers a tractable state-action set.

6. Conclusions

6.1. Summary of findings

In this study, a definition of local energy communities was derived on the basis of European legislation and practical examples of community-based energy projects. The proposed definition identified the traits of locality, energy sustainability, community engagement, information and communication technology, and transactions as the key traits for such an energy community. Based on this, related literature reviews and recent publications on machine learning methods were identified, specifically in the key areas of energy management systems, asset forecasting, power quality, stability, security, and optimal control of storage and demand response. Furthermore, the present study presented an overview of the three main categories of machine learning. Specifically, for reinforcement learning, supervised learning, and unsupervised learning, the specific methods applied to each of the identified application areas were detailed in this study. Accordingly, an analysis of the state-of-the-art techniques of each application was at the core of this study. Fig. 6 maps the literature on machine learning areas and techniques presented in the subsequent sections to the previously introduced components of LECs by classifying each source according to the four dimensions of technique, category, application, and criterion.

This analysis revealed the bulk of the literature on machine learning in local energy communities provided by recurrent neural networks that were applied to forecasting problems. In addition, demand response and storage control problems were solved via reinforcement learning, specifically pure value function approximation techniques in the form of Q-learning. Similarly, reinforcement learning was prevalent in the transaction tasks.

In general, several nonlinear methods, ranging from tree-based to deep learning-based methods, can be observed in recent publications, independent of the application. In contrast, this review revealed a lack of literature on probabilistic tasks and reinforcement learning methods that considered policy function approximations with or without the value function approximations. This finding will inform the future research direction.

6.2. Proposal for future work

The goals and implementation of local energy communities appear to revolve around the uncertainty created by the individualistic community participants and a high share of renewable energy. One result is the increasing uncertainty. Whereas most of the machine learning methods identified in this study do not consider such uncertainty as a core aspect, such uncertainty is considered for the applications of local energy communities. Consequently, a gap in the literature can be observed, which treats uncertainty as a central aspect, especially from a systems perspective in related control algorithms, energy management systems, and forecasting methods.

Another consequence of an individualistic community participation and the transition of the traditional market to a more decentralised market is the need for a faster response from individual participants and their assets. Large, centrally controlled systems might be too slow to operate in real-time, and thus require resource-intensive and in-depth scheduling and optimisation activities to optimally schedule and dispatch whilst still maintaining the system between the operational bounds. In contrast, a decentralised system can provide flexibility proximate to real-time and offer a more granular resolution than discrete decision frameworks such as Q-learning. This can be achieved using the aforementioned policy of approximation methods.

The findings from the literature review suggest that nonlinear methods outperform linear methods in terms of both solution time and quality. This discovery suggests a trend towards neural-network-based methods combined with modern, state-of-the-art hardware. Presumably, these nonlinear methods will gradually be introduced into other traditional power-system applications. A nonlinear method that is yet under-represented in local energy communities is the deep Markov model, i.e., neural network-based formulations of traditional hidden Markov models. Another example of such a method is the traditional nonlinear auto-regression. Because most forecasting tasks are conducted via recurrent neural networks or convolutional neural networks, both these representative nonlinear methods require iterative approaches and thus do not scale as effectively as non-iterative autoregressive processes.

Finally, a fundamental component that is yet to be applied to local energy communities is the analysis of interactions and social aspects

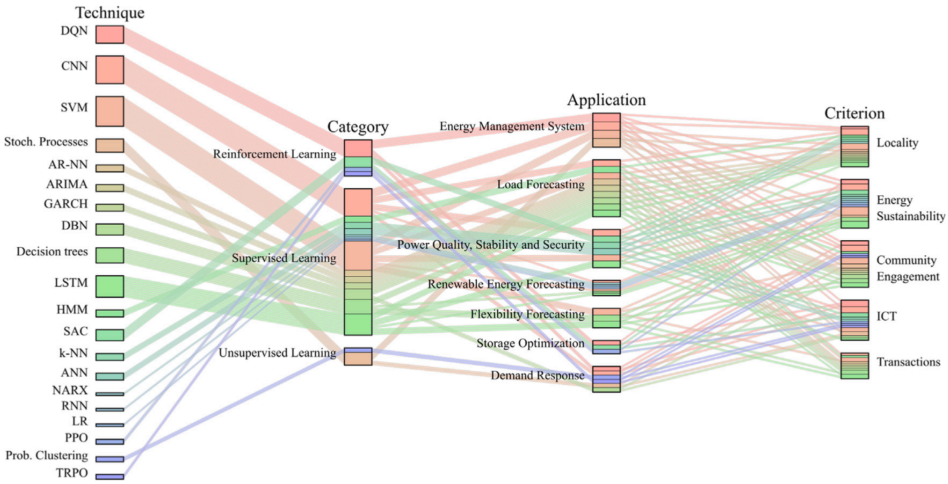

Fig. 6. LEC criteria and corresponding machine learning techniques.

using nonlinear methods. In particular, game-theoretic models and system analysis are not well-represented in the literature; however, they appear to rely on traditional methods and provide opportunities to build on the state-of-the-art methods of other applications, as presented in this paper.

CRediT authorship contribution statement

Alejandro Hernandez-Matheus: Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing, Visualization. **Markus Löschenbrand:** Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing, Visualization. **Kjersti Berg:** Investigation, Writing – original draft, Writing – review & editing, Visualization. **Ida Fuchs:** Investigation, Writing – original draft, Writing – review & editing, Visualization. **Mònica Aragüés-Peñalba:** Methodology, Supervision. **Eduard Bullich-Massagué:** Methodology, Supervision. **Andreas Sumper:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work has been supported by FINE, Spain (Flexible Integration of local energy communities into the Norwegian Electricity distribution system, project number 308833), financed by the Research Council of Norway (2020–2024) and the ENERGIX programme, Spain. We would like to thank Maren R. Brubæk for her contribution to the review on practical examples of energy communities. Eduard Bullich-Massagué and Mònica Aragüés-Peñalba are lecturers of the Serra Húnter programme.

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Paper II: The impact of degradation on the investment and operation of a community battery for multiple services

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Cite as:
K. Berg, S. Bjarghov, R. Rana, and H. Farahmand, "The impact of degradation on the investment and operation of a community battery for multiple services," in *2022 18th International Conference on the European Energy Market (EEM)*, Sep. 2022, pp. 1–8. `http://dx.doi.org/10.1109/EEM54602.2022.9921037`

The impact of degradation on the investment and operation of a community battery for multiple services

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***Abstract*—The emergence of local energy communities (LECs) introduces new concepts and dynamics to the operations of distribution grids. An important part of LECs is the shared ownership or control of assets such as photovoltaic systems and batteries. The aim of this article is to investigate how degradation impacts the investment and operation of a community battery which performs multiple services in a LEC. Two different grid tariffs are investigated: energy-based and demand charges. The case study set in Norway 2030 shows that the lifetime of the battery is significantly shortened when not considering degradation, highlighting the need to include cyclic degradation in models that investigates the profitability in investment and operational problems with batteries. In the case of a demand charge grid tariff, the expected lifetime was shortened by 6 years.**

***Index Terms*—Local energy community, Energy management system, Battery degradation, Grid tariffs**

I. Introduction

Local energy communities (LECs) are emerging as a way for prosumers and consumers to be actively engaged in using locally produced energy sources, while being connected to the distribution network. The members of a LEC often have shared ownership and control of assets such as community photovoltaics (PV) and community batteries [1]. Studies such as [1], [2] have shown that community-owned batteries are better for relieving the grid through peak shaving or self-consumption, compared to individually owned batteries.

Although there is no fuel cost related to batteries, there is still a cost of using them as the lifetime is limited. However, this is often ignored in literature, resulting in sub-optimal operation of batteries which in reality has high, non-counted costs. When included, optimal operation of batteries participating in day-head and reserve markets changes significantly [3]. The need for proper degradation modeling when participating in electricity markets with batteries has resulted in new methods to consider the cycle ageing mechanisms of lithium-ion (Li-ion) batteries, mostly based on factoring the cycle ageing [4], [5]. This type of approach has been suggested in multi-market optimisation [6], which are also relevant for LECs as the battery is meant to provide multiple services, such as arbitrage, self-consumption and reducing peak imports. A shared community battery for reducing costs while providing ancillary services was proposed in [7], but focuses more on participation in balancing markets. Ref. [8] studies how to maximise investment returns of a battery while considering a cyclic degradation cost, but the battery is grid-connected and not in a LEC. Ref. [9] presents a techno-economic optimisation model to analyse the economic viability of a PV-battery system for different residential customer groups. However, cyclic degradation of the battery is not considered, only calendaric degradation. Our hypothesis is that cyclic degradation of the battery must be included in an investment and operational problem because it will affect the investment decisions and the expected lifetime of the battery.

The aim of this article is to investigate how battery degradation impacts the investment and operation of a community battery which performs multiple services in a LEC (reduce peak import, arbitrage, peak shaving, self-consumption). The main contributions of the work presented in this article are:

- Optimisation models for investment and operation of shared PV and battery system in a LEC, including cyclic degradation cost.
- Evaluation of how two different grid tariff schemes impact battery operation and degradation.
- Evaluation of how the battery performs multiple services for the LEC when degradation cost is included.

II. Method

This section describes the optimisation models developed. The objective is to minimise both the investment costs of a shared PV system and battery, as well as operational costs related to electricity for the LEC, as illustrated in Fig. 1. It is assumed that the LEC shares the investment costs and the electricity costs.

A. *Optimisation models*

There are four cases as shown in Fig. 2, where each case refers to an optimisation model. In the energy tariff (ET) cases, the LEC has an energy-based grid tariff, where the LEC pays a grid tariff only based on the energy imported. In the demand charges (DC) cases, the LEC has a demand charge grid tariff which is often used for commercial buildings in Norway. The

This work has been supported by the consortium of the research project "FINE - Flexible Integration of Local Energy Communities into the Norwegian Electricity Distribution System" (308833), funded by the Research Council of Norway.

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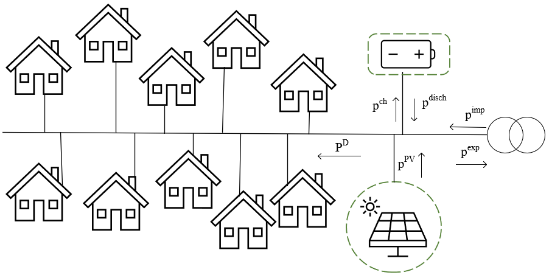

Fig. 1. Overview of LEC with shared PV and battery system

cost each month is decided from the monthly peak power, see [10] for more details.

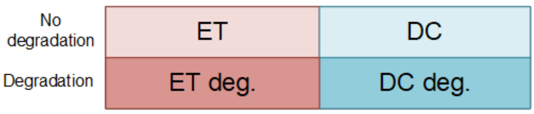

Fig. 2. Overview of cases

1) ET case: The ET case does not consider degradation. The model is shown in (1a)-(1l), see the nomenclature for an explanation of the variables and parameters. Eq. (1a) is the objective of the model, which minimises investment and operational costs. Eq. (1b) is the power balance, (1c) restrict the installed PV power, while (1d) and (1e) restrict the import from the grid. The power balance includes a curtailment variable to ensure feasibility in cases where the excess PV power exceeds the export limit. Eqs. (1f)-(1h) are state-of-charge (SOC) constraints for the battery. Eqs. (1i)-(1j) restrict the charge and discharge to be lower than available energy in the battery, and it is assumed that the power rating of the battery is equal to the battery capacity rating (C-rate of 1).

$$\begin{aligned}
\min \quad & C^B CRF^B e^B + C^{PV} CRF^{PV} p^{PV} \\
& + \sum_t \left[(C_t^{spot} + C^{tar,e}) p_t^{imp} - C_t^{spot} p_t^{exp} \right] && \text{(1a)}\\
& P_t^D - p^{PV} P_t^{PV} + p_t^{exp} - p_t^{imp} + p_t^{ch} \\
& \quad - p_t^{disch} + p_t^{PV,c} = 0 && \forall t \ \text{(1b)}\\
& p^{PV} \leq P^{PV,max} && \text{(1c)}\\
& p_t^{imp} \leq P^{imp,max} && \forall t \ \text{(1d)}\\
& p_t^{exp} \leq P^{exp,max} && \forall t \ \text{(1e)}\\
& soc_t = soc_{t-1} + \eta p_t^{ch} - \tfrac{1}{\eta} p_t^{disch} && \forall t > 0 \ \text{(1f)}\\
& soc_t = soc_T + \eta p_t^{ch} - \tfrac{1}{\eta} p_t^{disch} && \forall t = 0 \ \text{(1g)}\\
& soc_t \leq e^B && \forall t \ \text{(1h)}\\
& p_t^{ch} \leq e^B && \forall t \ \text{(1i)}\\
& p_t^{disch} \leq e^B && \forall t \ \text{(1j)}\\
& e^B, p^{PV} \geq 0 && \text{(1k)}\\
& p_t^{imp}, p_t^{exp}, p_t^{ch}, p_t^{disch}, soc_t, p_t^{PV,c} \geq 0 && \forall t \ \text{(1l)}
\end{aligned}$$

2) ET deg. case: The ET deg. case considers degradation. Here, the model from the ET case is modified by adding a degradation cost to the objective function as shown in (2).

$$\begin{aligned}
\min \quad & C^B CRF^B e^B + C^{PV} CRF^{PV} p^{PV} \\
& + \sum_t \left[(C_t^{spot} + C^{tar,e}) p_t^{imp} - C_t^{spot} p_t^{exp} \right] + \sum_t \beta_t^{deg} && \text{(2)}
\end{aligned}$$

Constraints (3a)-(3g) for battery degradation and non-negativity are added as described in [5], [11].

$$\begin{aligned}
& \beta_t^{deg} = \sum_j C_j^{deg} p_{jt}^{disch,seg} && \forall t \ \text{(3a)}\\
& p_{,t}^{ch} = \sum_j p_{jt}^{ch,seg} && \forall t \ \text{(3b)}\\
& p_t^{disch} = \sum_j p_{jt}^{disch,seg} && \forall t \ \text{(3c)}\\
& soc_{jt}^{seg} \leq \frac{e^B}{J} && \forall j,t \ \text{(3d)}\\
& soc_{jt}^{seg} = soc_{jt-1}^{seg} + \eta p_{jt}^{ch,seg} - \tfrac{1}{\eta} p_{jt}^{disch,seg} && \forall j, t > 0 \ \text{(3e)}\\
& soc_{jt}^{seg} = soc_{jT}^{seg} + \eta p_{jt}^{ch,seg} - \tfrac{1}{\eta} p_{jt}^{disch,seg} && \forall j, t = 0 \ \text{(3f)}\\
& p_{jt}^{ch,seg}, p_{jt}^{disch,seg}, soc_{jt}^{seg} \geq 0 && \forall j,t \ \text{(3g)}
\end{aligned}$$

3) DC case: In the DC case, degradation is not considered. The model from the ET case is modified by adding a monthly demand charge to the objective function as shown in (4a). Also, constraints (4b)-(4c) are added.

$$\begin{aligned}
\min \quad & C^B CRF^B e^B + C^{PV} CRF^{PV} p^{PV} && \text{(4a)}\\
& + \sum_t \left[(C_t^{spot} + C^{tar,e}) p_t^{imp} - C_t^{spot} p_t^{exp} \right] + \sum_m p_m^{max} C_m^{tar,d} \\
& p_t^{imp} \leq p_m^{max} && \forall t \quad \text{(4b)}\\
& p_m^{max} \geq 0 && \forall m \quad \text{(4c)}
\end{aligned}$$

4) DC deg. case: In the DC deg. case, degradation is considered. The model is equal to the DC case, except the objective function is replaced with (5).

$$\begin{aligned}
\min \quad & C^B CRF^B e^B + C^{PV} CRF^{PV} p^{PV} \\
& + \sum_t \left[(C_t^{spot} + C^{tar,e}) p_t^{imp} - C_t^{spot} p_t^{exp} \right] \\
& + \sum_t \beta_t^{deg} + \sum_m p_m^{max} C_m^{tar,d} && \text{(5)}
\end{aligned}$$

B. Battery specifications and degradation

The battery system is assumed to be a Li-ion nickel manganese cobalt (NMC) battery which follows the following cycle depth stress function [5], [12]:

$$\Phi(\delta) = (5.24 \cdot 10^{-4}) \delta^{2.03} \tag{6}$$

where Φ is the cycle depth stress and δ is the cycle depth. The degradation cost is then found from [5]:

$$C_j^{deg} = \frac{C^{B,rep}}{\eta} (\Delta\Phi(\delta_j)) \tag{7}$$

where $C^{B,rep}$ is the replacement cost of the battery in NOK/kWh and $\Delta\Phi(\delta_j)$ is the size of the cycle depth of segment j in %.

C. Annualised investment costs

Since the cases are run for one year, the investment costs for the battery system is annualised by a capital recovery factor:

$$CRF^B = \frac{i(1+i)^{n^B}}{(1+i)^{n^B} - 1} \tag{8}$$

where n^B is the lifetime of the battery in years, and i is the interest rate. The investment cost for the PV system is annualised in the same manner.

III. Case Study

The case study is set to Norway in 2030. Demand and PV production data are based on hourly data from 2015 while the spot price level and installation costs for PV and battery are based on cost projections for 2030. Total demand for the ten households in the LEC is shown in Fig. 3, based on the normalised household data described in [13] multiplied with a peak load of 6 kWh/h. It is assumed that there is a restriction on the distribution grid where the LEC is connected, leading to an import limit of 35 kWh/h as indicated in the figure. Without the battery, this limit would be violated in ten hours of the year.

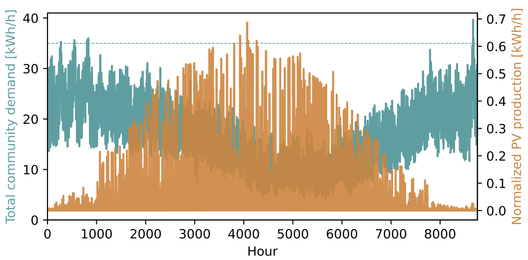

Fig. 3. Total demand of households in LEC and normalized PV production. Dashed line shows import limit of 35 kWh/h.

TABLE I
Input (same for all cases)

Parameter	Value	Unit
$P^{imp,max}$, $P^{exp,max}$	35	kWh/h
η	0.95	-
i	0.051	%
C^B	2000 [14][a]	NOK/kWh
C^{PV}	8000 [15][b]	NOK/kWp
$C^{B,rep}$	$CRF^B C^B$	NOK/kWh
n^{PV}	30	years
n^B	10	years

[a] IRENA projections for Li-ion NMC batteries in 2030 are approx. 200 USD/kWh, which corresponds to 1975 NOK/kWh
[b] IRENA projections for PV system costs in 2030 are in the range of 340-834 USD/kW, which corresponds to 3358-8200 NOK/kW

Tab. I summarises the input which is the same for all cases. The PV panels have the specifications from [16], and an assumed efficiency of 0.95. The power output from the PV system is calculated from irradiance and temperature data for Maere, Norway, as explained in more detail in [13]. The replacement cost for the battery, used to find the degradation cost in (7), is assumed to be the annualised investment cost of the battery since the analysis is carried out over one year. Fig. 4 illustrates the idea behind this assumption. For this case study, the battery degradation cycle depth stress function is linearised by four segments.

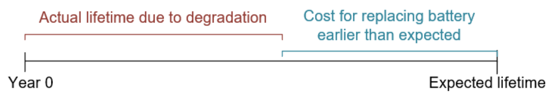

Fig. 4. Replacement cost as degradation cost

It is assumed that the spot prices in 2030 will be higher than the prices for 2015. The average spot price in 2015 was 0.19 NOK/kWh, while the future scenarios for spot prices in Norway are assumed to have an average of 0.52 NOK/kWh [17]. Therefore, the spot prices for NO3 prize zone in Norway for 2015 were multiplied with 2.75. The resulting electricity spot price used in the case studies, including VAT (25 %), is shown in Fig. 5.

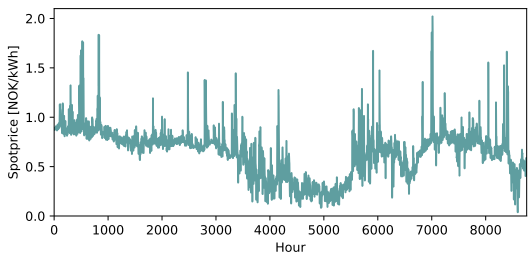

Fig. 5. Projected spot price for 2030 including VAT (25 %)

The grid tariffs are based on tariffs from the Norwegian DSO Tensio TN [18]: The ET case has an energy tariff, $C^{tar,e}$, of 0.4126 NOK/kWh and no demand charge. The DC case has an energy tariff, $C^{tar,e}$, of 0.2564 NOK/kWh and a demand charge, $C^{tar,D}$, of 89 NOK/kW-peak in winter months (Nov.-Feb.) and 13 NOK/kW-peak in summer months (May-Oct.). These numbers include consumption tax and VAT (25%).

IV. Results and Discussion

This section shows the results for the four cases when run for one year with hourly time-resolution.

A. Battery operation and degradation

Fig. 6 shows the battery operation in January for ET deg. and DC deg. cases. Due to the demand charges grid tariff, the battery peak shaves demand above 31.4 kWh/h, indicated by the dashed line. The plots for SOC and degradation cost indicate that the battery finds profitability in peak shaving in the DC deg. case, even though this amounts to a higher degradation cost.

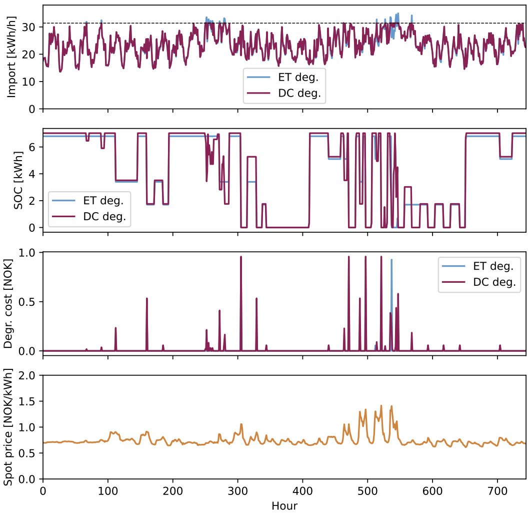

Fig. 6. ET deg. and DC deg. cases in January

Fig. 7 shows the battery operation in October for cases DC and DC deg. The battery peak shaves demand above 22.7 kWh/h, indicated by the dashed line. In the DC case, the battery is doing arbitrage on the spot price in almost all hours where there is a variation in the price. In the DC deg. case, the battery is more restrictive to when it responds to price variations, because it does not find it profitable to do arbitrage on small price variations when it leads to a high degradation cost.

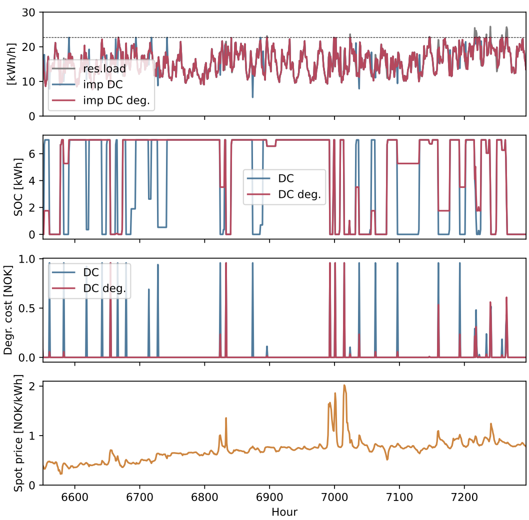

Fig. 7. DC and DC deg. case for October

Fig. 8 shows the battery operation for ET and ET deg. cases for one week in June. In the ET deg. case, the battery does not prioritise to charge all of the excess PV power and therefore exports some energy during the first day. When looking closely at the hours of export, we see that the battery balances some of the PV production but not all. This is due to the non-linear degradation cost of using the battery. Essentially, the battery ”fuel cost” is low enough for balancing using shallow cycles, but only using the cheapest segments of the battery. This preservation of battery lifetime is not captured in the ET case, which is an important feature of the degradation model.

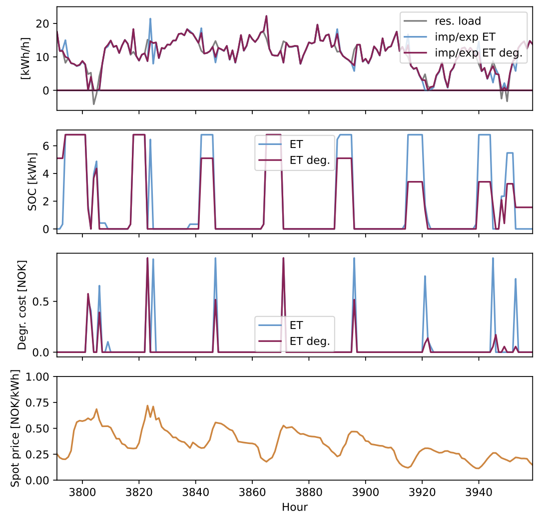

Fig. 8. ET and ET deg. cases for 8.-14. June

Fig. 9 shows the battery operation in December for ET and ET deg. case. The battery peak shaves the demand to meet the import limit of 35 kWh/h. It can also be seen that the battery operation of ET and ET deg. agree when there is very little spot price variation from hour 8100-8190.

Fig. 10 shows the accumulated degradation costs for all cases. As expected, the degradation cost is increasing much faster when degradation is not considered. Cases ET and DC show a clear distinction between the two grid tariffs. After approx. hour 500, the utilisation of the battery in the DC case is higher compared to the ET case. This is caused by the difference in grid tariffs along with the fact that the ET case has PV production. After approx. hour 3400, the degradation cost for the ET case is increasing faster than for the DC case, due to self-consumption of PV power and the fact that demand charges are lower in the summer months. At approx. 5800 hours the two cases are almost at the same level, until the DC case again increases faster due to higher demand charges in the winter months, in addition to almost no excess power from the PV system in the ET case. When looking at the cases ET deg. and DC deg. (dashed lines), they follow the same trend as the cases without degradation, except for one thing: they actually cross at hour 5300. This is because the ET deg. case is

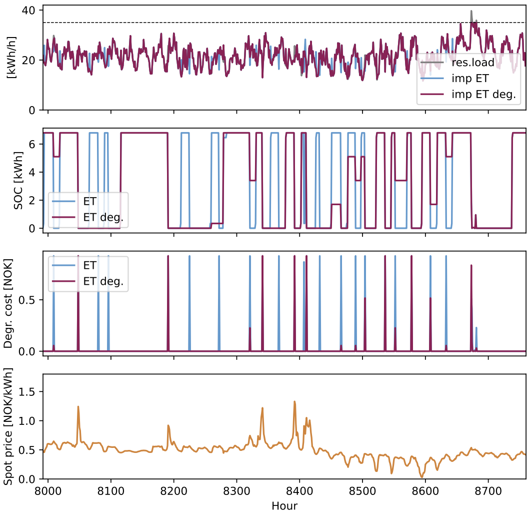

Fig. 9. ET and ET deg. cases for December

maximising self-consumption of PV power and doing arbitrage while the spot price is around 1.0 and 1.5 NOK/kWh (see Fig. 5).

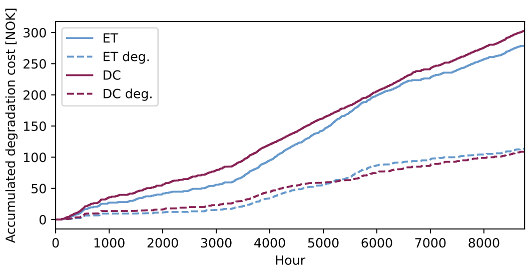

Fig. 10. Accumulated degradation costs for each case, with and without degradation

B. Yearly summary

Tab. II shows the results for all cases. The battery size is approx. equal, 6.8 and 7.0 kWh, and for this case study the main reason for installing a battery is to meet the restriction on grid import. The model did not find it profitable to invest in a PV system for the cases DC and DC deg. This difference in PV investment reflects on the results for grid exchange, where there is approx. 14,000 kWh more import from the grid in the DC case compared to ET case. A significant reason for the lack of PV investments under demand charges, is that self-consumption saves less in terms of grid tariffs, as the energy term is much lower. Although the number of cycles are relatively similar between cases ET deg. and DC deg., the reasons are different. Under demand charges, it is profitable to avoid peak loads to save on the costly peak import hours, whereas energy-based tariffs has little incentive for peak shaving, but rather benefits from self-consumption of PV production. Essentially, the grid tariff structure impacts heavily which services the battery finds profitable.

The number of full cycles in the ET case is 1.9 times higher than the ET deg. case. Subsequently, if we assume that the battery lifetime is 2,000 cycles at full discharge cycles, the lifetime of the battery is almost halved. The other cases show the same result, with slightly different numbers. In any case, it is an understatement to say that the degradation heavily affects the lifetime of the battery.

TABLE II
COMPARING CASES

Cost	ET	ET deg.	DC	DC deg.
e^B	6.8	6.8	7.0	7.0
p^{PV}	25.4	24.9	0	0
$\sum p^{imp}$	131,853	131,994	145,986	145,869
$\sum p^{exp}$	402	358	0	0
max. p^{imp}	35	35	35	35
max. p^{exp}	10.0	8.0	0	0
$\sum p^{ch}$	2,152	1,124	2,348	1,152
$\sum p^{disch}$	1,942	1,014	2,119	1,040
no. of cycles[a]	317	165	334	164
lifetime [y][b]	6.3	12.1	6.0	12.2

[a] no. of cycles is here calculated in a simplified manner, by $\frac{\sum p^{disch}}{e^B}$
[b] lifetime is here calculated from the cycle lifetime of the battery, which is 2000 cycles at full discharge [5]

V. Conclusion

The aim of this article was to investigate how battery degradation impacts the investment and operation of a community battery which performs multiple services. Optimisation models have been developed for energy-based and demand charge grid tariffs, with and without considering battery degradation.

When including degradation cost, the battery assesses whether or not the revenues from the service outweighs the degradation cost of the battery cycle. Under demand charges, the battery finds it profitable to do peak shaving. In the energy-based tariff cases, the battery gains value mainly through self-consumption and spot price arbitrage when the price is high, despite the degradation costs.

The lifetime of the battery is significantly shortened when not considering degradation, highlighting the need to include cyclic degradation in models that investigate the profitability in investment and operational problems with batteries. For both grid tariffs, the expected lifetime was shortened by approx. 6 years when not considering degradation.

Future work includes further development of the degradation model, case studies on LECs with different types of load profiles, and investigation of how the battery operation affects the distribution grid voltage.

Acknowledgment

The authors would like to thank Magnus Korpås, Merkebu Z. Degefa, Kasper E. Thorvaldsen and Emil Dimanchev for discussions regarding this work.

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Nomenclature

Parameters

δ Cycle depth [%]
$\Delta\Phi(\delta_j)$ Size of cycle depth of segment j [%]
η Battery efficiency
C^B Investment cost of battery [NOK/kWh]
$C^{B,rep}$ Replacement cost of battery [NOK/kWh]
C_j^{deg} Degradation cost for segment j
C^{PV} Investment cost of PV [NOK/kWp]
C_t^{spot} Electricity spot price in hour t [NOK/kWh]
$C_m^{tar,d}$ Demand charge grid tariff for month m [NOK/kW]
$C^{tar,e}$ Energy based grid tariff [NOK/kWh]
CRF^B Capacity recovery factor battery
CRF^{PV} Capacity recovery factor battery
i Interest rate
n^B Lifetime of battery [y]
n^{PV} Lifetime of PV system [y]
P_t^D Demand households in hour t [kWh/h]
$P^{exp,max}$ Grid export limit [kWh/h]
$P^{imp,max}$ Grid import limit [kWh/h]
$P^{PV,max}$ Maximum PV size [kWp]
P_t^{PV} PV production in hour t [kWh/kWp]

Indices

J Number of segments
j degradation segment
m month
T Last hour of year [t]
t hour
y year

Variables

β_t^{deg} Battery degradation cost in hour t [NOK]
e^B Energy capacity of battery [kWh]
$p_{jt}^{ch,seg}$ Battery charging for segment j in hour t [kWh/h]
p_t^{ch} Battery charging in hour t [kWh/h]
$p_{jt}^{dich,seg}$ Battery discharging for segment j in hour t [kWh/h]
p_t^{disch} Battery discharging in hour t [kWh/h]
p_t^{exp} Export to grid in hour t [kWh/h]
p_t^{imp} Import from grid in hour t [kWh/h]
p_m^{max} Maximum import from grid in month m [kWh/h]
$p_t^{PV,c}$ Curtailed energy in hour t [kWh/h]
p^{PV} Size of PV system [kWp]
soc_{jt}^{seg} Battery state of charge for segment j in hour t [kWh]
soc_t Battery state of charge in hour t [kWh]

Appendix

A. Yearly plots

Fig. 11 shows the results from ET case.
Fig. 12 shows the results from ET deg. case.
Fig. 13 shows the results from DC case.
Fig. 14 shows the results from DC deg. case.

B. Costs

Fig. 15 shows the yearly degradation cost for all cases.
Tab. III shows the resulting costs for all cases.

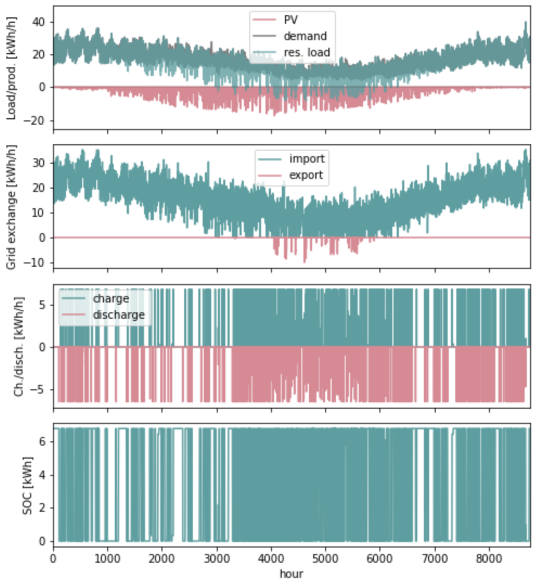

Fig. 11. ET case

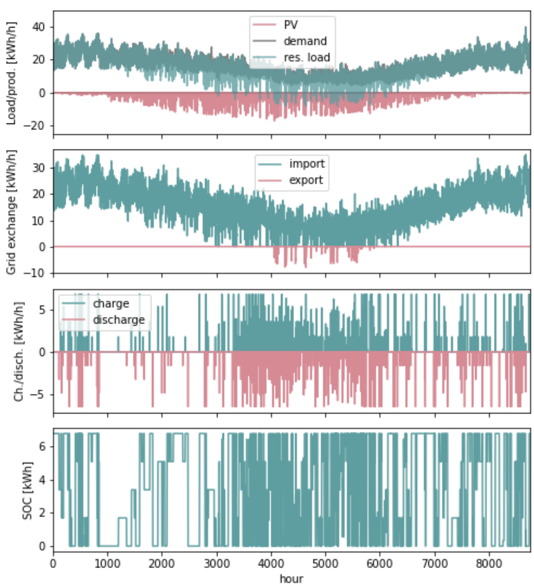

Fig. 12. ET deg. case

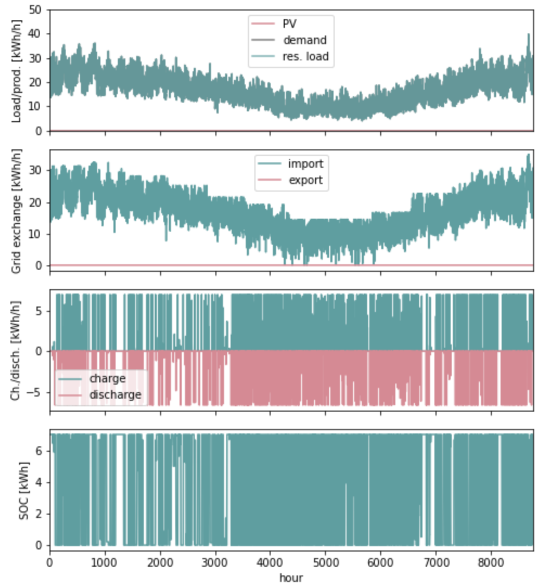

Fig. 13. DC case

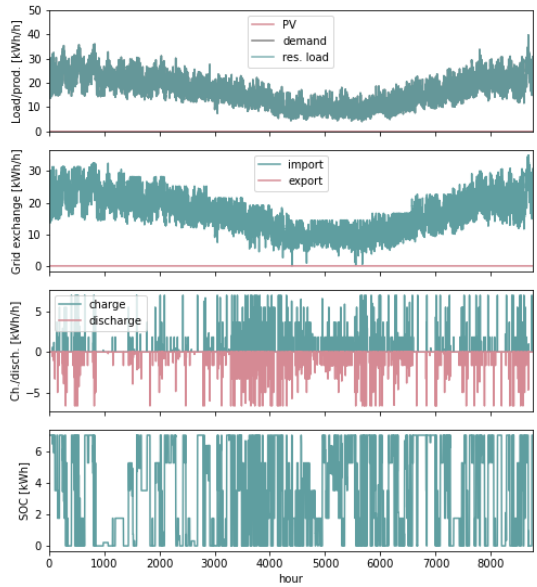

Fig. 14. DC deg. case

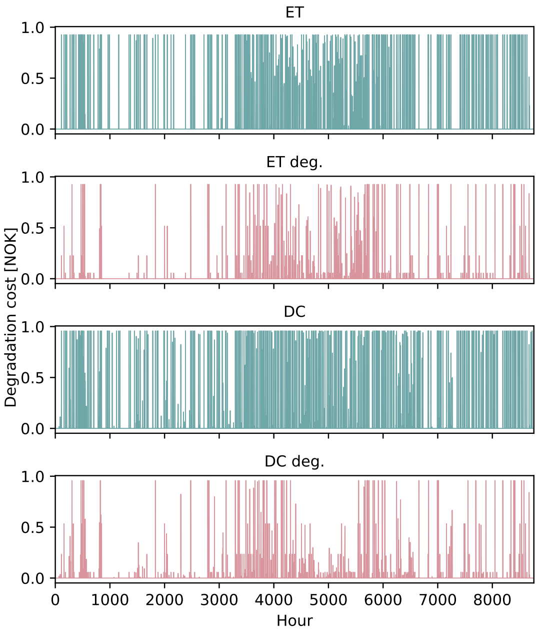

Fig. 15. Comparing degradation cost for cases

TABLE III
COMPARING CASES - COSTS [NOK]

Cost	ET	ET deg.	DC	DC deg.
Ann. cost battery	1,769	1,769	1,829	1,829
Ann. cost PV	13,346	13,083	0	0
Energy cost	129,281	129,551	119,150	119,198
Demand cost	0	0	17,654	17,654
Degr. cost[a]	278	114	302	109
Objective function	163,151	163,321	159,063	159,239

[a] The degradation cost is reported for all cases, but is only included in the objective function for cases ET deg. and DC deg.

Paper III: Economic assessment and grid impact of different sharing keys in collective self-consumption

The conference paper **"Economic assessment and grid impact of different sharing keys in collective self-consumption"** is currently under review.

This paper is under review for publication and is therefore not included.

Paper IV: Optimal control of domestic hot water tanks in a housing cooperative - Benefits for the grid

The paper **“Optimal control of domestic hot water tanks in a housing cooperative - benefits for the grid”** is published by **IEEE** in the conference proceedings of the **IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)**. The accepted version of the paper is reprinted here with permission from the authors and publisher, ©2023 IEEE.

Cite as:
K. Berg, V. H. Lenes, and K. B. Lindberg, “Optimal control of domestic hot water tanks in a housing cooperative - benefits for the grid,” in *2023 IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*, Oct. 2023, pp. 1–5. http://dx.doi.org/10.1109/ISGTEUROPE56780.2023.10407406

Optimal control of domestic hot water tanks in a housing cooperative - benefits for the grid

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***Abstract*—Energy communities (ECs) are emerging, and there is a need to understand how they will impact the distribution grid. One example of ECs in Norway today are housing cooperations with common assets such as thermal energy storage. This paper aims to quantify the benefit electric domestic hot water (DHW) tanks can give to a housing cooperative and the distribution grid. A real housing cooperative in Norway with six apartment blocks, roof-top PV and a common electric vehicle garage is investigated in three cases: a base case with no optimisation of the DHW tanks; individual optimisation of DHW tanks in each apartment block; and central optimisation of all DHW tanks in the housing cooperative as an EC with aggregated net metering. Compared to the base case, individual optimisation leads to a 4.4% reduction in peak demand, while central optimising leads to a 10.6% reduction in peak demand. With central optimisation, the electricity costs are reduced by 2.6%, mainly due to a reduction in the demand charge electricity grid tariff. If the demand charges are omitted from the objective function, central optimisation yields a higher peak demand compared to individual optimisation.**

***Index Terms*—housing cooperative, hot water tank, aggregated net metering, grid impact, energy community**

I. Introduction

Energy communities (ECs) are emerging as a way to increase local energy production by common investments in and ownership of assets such as energy storage. As the distribution grid is facing an increase in load and distributed production in the years to come, it is important to utilise flexibility and reduce peak demand wherever possible. ECs with common assets can be a way to achieve this.

Since ECs should be controlled by its members, housing cooperatives might be the closest to ECs that exists in Norway today. Housing cooperatives are legal entities of one or several apartment blocks that often share costs for investments and maintenance of properties, and they might have common assets such as electric vehicle (EV) chargers and thermal energy storage for tap water and/or space heating. However, housing cooperatives with several apartment blocks are metered separately, and they therefore do not have an incentive today to reduce the aggregated peak load.

Studies have shown that domestic roof-top PV, electric domestic hot water (DHW) tanks and heat pumps (HPs) can be used to reduce electricity costs and CO_2 emissions in dwellings [1]–[5]. Furthermore, community-owned storage reduces costs compared to individual storage, due to economies of scale and aggregation [6], and it has been shown that thermal energy storage can be used in ECs for peak shaving [6]. These assets can also reduce peak load demand from the grid [7], [8]. Ref. [9] optimised PV-coupled HPs, with and without electricity and heat storage, and found that both electricity and heat storage have benefits for the grid as long as there is a capacity-based grid tariff.

The aim of this paper is to quantify the benefit that electric DHW tanks can give to a housing cooperative and the distribution grid by optimising the operation of the DHW tanks. We also investigate how aggregated net metering will impact the costs for the housing cooperative and the grid exchange. The main contributions are:

- linear optimisation model for a housing cooperative, with PV and EV charging, including a thermal energy storage heated by HPs and electric heating element
- quantification of reduced costs and grid exchange when operating DHW tanks optimally
- quantification of the differences in electricity costs and grid exchange when optimizing each apartment block in the EC individually or centrally

II. Method and case study

Fig. 1 shows the concept of the paper. The case study is Røverkollen housing cooperative in Norway, which is located north-east of Oslo. It consists of six apartment blocks, each with common DHW tanks used for tap water which can be heated by air-source HPs and electric heating elements. The apartments are heated with electric space heating [8]. There is also a common garage with electric vehicle (EV) charging and photovoltaic (PV) production. There is no rooftop PV on the apartment blocks today, but this has been included in this case study. Three cases are compared:

1) Case B: Base case where there is no optimisation of the DHW tanks, and it is assumed that the electricity demand for DHW is imported from the grid directly (no storage). All apartments have electricity demand for lighting, appliances and electric space heating[1], and a synthetic PV production profile is included. The garage net demand is added when calculating the grid exchange at the point of common coupling (PCC).

This work was supported by the Research Council of Norway and the partners of the FINE project (project no. 308833). This paper has been written using data from the H2020 GreenCharge project (greencharge2020.eu). The authors of this paper, on behalf of the GreenCharge consortium, acknowledge the European Union and the Horizon 2020 Research and Innovation Framework Programme for funding the project (grant agreement no. 769016).

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[1] This is further referred to as el. demand

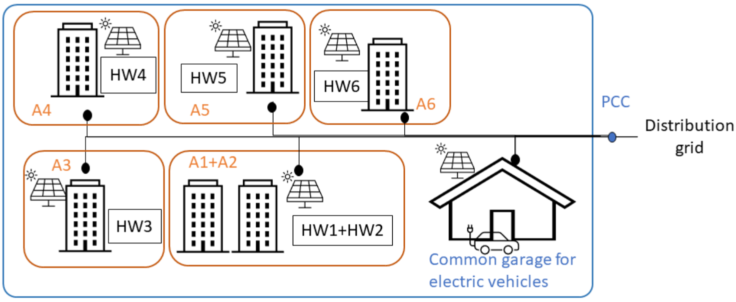

Fig. 1. Paper concept. Orange squares show the individual optimisation for each apartment block in Case I. Blue square shows the optimisation for the whole EC, including the garage with EVs, in Case C. Apartment buildings 1 and 2 are combined due to GDPR.

2) Case I: Individual optimisation of the DHW tanks in each apartment block. The garage net demand is added after the optimisation when calculating the grid exchange at the PCC.
3) Case C: Central optimisation of all DHW tanks for the whole EC, including the garage net demand.

Due to GDPR, the measured data for apartment blocks 1 and 2 are aggregated.

A. Optimisation model

The optimisation model is shown in (1a)-(1m) and the variables and parameters are given in Tabs. I, II and III.

$$\min \quad \sum_m C_m^{dc} \gamma \overline{p_m^{dc}} + \sum_t \Big[(C_t^{spot} + C^{et} \qquad (1a)$$

$$+ C^{fee}) \gamma p_t^{imp} - (C_t^{spot} + C^{Rem}) p_t^{exp} \Big]$$

$$p_t^{imp} - p_t^{exp} = P_t^d - P_t^{pv} + p_t^{hp} + p_t^h \qquad \forall t \quad (1b)$$

$$p_t^{imp} \leq \overline{p_m^{dc}} \qquad \forall t \quad (1c)$$

$$p_t^{hp} = \frac{q_t^{hp}}{COP_t} \qquad \forall t \quad (1d)$$

$$p_t^h = q_t^h \qquad \forall t \quad (1e)$$

$$p_t^{hp} \leq N^{hp} \overline{P^{hp}} \qquad \forall t \quad (1f)$$

$$p_t^h \leq \overline{P^h} \qquad \forall t \quad (1g)$$

$$q_t^{loss} = U \cdot A \cdot N^{wt} \left(\frac{e_t}{V \cdot c_p} + T^0 - T_t^{amb} \right) \qquad \forall t \quad (1h)$$

$$e_t = \overline{E} \qquad t = 0 \quad (1i)$$

$$e_t = e_{t-1} + q_t^{hp} + q_t^h - Q_t^d - q_t^{loss} \qquad \forall t > 0 \quad (1j)$$

$$\underline{E} \leq e_t \leq \overline{E} \qquad \forall t \quad (1k)$$

$$p_t^{imp}, p_t^{exp}, p_t^{hp}, p_t^h, q^{hp}, q^h, q^{loss}, e_t \geq 0 \qquad \forall t \quad (1l)$$

$$\overline{p_m^{dc}} \geq 0 \qquad \forall m \quad (1m)$$

The objective is to minimise total costs for electricity, consisting of demand charge grid tariff[2], energy grid tariff, electricity fee, spot price, and remuneration for loss reduction. In Case B/I, the input for demand, production, and characteristics of the DHW tanks are given for one apartment block. In Case C, the input is the aggregated demand, production, and sum of all DHW tanks for the EC. (1b) is the power balance for the connection point, which is the apartment block in Case B/I, and the PCC in Case C. The equation includes the imported and exported power, the el. demand in the apartment blocks (and garage in Case C), PV production of the apartment blocks (and garage in Case C), the HP power, and the heating element power. (1c) keeps track of the highest monthly electricity consumption, which is used to calculate the demand charges. (1d)-(1g) are the constraints of the HP and heating element which heat the DHW tank. (1h)-(1k) determine the loss and state-of-energy of the tank. The DHW tank is modelled as a one-mass model and therefore assumes a uniform temperature in the tank.

TABLE I
VARIABLES

Variable	Explanation
$\overline{p_m^{dc}}$	Peak el. import in month m [kWh/h]
p_t^{imp}	Imported power in hour t [kWh/h]
p_t^{exp}	Exported power in hour t [kWh/h]
p_t^{hp}	HP el. consumption in hour t [kWh/h]
q_t^{hp}	HP thermal output in hour t [kWh/h]
p_t^h	Heating element el. consumption in hour t [kWh/h]
q_t^h	Heating element thermal output in hour t [kWh/h]
q_t^{loss}	DHW tank thermal loss in hour t [kWh]
e_t	Energy in tank in hour t [kWh]
t, m	hour, month

The DHW demand in kWh/h is found from $Q^d = Q^v \cdot c_p \cdot (T^{out} - T^0)$, where Q^v is the DHW demand in L/h. The coefficient of performance (COP) of the HP is calculated as $COP_t = Q^{del}/\overline{P^{hp}}$, where Q^{del} is delivered heat at given temperature differences and $\overline{P^{hp}}$ is rated power. The HP has a heat capacity of 6 kW and 2 kW when the outdoor temperature is 22°C and 0°C, respectively[3]:

$$COP_t = \begin{cases} 1.1, & T_t < 0°C \\ 1.1 + 0.1(\overline{T} - T_t), & 0°C < T_t < 22°C \\ 3.3, & T_t > 22°C \end{cases} \qquad (2)$$

[2]The demand charge grid tariff is calculated from the monthly peak demand (hourly) and is further referred to as only demand charges.

[3]The COP is assumed linear between the operating points and constant outside.

TABLE II
PARAMETERS

Parameter	Explanation	Value
γ	Value-added tax (VAT)	1.25
C_m^{dc}	Demand charge in month m excl. VAT	7.2 €/kW in Oct-Mar and 3.2 €/kW in Apr-Sep [10]
C^{et}	Energy tariff excl. VAT	0.005 €/kWh [10]
C^{fee}	Electricity fee	0.01584 €/kWh [10]
C^{Rem}	Remuneration from DSO for loss reduction	0.005 €/kWh [10]
U	Thermal transmittance	0.00091 W/(m^2·K)
A	Surface area of DHW tank	5.72 m^2
V	Volume of DHW tank	400 L
c_p	Specific heat capacity water	$1.16 \cdot 10^{-3}$ kWh/(L·K)
COP_t	Coefficient of performance of HP	
$\overline{P^{hp}}$	HP max. power	1.818 kW
T^0, T^{out}	Temperature of water into tank (reference) and out of tank	9 °C, 40 °C
T^{amb}	Ambient temperature	20 °C
$\underline{T}, \overline{T}$	Min. and max. temperature in tank	60 °C, 80 °C
$\overline{E}$	Max. energy in tank	kWh
$\underline{E}$	Min. energy in tank	kWh
C_t^{spot}	Electricity spot price	time series [€/kWh]
P_t^d	Electricity demand	time series [kWh/h]
P_t^{pv}	PV generation	time series [kWh/h]
Q_t^d, Q_t^v	DHW demand in energy and volume	energy [kWh/h] and volume [L/h] time series
T_t	Temperature	time series [°C]

B. Input data

All input data is given in hourly resolution for the year 2021. Tab. III shows the characteristics for the cases. As the table shows, the number of HPs and DHW tanks, and max. of the heating element are summed in Case C. The max. PV production, el. demand and DHW demand in Case C is a lower value than the sum of all buildings in Cases B/I since the peaks do not occur in the same hour. Fig. 2 shows the apartment load and garage net load in week 1. It should be noted that el. consumption for common areas in the apartment buildings is excluded in this study due to lack of data. Fig. 3 shows the DHW demand in week 1.

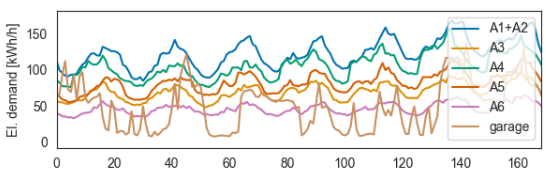

Fig. 2. Load for individual apartments within each apartment block (A1 to A6) and net load for garage, week 1

Synthetic PV profiles for the apartment blocks are created from PVsyst based on the available roof area, a 10° tilt, orientation (east/west), and shading[4]. Fig. 4 shows the yearly input data for the EC. We can see that the apartment el.

[4]Installed PV capacity is assumed to be 34.2 kWp for A2, A4 and A6, and 50.24 kWp for A1, A3 and A5.

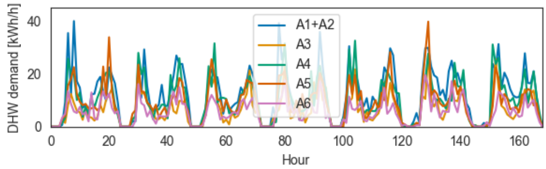

Fig. 3. DHW consumption for individual apartments within each apartment block (A1 to A6), week 1

demand has the major part of the total electricity demand, whereas the DHW demand is quite even throughout the year. Also, there is very little PV production in winter. When adding all demand together, the peak demand is 788 kWh/h and occurs in hour 162 (week 1), when the DHW demand constitutes 88 kWh/h. The electricity spot price used is from

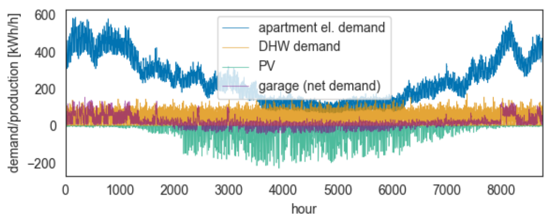

Fig. 4. Yearly apartment load, PV production, DHW demand for the entire EC and garage import/export

NO1 2019, increased to an average level of 0.058 EUR/kWh to represent the future expected spot price [11]. The energy tariff, electricity fee, loss remuneration, and demand charges are given in Tab. II. Synthetic, stochastic consumption profiles of DHW were created based on an extension of the model in [12], [13]. DHW consumption profiles are created based on Markov chains, flow rate data, number of apartments and number of residents[5]. The number of residents is estimated based on [14], which reports that 52% live alone and 22% live with children. Due to the size of the apartments, the following assumption is made: 50% apartments for a single person, 30% two people and 20% three people.

III. RESULTS AND DISCUSSION

This section presents the DHW tank operation, yearly costs and grid exchange for all cases. We also show how the results change if there is no PV on the apartment blocks or if the EC does not pay demand charges.

A. DHW tank operation

The main decision variables in the optimisation model are the electricity consumption of the HP and the heating element. Fig. 5 shows the operation of the DHW tank for the EC for Case C in week 1. This week is chosen since it has the highest peak demand. In the upper figure, we observe that the DHW demand (blue line) is mainly covered by the HP (orange bars),

[5]Parameters for creating profiles are: Shower: 10 L/min, 4 min. duration. Bath: 16 L/min, 6 min. duration. Misc.: 4 L/min, 2 min. duration.

TABLE III
INPUT CHARACTERISTICS FOR EACH APARTMENT BLOCK AND GARAGE

Case	Building	# HPs, N^{hp}	# DHW tanks, N^{wt*}	Max. heating element [kW], P^h	Max. PV production [kWh/h], P^{pv}	# residents	Max. el. import [kWh/h], P^d	Max. DHW demand [kWh/h], Q^d
B/I	1+2	3+1	6+3	28+14	39+26	52+18	173	60
	3	2	4	28	40	40	104	35
	4	3	6	28	26	54	156	43
	5	3	6	28	40	52	122	47
	6	2	4	28	25	30	69	29
	garage	-	-	-	47	-	156	-
C	all	14	29	154	229	246	701	174

*In Case B, there are no DHW tanks.

while the heating element (green bars) is used in hours of high demand. The lower graph shows the temperature and energy state of the DHW tank, where we can see that the temperature in the tank reaches the max. temperature on several days of the week.

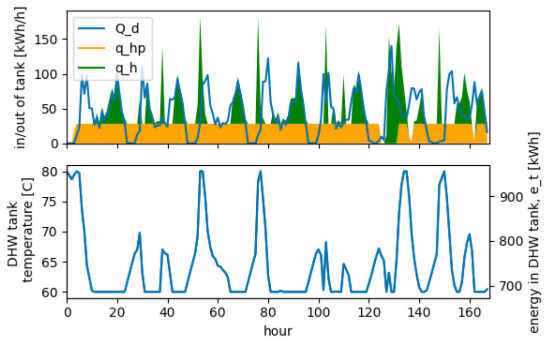

Fig. 5. DHW tank operation in Case C, week 1

Fig. 6 shows the import to the EC at the PCC split in the different el. consumption for Case C in week 1. The apartment el. demand (green) has the largest share of the load by far, and the EV charging in the garage (purple) also contributes to the peaks. The el. consumption of the HP (yellow) and the heating element (blue) correspond to Fig. 5.

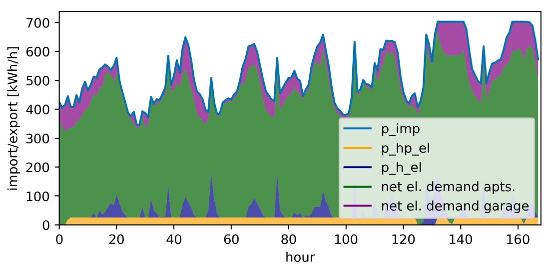

Fig. 6. Grid exchange for EC in Case C, week 1

The total imported power to the EC for the three cases can be seen in Fig. 7. Peak import is highest in Case B (785.6 kWh/h). In Case I, the DHW tanks are optimised individually for each apartment block, leading to a peak import of 751.1 kWh/h for the EC (reduction of 4.4% compared to Case B). In Case C, the peak import is lowered to 702.7 kWh/h, when the EC optimises all el. consumption and DHW tanks together, including the EV charging in the garage. Compared to Case B, this amounts to a reduction in peak import of 10.6%.

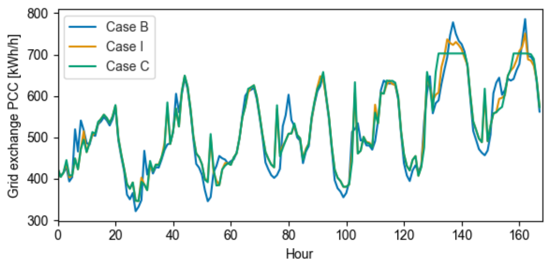

Fig. 7. Grid import to EC (at PCC) for all cases, week 1

B. Yearly grid exchange and costs for all cases

The yearly results are given in Tab. IV. The max. import occurs in week 1 as previously shown in Fig. 7. The sum of imported power to the EC is highest in Case I, followed by Case C, and then Case B. The max. exported power from the EC is 72.1 kWh/h for Cases I and C, and 83.1 for Case B. Compared to Case B, the electricity costs are reduced by 1.5% in Case I and 2.6% in Case C. Hence, if the EC could have aggregated net metering at the PCC and activated smart DHW controls, it could reduce its annual electricity costs by 2.6% and the peak demand by 10.6%.

TABLE IV
YEARLY RESULTS - COMPARING CASES

case	max [kWh/h] imp	max [kWh/h] exp	sum [kWh] imp	sum [kWh] exp	tot cost [€]
B	785.6	83.1	2,448,526	6,769	301,279
I	751.1	72.1	2,464,108	4,737	296,887
C	702.7	72.1	2,463,158	4,275	293,300

Tab. V shows a breakdown of the costs for all cases. *elCost* denotes all electricity costs excluding demand charges, *demCh* denotes the demand charges and *elRev* denotes the revenue from exported electricity. The cost reduction observed in Tab. IV is mainly due to reduced demand charges. Electricity revenue is also reduced, as more PV production is consumed within the EC. The electricity cost follows the same trend as the sum of imported power, hence being the highest in Case I, followed by Case B and then Case C.

TABLE V
YEARLY RESULTS - BREAKDOWN OF TOTAL COSTS AND RATES

case	elCost [€]	demCh [€]	elRev [€]	SCR [%]	SSR [%]
B	255,110	47,951	1,783	96.7	7.5
I	256,458	42,087	1,658	97.7	7.5
C	254,924	38,624	248	97.9	7.6

The self-sufficiency rate (SSR) and the self-consumption rate (SCR)[6] for the EC are also reported in Tab. V. In general, the SCR is high (above 96%), while the SSR is quite low (7%), due to the low share of PV.

C. PV and demand charges impact on results

Tab. VI shows the results if there is no PV on the apartment blocks, and if the demand charges are removed from the objective. Comparing the original results with *no PV* shows that the PV has no impact on the max. import. Furthermore, the costs are higher since the EC naturally needs to import more electricity from the grid. When demand charges are omitted from the objective, the total costs decrease in all cases, as expected. Also, the max. import increases in Cases I and C, to 830.2 and 841.4 kWh/h, respectively. Hence, demand charges are an important part of incentivising peak demand reduction. This case study shows that if they are omitted, central optimisation and aggregated net demand would lead to *higher* peak demand.

TABLE VI
SENSITIVITY ANALYSIS ON YEARLY COSTS AND GRID EXCHANGE

	case	max. imp [kWh/h]	max. exp [kWh/h]	cost [€]
original	B	785.6	83.1	301,279
	I	751.1	72.1	296,887
	C	702.7	72.1	293,300
no PV	B	785.6	0	318,940
	I	751.1	0	314,547
	C	702.7	0	312,953
no demCh	B	785.6	83.1	254,616
	I	830.2	72.1	253,327
	C	841.4	72.1	254,737

IV. CONCLUSION

The aim of this paper was to quantify the benefit that DHW tanks can give to a housing cooperative and the distribution grid by optimising the operation of the DHW tanks. The results showed that central optimisation could give a 10.6% reduction in peak demand, as well as a 2.6% cost reduction for the EC, compared to the base case with no storage. Removing PV had no impact on peak demand, while removing demand charges from the objective led to an increase in peak demand when optimising the DHW tanks. The exported power from the EC was relatively low in all cases, compared to the imported power. Therefore, it might seem that roof-top PV on apartment blocks is unlikely to create overvoltage problems in the grid, since the local production is low compared to the demand. It should be noted that in this paper, only DHW tanks are considered as flexible assets. In reality, it would also be possible to control EV charging and space heating, and thereby reduce the peak load further and/or increase the SSR and SCR for the EC. Possible future work includes modeling the DHW tank with temperature stratification.

[6]The import and export of the garage are considered as load and production since we do not have data on PV production and load separately.

ACKNOWLEDGMENT

The authors would like to thank Sverre S. Foslie for discussions about this work. We are grateful to Røverkollen housing cooperative for sharing data used in this study.

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Paper V: Industrial energy communities: Energy storage investment, grid impact and cost distribution

The paper **"Industrial Energy Communities: Energy Storage Investment, Grid Impact and Cost Distribution"** is currently under review.

This paper is under review for publication and is therefore not included.

Paper VI: Load configuration impact on energy community and distribution grid: Quantifying costs, emissions and grid exchange

The paper **"Load configuration impact on energy community and distribution grid: Quantifying costs, emissions and grid exchange"** is published by **Elsevier** in **Applied Energy**. The final published paper is reprinted here without changes in compliance with the CC-BY 4.0 license[2] it is published under.

Cite as:
K. Berg, A. Hernandez-Matheus, M. Aragüés Peñalba, E. Bullich-Massagué, and H. Farahmand. "Load configuration impact on energy community and distribution grid: Quantifying costs, emissions and grid exchange." Applied Energy 363 (June 2024): 123060. https://doi.org/10.1016/j.apenergy.2024.123060.

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Applied Energy 363 (2024) 123060

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Load configuration impact on energy community and distribution grid: Quantifying costs, emissions and grid exchange

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ARTICLE INFO

Keywords:
Energy community
Distribution grid
Load profiles
Optimisation
Batteries
Load shifting

ABSTRACT

Energy communities are emerging across Europe, and each country is currently in the process of forming regulations for their integration into the electricity grid. The efficacy of energy communities depends upon various factors, including member demographics, technological aspects, load profiles, solar irradiation, and spot prices within the community's geographical location. Notably, existing studies on energy communities predominantly focus on residential load profiles, with limited exploration into their impact on the distribution grid. This article aims to contribute to the existing literature by investigating the benefits of energy communities and their grid impact under diverse member configurations. Our approach involves the development of an optimisation model incorporating battery energy storage and shiftable loads, aimed at minimising the operational costs of energy communities over a one-year period. Case studies in Norway and Spain, with different load configurations: residential, commercial, and mixed load, are undertaken, utilising real hourly measurements to identify operational variations influenced by geographical location and seasonal fluctuations in load and photovoltaic (PV) generation. Additionally, we quantify the costs, CO_2 emissions, and self-consumption rates for energy communities. Furthermore, we assess the distribution grid impact in terms of import and export dynamics. The results underscore the substantial influence of load configurations on member benefits and distribution grid impacts, attributable to the inherent correlation between load and PV generation. In the context of energy community benefits, commercial loads demonstrate the best outcomes in Norway, whereas residential loads exhibit superior results in Spain. Conversely, concerning distribution grid impact, commercial loads prove most advantageous in Norway, while mixed loads yield the best results in Spain. Overall, our findings indicate that Spanish energy communities consistently achieve more substantial reductions in costs and CO_2 emissions compared to their Norwegian counterparts, irrespective of the load configuration. This study contributes valuable insights for policymakers, researchers, and industry stakeholders involved in the development and regulation of energy communities across Europe.

1. Introduction

Energy communities are the subject of increased attention in Europe since the release of the two directives allowing regulatory adjustments for the formation of 'Renewable Energy Communities' [1] and 'Citizen Energy Communities' [2]. Energy communities can vary in size, members, available technologies and extent [3,4]. They may also have different objectives, i.e. maximise self-consumption, reduce total costs, or reduce CO_2 emissions related to electricity consumption [4].

The distribution grid is under stress in the following years, due to increased electrification and distributed energy resources, which can lead to voltage problems and congestion. As energy communities are still a new concept, there is a need to understand their behaviour and their impact in the distribution grid. Most studies on energy communities have until now focused merely on the energy community benefits, such as costs, emission reduction and self-consumption. Very few have investigated how the energy communities impact the distribution grid [4]. One exception is [5], which showed that shared assets such as community batteries can introduce voltage problems when their dispatch is decided by optimisation models, due to spot price arbitrage.

The directives state that energy communities can consist of individuals and small- and medium-sized enterprises, as long as the community gives benefit to the members and/or the local area. Despite this, the majority of energy community studies use residential load profiles.

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https://doi.org/10.1016/j.apenergy.2024.123060
Received 30 January 2024; Received in revised form 4 March 2024; Accepted 16 March 2024
Available online 22 March 2024

Table 1
Related literature on energy communities with different load configurations compared to this article.

Ref.	Optimisation	Load profiles	Country	Member benefit	Grid impact	Flexible resource
[8]	✓[1]	Urban, industrial	Spain	Cost, SCR	–	Battery
[12]	–	Residential, commercial	Portugal	Cost, SCR	–	Battery
[13]	✓	Residential, commercial	Spain	Cost, SCR, emissions	–	Battery
[14]	–	Residential, school	Portugal	Cost, SCR, emissions	–	Battery
[15]	✓	Residential, commercial	Austria	Cost	–	Battery, hot water tank
[16]	–	Residential	UK	Cost, SCR	✓	–
[17]	✓	Urban, rural[2]	Italy	SCR	✓	Battery
[18]	✓	Residential, commercial	Germany	Cost, SCR	✓	Battery
[19]	✓	Residential, commercial	Germany	Cost, SCR	✓	Battery, shiftable loads
This paper	✓	Residential, commercial	Norway, Spain	Cost, SCR, emissions	✓	Battery, shiftable loads

[1] No information about optimisation model.
[2] Medium-voltage load profiles, customer types are not specified.

Since energy communities can consist of many different members, it is important to investigate different load profiles. Aligning demand and generation profiles can lead to an increased cost reduction [6]. Commercial consumers, with distinct daily and weekly consumption patterns compared to residential consumers, may have varied correlations with PV generation, resulting in different grid impacts in terms of export and import.

Energy communities, incorporating flexible resources like energy storage and optimising for costs, are further influenced by the country's spot price, shaping their operation and, consequently, grid impact. The characteristics and operation of energy communities vary significantly across different European countries [7]. To address this diversity in European energy communities, we investigate case studies for two countries with low numbers of energy communities and PV installations [8–10]: Norway and Spain. These countries differ significantly in both electricity use and solar irradiance, i.e. the average annual electricity use per dwelling for Norway is 16 MWh, while it is 4 MWh for Spain [11].

The aim of this article is to investigate the energy community benefits and grid impact for different member configurations. We aim to answer the following questions:

- How do energy communities with different member types, and therefore different load profiles, impact the grid?
- How do different technologies impact the operation of the energy community?
- How does the grid impact relate to the energy community benefits of reduced costs, reduced CO_2 emissions and increased self-consumption?
- What is the impact of country-specific characteristics, seasonal variations and different technologies on the energy community benefits and grid impact?

1.1. Related literature

Several studies have investigated different load profiles in energy communities, without quantifying the grid impact [8,12–15]. Ref. [8] analysed and estimated the electricity generation potential of energy communities in both urban and industrial areas in Spain. The authors concluded that the industrial sector offers an opportunity for deploying renewable energy resources to supply a mixed area, suggesting that adding PV panels to public buildings can be a strategy to meet residential energy demand. Regarding the aggregation of customer loads in an energy community, [12] evaluated the impact of load aggregation with regard to self-consumption for households and small businesses. The authors concluded that aggregation of electricity consumption, from different users with different consumption profiles, leads to an improvement in the collective load diagram, meaning that the load was better adapted to the PV generation profile and thereby also reduced the need for additional energy storage. In addition to not focusing on the grid impact, neither of these studies quantified emissions, nor did they include other flexible resources than batteries.

Refs. [13,14] are examples of literature that did quantify both costs and emissions. Ref. [13] looked at optimisation of local energy communities in Spain. It compared residential and commercial loads and numbers of loads. The authors found that it is only advisable to install storage to increase the degree of self-consumption, and not to reduce costs or emissions. Furthermore, the best financial and environmental results were obtained for large communities with 75% residential consumption. In [14], a modelling framework was developed to assess the potential of energy community creation. Three cases were considered for different buildings (households, apartment blocks and schools). It was concluded that both environmental and economic benefits were greater when considering energy communities with diverse load profiles (residential and school), since higher self-sufficiency results were achieved due to the sharing rates through buildings. These studies did not, however, quantify the grid impact of the energy communities, and they did not investigate other flexible resources than batteries. A paper that did include other flexible resources than batteries is [15]. The authors investigated the profitability and optimal installation capacities of PV systems for energy communities with different building types, including battery systems and hot water storage. The authors found that different load profiles bring synergy effects, and therefore higher cost-saving potential. They also found that battery and hot water storage, which complement PV systems and heat pumps, only marginally contributed to saving energy costs. The authors did not, however, quantify the grid impact of the energy communities.

As stated in [4], there is limited literature focusing on how energy communities affect the distribution grid. Exceptions are [16–19]. Ref. [16] analysed the configuration of a solar energy community. The authors found that various prosumer ratios, community sizes and PV sizes impacted the grid, where medium and large energy communities led to the need for grid infrastructure upgrades. However, the study only included residential load profiles, and did not consider any flexible resources such as batteries or shiftable loads. Ref. [17] investigated the grid impact of urban and rural Italian energy communities. The authors found that maximising self-consumption led to a lower grid impact than when the objective was to achieve a net-zero energy balance. The study did not include the operational costs or emissions for the energy community. Refs. [18,19] included residential and commercial loads. Ref. [18] investigated the optimal sizing of PV and battery systems and different optimisation strategies. The authors found that when energy communities maximised economic benefit, the grid line loading was the highest, due to the battery doing energy arbitrage. The optimisation model did not, however, include flexible sources such as load shifting. In [19], the authors investigated how energy communities can change their operation to reduce peak power exchange. Similarly to this paper, the authors included PV, battery and shiftable loads. The authors found that a grid-friendly operation could reduce peak power with up to 55%. Neither of these studies, however, included a battery degradation model, nor quantified the CO_2 emissions reduction. Table 1 summarises the relevant literature, highlighting the differences from this work.

1.2. Research gap and contributions

The main research gaps identified are as follows: There is little literature on grid impact arising from energy communities. Furthermore, most studies consider battery systems as the only flexible resource in energy communities, thereby disregarding more cost-effective options such as shiftable loads. If battery systems are included, they most often do not include a cyclic degradation model, leading to unrealistically low costs for battery operation. Few studies investigate the CO2 emission reduction from energy communities, despite its potential significance as a motivating factor for community members. Moreover, many studies of energy communities do not use real datasets, but synthetic data, and limited simulation time periods, such as one day or week of the year [16]]. This temporal constraint proves inadequate when studying countries with high seasonal variations in electricity demand and solar irradiance. Finally, none of the literature on various load configurations in energy communities includes a country comparison, highlighting how different solar irradiance, load and spot prices impact the results. This comparative analysis is particularly important to clarify how regulations on energy communities can lead to different results for European countries

The main contributions of this article are as follows:

- Investigation of energy communities with three different load configurations: residential, commercial and mixed. Grid impact is quantified through maximum import to and export from the energy community.
- Study the optimal operation of energy communities by incorporating a community battery with a degradation model, and shiftable loads. This approach provides insight into the use of different flexible resources in the energy community. We also explore the interaction among technologies – PV, community battery, and shiftable loads – by systematically excluding each one from the optimisation.
- A comprehensive comparison of the aforementioned grid impact with the energy community benefits of costs, self-consumption and CO_2 emissions for all load configurations. A sensitivity analysis on the ratio of commercial and residential loads in the mixed load configuration is also performed.
- Case studies are run for two countries, Norway and Spain, to get insight into how the seasonal variations in load and PV impact the results. Real, hourly measurements for one year are used as input data. We investigate the impact of battery size, PV size, spot price level, grid tariff and load shifting percentage.

The novelty of this paper stems from quantifying both the member benefits and the grid impact of energy communities while varying several dimensions: technology present in the energy community, members of the energy community and location. This analysis provides a comprehensive perspective on the potential influence of energy communities on the distribution grid. Such insights are instrumental in the formulation of well-informed policies and regulations on energy communities. Furthermore, we quantify the CO_2 emissions reduction, which is an important motivation in many energy communities, albeit frequently overlooked. Another important novelty of the paper is the direct comparison between two European countries, where the peak demand of the energy communities is the same, but the PV production, load profiles and spot prices are country-dependent.

1.3. Outline of paper

The outline of the paper is as follows: In Section 2, the methodology of the paper is described. Section 3 describes the input parameters used for the case studies of the two countries. Section 4 shows the results of the optimisation, together with a sensitivity analysis of input parameters, and an analysis of the technologies present in the energy community, followed by a discussion. In Section 5, the concluding remarks are given.

2. Method

The following subsections describe the equations of the optimisation model and how the battery energy storage system is sized. Fig. 1 shows the overall paper concept.

2.1. Optimisation model

The optimisation model is given in (1)–(21). The objective of the optimisation is to minimise the total costs for the energy community, where the decision variables are the grid import and export, battery discharging and load shifting. For simplicity and to achieve a fair comparison, identical grid tariffs are set for both countries, to avoid modelling country-specific conditions. We assume that the energy community has a common grid tariff, decided from the aggregated import to and export from the energy community. The objective function therefore consists of the following costs and revenues: Costs of importing electricity due to spot market price (C_t^{spot}) and a uniform, volumetric grid tariff (C^{tar}), revenues from exporting electricity due to spot market price and remuneration from the DSO (R^{grid}), discomfort cost for shifting load (C^{sh}) and degradation cost for using battery (C_s^{deg}):

$$\min \sum_t \Big[(C_t^{spot} + C^{grid}) p_t^{imp} - (C_t^{spot} + R^{grid}) \cdot p_t^{exp} + C^{sh} p_t^{sh,down} + \sum_s C_s^{deg} p_{st}^{disch,seg} \Big] \quad (1)$$

(2) denotes the energy balance at the point of common coupling for the energy community in every hour, where the grid import (p_t^{imp}) minus export (p_t^{exp}) must equal the aggregated demand (P_t^D), aggregated PV generation (P_t^{PV}), battery charging (p_t^{ch}) and discharging (p_t^{disch}), and upwards ($p_t^{sh,up}$) and downwards ($p_t^{sh,down}$) load shifting:

$$p_t^{imp} - p_t^{exp} = P_t^D - P_t^{PV} + p_t^{ch} - p_t^{disch} + p_t^{sh,up} - p_t^{sh,down} \quad \forall t \quad (2)$$

The constraints for battery charging, discharging and state-of-charge (SOC) are given in (3)–(8). Since the optimisation model is deterministic and has perfect foresight, (6) is included to limit the possible planning of the battery scheduling. This constraint ensures that the battery SOC is the same at the beginning of each week (w).

$$soc_t = soc_{t-1} + \eta p_t^{ch} - \frac{1}{\eta} p_t^{disch} \quad \forall t > 0 \quad (3)$$

$$soc_t = soc_T + \eta p_t^{ch} - \frac{1}{\eta} p_t^{disch} \quad t = 0 \quad (4)$$

$$soc_t \leq E^B \quad \forall t \quad (5)$$

$$soc_w = soc_{w+1} \quad w \in W \quad (6)$$

$$p_t^{ch} \leq E^B R^{PE} \quad \forall t \quad (7)$$

$$p_t^{disch} \leq E^B R^{PE} \quad \forall t \quad (8)$$

Eqs. (9)–(13) describes the battery degradation constraints. These constraints are based on the model presented in [20], and are a way for the optimisation model to account for the cyclic degradation imposed on the battery for different discharging powers. The battery is therefore divided into segments (S), where discharging through each segment has a cost which is connected to the replacement cost of the battery. The more segments the battery discharges through, the higher the degradation cost.

$$p_t^{ch} = \sum_s p_{st}^{ch,seg} \quad \forall t \quad (9)$$

$$p_t^{disch} = \sum_s p_{st}^{disch,seg} \quad \forall t \quad (10)$$

$$soc_{st}^{seg} \leq E^B / S \quad \forall s, t \quad (11)$$

$$soc_{st}^{seg} = soc_{st-1}^{seg} + \eta p_{st}^{ch,seg} - \frac{1}{\eta} p_{st}^{disch,seg} \quad \forall s, t > 0 \quad (12)$$

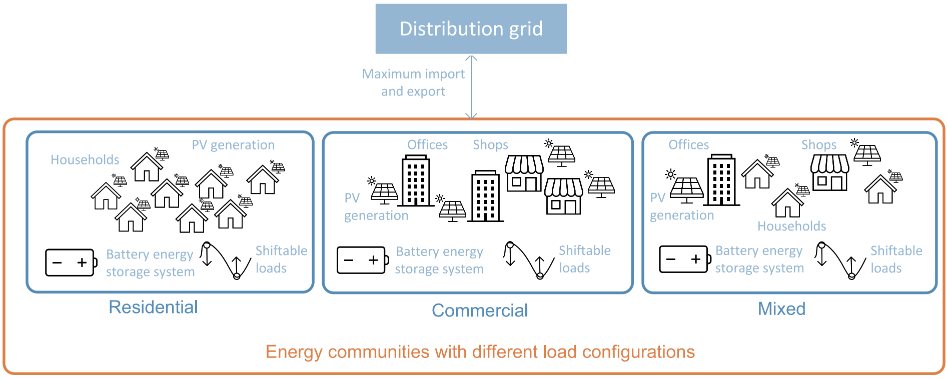

Fig. 1. Paper concept: different load configurations and technologies in energy community and their impact on the distribution grid.

$$soc_{st}^{seg} = soc_{sT}^{seg} + \eta p_{st}^{ch,seg} - \frac{1}{\eta} p_{st}^{disch,seg} \qquad \forall s, t = 0 \quad (13)$$

The degradation cost for each segment s is then found from [20]:

$$C_s^{deg} = \frac{C^B}{\eta} \cdot \Delta\Phi(\delta) \quad (14)$$

where C^B is the battery replacement cost in €/kWh, η is the battery efficiency and Φ is the cycle depth stress function of the battery type. Hence, the battery degradation cost depends on the battery technology, which will be explained in further detail in Section 3.

The load shifting constraints are given in (15)–(19). These constraints are based on [21], which has developed a general model for load shifting, assuming that it is possible to shift up to a certain percentage, S^{max}, of the load. In every hour, the model can reduce or increase the load, as long as the total amount of energy shifted is the same at the end of the day (d).

$$p_t^{sh,up} \le S^{max} P_t^D \qquad \forall t \quad (15)$$

$$p_t^{sh,down} \le S^{max} P_t^D \qquad \forall t \quad (16)$$

$$e_t^{sh,down} = e_{t-1}^{sh,down} + p_t^{sh,down} \qquad \forall t > 0 \quad (17)$$

$$e_t^{sh,up} = e_{t-1}^{sh,up} + p_t^{sh,up} \qquad \forall t > 0 \quad (18)$$

$$e_d^{sh,up} = e_d^{sh,down} \qquad d \in D \quad (19)$$

(20)–(21) shows the non-negativity constraints.

$$p_t^{exp}, p_t^{imp}, p_t^{ch}, p_t^{disch}, soc_t, \quad p_t^{sh,up}, p_t^{sh,down}, e_t^{sh,down}, e_t^{sh,up} \ge 0 \qquad \forall t \quad (20)$$

$$p_{st}^{ch,seg}, p_{st}^{disch,seg}, soc_{st}^{seg} \ge 0 \qquad \forall s, t \quad (21)$$

2.2. SCR

The annual collective self-consumption rate (SCR) is calculated as:

$$\frac{\text{PV generation consumed in energy community}}{\text{Total PV generated}} \quad (22)$$

2.3. Annualised investment costs for PV generation and battery system

The annualised investment costs are found by multiplying with the capital recovery factor:

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1} \quad (23)$$

where i is the interest rate and n is the lifetime in years.

Table 2
Data input for each country.

Data	Norway	Spain
Household load profiles	Measurements, Oslo area, 2021 [24]	Measurements, Spain, 2019 [25]
Office and shop load profiles	Synthetic profiles PROFet, 2021 [26,27]	Measurements, Spain, 2019 [25]
PV generation profiles	Renewables Ninja, Oslo, 2019 [28]	Renewables Ninja, Madrid, 2019 [28]
Spot market prices	NO1, Nord Pool, 2019 [29]	Spain, OMIE, 2019 [30]
CO_2 emission equivalents	ElectricityMaps [31]	ElectricityMaps [31]

2.4. Sizing battery energy and power capacity

We determine the capacity of the shared battery energy storage system using a rule-based approach with the goal of enhancing the self-consumption of PV generation. The battery is sized by following the method proposed in [22]. The daily energy export is quantified and the battery energy capacity is assumed to be a percentile of that value. This method ensures an efficient rule-based sizing of the battery, avoiding unrealistic investments for the energy community's storage system [23]. The power capacity of the battery system is set to be equivalent to the maximum hourly export over the year.

3. Data input analysis and case study

This section details the case study for both countries and the data collected for each case. Table 2 shows the data input for each country and Table 3 shows the input parameters for the optimisation.

3.1. Load profiles

The Norwegian load profiles for residential loads are retrieved from [34], which is a dataset containing hourly, real measurements from the Oslo region for 2021. The PROFet tool [26,27] is used for the commercial loads. The load profiles for Spain are taken from [25], which is a dataset from Spain containing hourly, real measurements for 2019 for several customer groups. Detailed information about the load profiles can be found in A. Fig. 2 shows the normalised daily average consumption over the year for all datasets to show how the trend over the year varies for each country and each load type. Note that this figure shows the original datasets for offices, shops and households,

Table 3
Input parameters for optimisation.

Parameter	Value
Maximum load shift	20% [21]
Total PV size	$33.3 \cdot 1.25 = 42$ kWp
Battery investment cost, C^B	200 €/kWh [32]
PV investment cost	800 €/kWp [33]
Interest rate	5.1%
Lifetime battery system	15 years [32]
Lifetime PV system	30 years [33]
Grid tariff, C^{grid}	0.0448 €/kWh
Grid remuneration, R^{grid}	0.006 €/kWh
Battery percentile of daily export	75
Battery power	max. hourly export
Battery degradation segments, S	8
Load shifting discomfort cost, C^{sh}	0.02 €/kWh [21]
Commercial ratio (for mixed loads)	0.5

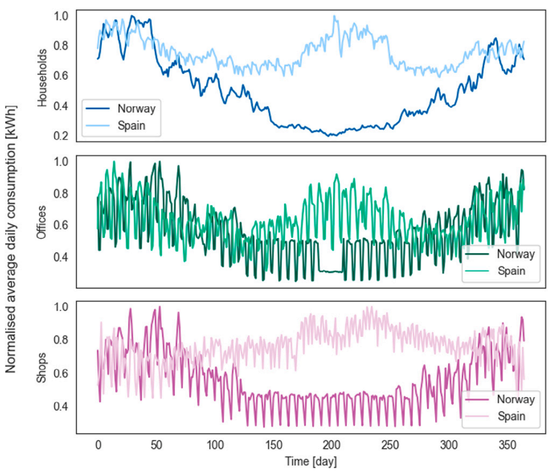

Fig. 2. Daily average electricity consumption for each load type.

Table 4
Reference weeks.

Country	Week	Dates
Norway	Winter	18–24 Jan 2021
	Summer	21–27 June 2021
Spain	Winter	14–20 Jan 2019
	Summer	17–23 June 2019

which later is used to create the residential, commercial and mixed load configurations. In Norway, electricity consumption is always highest in winter and lowest during summer. In Spain, on the other hand, the electricity consumption remains at a similar level during the winter and summer months, but the average consumption profile tends to be higher in the summer months, primarily because of the increased use of cooling systems.

As seen in Fig. 2, there are great differences between summer and winter for the two countries due to outdoor temperature. Two reference weeks have therefore been chosen to effectively illustrate the differences in seasonal load profiles; see Table 4. The third week of January and the third week of June are chosen since there are no holidays in either country during these weeks. To illustrate the differences in the daily profiles, Fig. 3 shows the normalised mean load profile (divided by the maximum hourly load of the year) for the winter reference week. The mean is not calculated for offices and shops in Norway, since we only have one synthetic profile instead of a cluster of profiles. Fig. 3 shows that offices and shops have a significant reduction in electricity

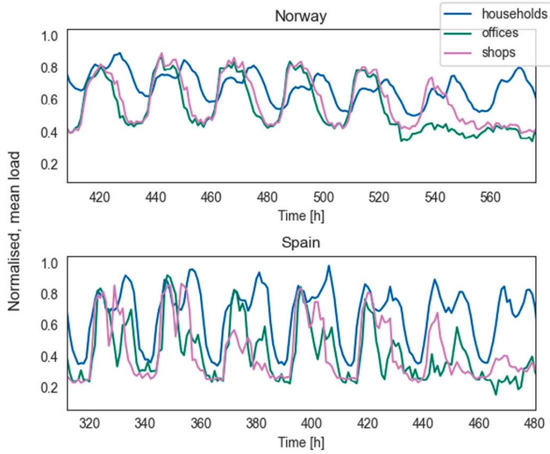

Fig. 3. Normalised, mean load profiles winter week.

consumption during the weekend in both countries. Looking at the hourly consumption within a day, we see that households in Norway and Spain have similar trends with two peaks, where the afternoon peak is the highest. In Norway, the consumption trends for office and shop are similar, with the peak during midday. In Spain, the profiles for offices and shops usually have two peaks during the day, where the morning peak is the highest.

Given that the focus of this study is the overall benefits for the energy community and the impact on the distribution grid, aggregated load profiles are used as input to the optimisation model. The aggregated load profile of the energy community is created by picking random load profiles until the load limit of 33.3 kW is reached. This load limit is taken from the European CIGRE LV grid [35], and is merely used to have a common load limit for all cases. For the mixed load configuration, the ratio of commercial load profiles is set to be half of the total load, meaning that we first stack commercial load profiles until we reach 16.65 kW, and then add residential profiles until we reach the load limit. This ratio of commercial load profiles is investigated further in the sensitivity analysis in Section 4.4.2.

3.2. PV generation profiles

Hourly PV generation profiles for 1 kWp for one year were taken from Renewables Ninja [28] for the Oslo and Madrid locations. Further, the profiles were upscaled with a factor of 1.25 times the power limit at the connection bus of the energy community, which amounts to a PV size of 42 kWp. We therefore maintain the seasonal differences between the countries, while keeping the PV generation size equal for comparison purposes. We investigate other PV sizes in the sensitivity analysis described in Section 4.4.2. In this work, we do not consider how this PV generation is distributed within the energy community, as we focus primarily on the aggregated impact on the distribution grid.

Since it is not realistic that all PV panels would be facing directly south, it is assumed that 1/3 of the panels are oriented south, 1/3 south-east and 1/3 south-west, as mentioned in Section 2. For households, the tilt of the panels is assumed to be 40° for Norway, and 36° for Spain [36]. For offices and shops, the roofs are assumed to be flat (0° tilt).

3.3. Grid tariff and electricity prices

Since grid tariffs are changing constantly and heavily impact the results of the optimisation, we choose a basic grid tariff as a foundational

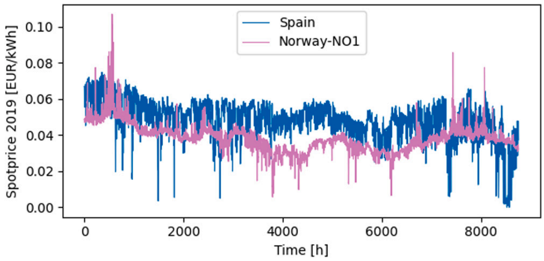

Fig. 4. Spot prices 2019 for price areas Norway-NO1 and Spain.

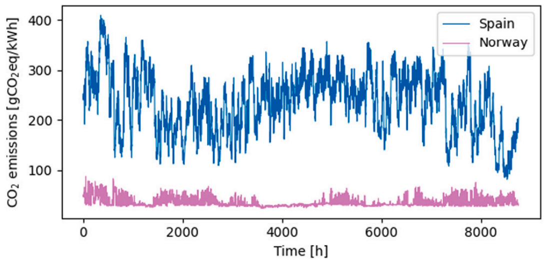

Fig. 5. CO2eq emissions for Norway and Spain, 2019 [31].

reference point. This choice allows for easier comparison between the two countries. Therefore, we assume that the energy community pays a uniform, volumetric grid tariff (assumed to be 0.0448 €/kWh [37]), in addition to the spot market area price. We further assume that the energy community receives a uniform, volumetric remuneration for export of 0.006 €/kWh [38] in addition to the spot market price.

Although the load and PV data for Norway pertain to the year 2021, we use the day-ahead electricity spot market prices for year 2019, since 2021 witnessed exceptionally high prices towards the end of the year, primarily driven by soaring gas prices in Europe. The spot market price for Norway is then shifted to match the weekdays of the load and PV generation in 2021. The spot prices can be seen in Fig. 4, where we can observe that the Norwegian spot price for bidding zone NO1[1] in general is lower (with an average price of 0.04 €/kWh) than the spot price for Spain (an average price of 0.05 €/kWh). Furthermore, the spot price in Spain has greater variation than the spot price in Norway. A value added tax of 25% is added for spot price and grid tariff.

It is assumed that the energy community has aggregated net metering, meaning that the aggregated net electricity consumption and generation for each hour is used to calculate the costs and revenues. The allocation of these costs and revenues within the energy community falls outside the scope of this paper.

3.4. Co_2 emissions

The CO_2 emission equivalents (*Carbon intensity average*) are retrieved from [31] for both countries and are shown in Fig. 5. The year 2019 is used for both countries, to match the electricity spot market price used.

3.5. Battery degradation cost

The battery in this study is assumed to be a nickel manganese cobalt (NMC) lithium-ion battery, where the cycle depth stress function is

[1] Norway is divided into 5 different bidding zones, where Oslo is in NO1.

Table 5
Load characteristics (max. in [kWh/h] and sum in [kWh]).

Country		Residential	Commercial	Mixed
Norway	max.	34.3	33.5	35.7
	sum	118,164	119,773	133,914
	CF	0.71	1	0.73
Spain	max.	34.8	36.7	35.5
	sum	85,877	118,942	135,556
	CF	0.34	0.43	0.30

Table 6
Correlation coefficients for load and PV generation.

Country	Residential	Commercial	Mixed
Norway	−0.28	0.04	−0.19
Spain	0.34	0.45	0.45

defined as [39]:

$$\Phi(\delta) = 5.24 \cdot 10^{-4} \cdot \delta^{2.03} \quad (24)$$

where δ is the cycle depth of the battery.

4. Optimisation results and discussion

In this section, we show the optimisation results for various load configurations (residential, commercial and mixed) across two countries (Norway and Spain). Firstly, we show the characteristics of the aggregated load profiles and the battery energy and power sizes. Secondly, we show how the battery operation and load shifting impact the optimisation results in two reference weeks. Thirdly, the annual results for the energy community and grid are given. Subsequently, three sensitivity analyses are presented, where input parameters are altered and specific technologies are excluded. Finally, the limitations of the study are discussed.

The optimisation model is formulated as a deterministic linear program, and is implemented in Python/Pyomo [40], using Gurobi [41] as solver.

4.1. Pre-optimisation

The aggregated load profiles for the energy community have the characteristics as given in Table 5. Even though the load profiles have approximately the same peak, the yearly consumption in Norway is much higher than in Spain for residential and commercial load configurations. It can also be seen that the coincidence factor (CF)[2] in Norway is much higher than in Spain. Hence, the peaks of the different loads in Spain are distributed more evenly than in Norway.

Table 6 shows the load and PV generation correlation coefficients for all load configurations in both countries. In Norway, the load and PV generation are negatively correlated for residential and mixed load configurations, while they are slightly positive for commercial loads. This can be explained by Fig. 3, where we see that the daily profile of the commercial loads shows a higher consumption in the middle of the day, when the PV generation is the highest. This stands in contrast to Spain, where all load configurations show a positive correlation between load and PV generation, ranging from 0.34 to 0.45. This follows the seasonal load shown in Fig. 2, where we see that the consumption in Spain increases in summer, when PV generation is high.

The battery size is determined before the optimisation on the basis of daily exported energy, as explained in Section 2.4. Table 7 shows the battery energy and power capacities for each load configuration. In general, we see that the energy capacities are larger for Norway,

[2] Coincidence factor is calculated as the maximum total load divided by the sum of individual maximum load.

Table 7
Battery energy and power capacity for each load config. (kWh/kW).

Country	Residential	Commercial	Mixed
Norway	132/28	73/21	91/23
Spain	127/28	66/23	59/20

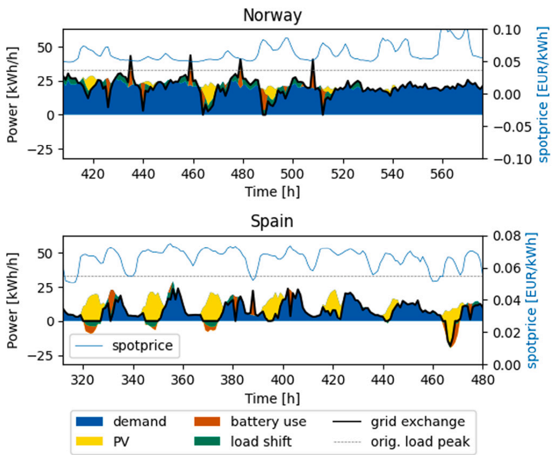

Fig. 6. Grid exchange residential winter week.

compared to Spain, and that residential is the load configuration that always has the highest capacity within the country. In Norway, the highest energy capacity is 132 kWh for residential loads, and the lowest is 73 kWh for commercial loads. In Spain, the highest energy capacity is 127 kWh for residential loads, and the lowest is 59 kWh for mixed loads.

4.2. Optimisation results — reference weeks

In this section, we display the results for the residential load configuration for the reference weeks, to showcase how the battery operation and load shifting impact the results.

Fig. 6 shows the grid exchange (black line) for residential loads in the winter week. We see that for Norway, there is no export in winter due to the low PV generation (yellow area) and high demand (blue area). The battery (red area) is used for 14 h for price arbitrage, charging when the spot price is low and discharging when the price is high. The charging causes four new load spikes, which exceeds the original load peak of 33.3 kW. Load is being shifted for 82 h (green area). For Spain, the PV generation covers more of the load, and also leads to export in the weekend. The battery is used for 26 h to charge excess PV generation and discharge at hours with high spot prices, while load is shifted in 67 h. Note that the battery in Norway is slightly larger than in Spain (see Table 7).

Fig. 7 shows the grid exchange for residential loads in the summer week. Both countries are exporting power due to excess PV generation, and there is more export from the energy community in Norway than in Spain. This is rather counter-intuitive, following the countries' solar irradiance, but the reason is that the demand in Norway is low during the summer, compared to Spain (see Fig. 2). When the load is low throughout the day, it is difficult for the battery or shiftable loads to shift PV generation to other hours, and therefore this leads to high export. The battery is used more often in Norway (79 h) compared to Spain (63 h). Load is shifted in 151 h in Norway, and 159 h in Spain.

Fig. 8 shows the grid exchange for all load configurations in the winter reference week. The load is higher in Norway for all load configurations, and there is no export. For Spain, on the other hand, there is export in the weekend. The load spikes due to battery charging are highest for residential loads in Norway.

Fig. 9 shows the grid exchange in the summer reference week. We can see the same trend as in Fig. 7, where the export is much higher for Norway than for Spain. The commercial loads have the least export in Norway, while in Spain it is the mixed loads. This is supported by the finding in Table 6.

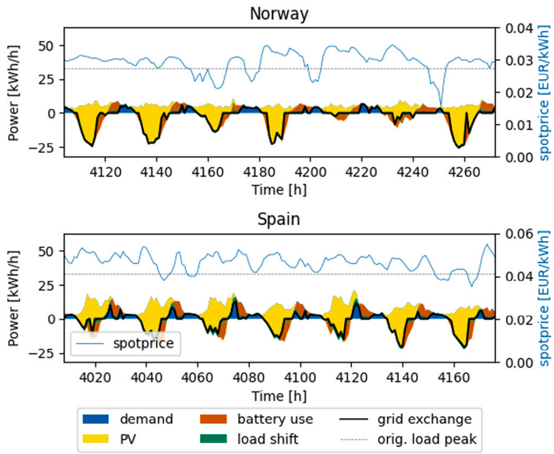

Fig. 7. Grid exchange residential summer week.

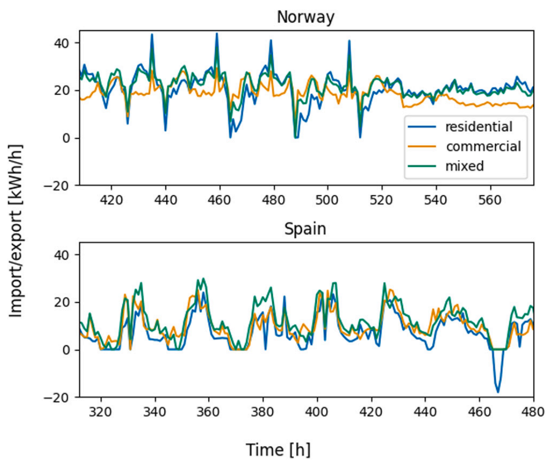

Fig. 8. Grid exchange comparison for all load configurations, winter week.

4.3. Optimisation results — annual impact on energy community and distribution grid

This section summarises the annual results of the optimisation to give an overview of the impact of the load, PV generation, battery operation and shiftable loads on the energy community and the distribution grid. Case ref. denotes the reference case where there is only load, and no PV generation, battery system or load shifting. Case opt. denotes the main case where all technologies are present in the optimisation model.

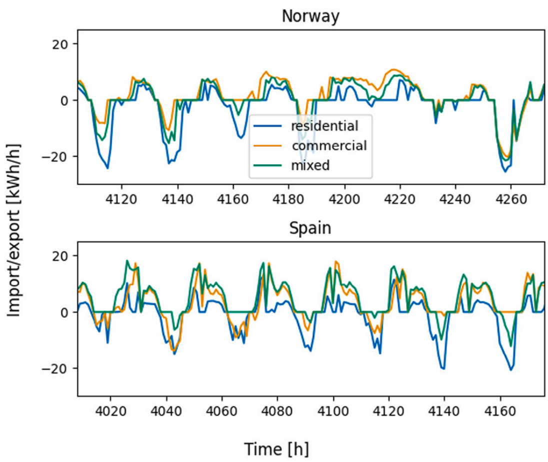

Fig. 9. Grid exchange comparison for all load configurations, summer week.

Table 8
Annual energy community costs, emissions and SCR, Norway.

	Case	Residential	Commercial	Mixed
Op. costs [€]	ref.	11,451	11,425	12,879
	opt.	8437	8457	9785
Tot. em. [kgCO_2]	ref	4305	4194	4791
	opt.	3315	3137	3705
SCR [%]	opt.	76	91	88

Table 9
Annual energy community costs, emissions and SCR, Spain.

	Case	Residential	Commercial	Mixed
Op. costs [€]	ref.	9192	12,516	14,341
	opt.	2753	6095	7451
Tot. em. [kgCO_2]	ref.	20,393	28,117	32,130
	opt.	7335	14,142	17,051
SCR [%]	opt.	78	93	95

4.3.1. Impact on the energy community

We here quantify the benefits for the energy community, in terms of annual costs, SCR and CO_2 emissions from imported electricity, as shown in Table 8 and Table 9.

The costs in Norway when optimising, compared to the reference case, are decreased by 26%, 26% and 24% for residential, commercial and mixed loads, respectively. For Spain, on the other hand, the story is quite different. Table 9 shows a cost reduction of 70%, 51% and 48%, for residential, commercial and mixed loads, respectively. Hence, there is more to gain economically from optimisation of common flexible assets in Spain, than in Norway, and residential loads have the most to gain.

The reduction in CO_2 emissions is around 24% for all load configurations for Norway. Spain, on the other hand, has much higher reductions, with the highest at 64% for residential loads, followed by 50% for commercial and 47% for mixed loads. Hence, concerning emission reductions, the potential benefits of establishing energy communities appear greater in Spain compared to Norway. It is worth mentioning that Spain has significantly higher CO_2 emissions overall, primarily attributable to the energy mix of imported electricity, as illustrated in Fig. 5.

In Norway, commercial loads have the highest SCR (91%), followed by mixed (88%) and residential (76%). In Spain, on the other hand, mixed loads have the highest SCR (95%), followed by commercial (93%) and residential (78%).

Table 10
Breakdown of costs for Norway, Case opt. [€].

Cost	Residential	Commercial	Mixed
Battery degradation	119	41	64
El. cost	8654	8491	9848
El. revenue	−394	−121	−184
Shift discomfort	57	46	56
Ann. PV system	2191	2191	2191
Ann. battery system	2561	1416	1765

Table 11
Breakdown of costs for Spain, Case opt. [€].

Cost	Residential	Commercial	Mixed
Battery degradation	241	93	79
El. cost	3240	6113	7417
El. revenue	−853	−238	−172
Shift discomfort	125	127	127
Ann. PV system	2191	2191	2191
Ann. battery system	2464	1280	1145

Table 12
Grid exchange, Norway.

	Case	Residential	Commercial	Mixed
Max. import [kWh/h]	ref.	34	34	36
	opt.	59	36	48
Max. export [kWh/h]	ref.	0	0	0
	opt.	27	20	22

Table 13
Grid exchange, Spain.

	Case	Residential	Commercial	Mixed
Max. import [kWh/h]	ref.	35	37	35
	opt.	36	36	35
Max. export [kWh/h]	ref.	0	0	0
	opt.	26	20	17

Table 10 and Table 11 give a breakdown of the costs. Residential loads in Spain gain more revenue from exporting electricity than in Norway, due to the higher spot prices. It can also be noted that the electricity costs in Norway are significantly higher than in Spain, which can be explained by Table 5, which shows that the yearly electricity consumption is higher in Norway, despite the peak load being approximately the same. The degradation cost is a measure of how much the battery is used and how profitable the model considers the battery use to be. The degradation cost is higher for Spain for all load configurations, compared to Norway, indicating that the model considers the battery to be more profitable in Spain than in Norway. This behaviour is linked to the higher level and variability of the spot price (see Fig. 4). The shift cost is a measure of how often the model decides to shift load, at a discomfort cost. In general, the shift cost is higher in Spain than in Norway. Just as for the battery, this means that the model finds it more profitable to shift load in Spain than in Norway, due to the higher spot prices. The table also shows the annualised investment costs of the PV and battery systems, which are not accounted for in the optimisation model. The annualised battery costs are slightly higher in Norway, since the battery sizes are larger when the battery is sized on the basis of self-consumption (see Table 7).

4.3.2. Impact on the distribution grid

We here quantify the impact on the distribution grid by maximum import and export as shown in Table 12 and Table 13.

For Norway, the maximum import increased by 74% for residential loads and 33% for mixed loads, when comparing the optimisation to

Table 14
Summary of optimisation results per load configuration.

Norway	Energy community benefit			Grid benefit	
	SCR	Cost	Emissions	Max. export	Max. import
Residential	Low	Low	Low	Low	Low
Commercial	High	Low	Low	Medium	Medium
Mixed	Medium	Low	Low	Medium	Low
Spain	SCR	Cost	Emissions	Max. export	Max. import
Residential	Low	High	High	Low	Medium
Commercial	High	Medium	Medium	Medium	High
Mixed	High	Medium	Medium	High	High

the reference case. This is due to battery charging when the spot price is low, causing new load spikes in winter. For commercial loads, the maximum import was increased by 6%. For Spain, the maximum import was only increased by 3% for residential loads. For the commercial loads, it was reduced by 3%, while it remained unchanged for the mixed loads.

The maximum export is zero in the reference case, since there is no PV generation or battery present. The maximum export is approximately the same for residential loads in Norway (27 kWh/h) and Spain (26 kWh/h). It is noteworthy that mixed loads have the lowest maximum export for Spain (17 kWh/h). To summarise, the grid experiences the highest maximum import and export for residential loads in Norway. Interestingly, this happens even though the battery size for residential loads is approximately the same as for Spain (see Table 7).

Since the load profiles are chosen randomly from a larger dataset, a validation of the optimisation results has been carried out, as explained in B. The results show that the optimisation results obtained are representative for the whole dataset.

4.3.3. *Summary of energy community benefit and grid impact*

Table 14 shows a summary of the energy community benefits and grid impact for the different load configurations, where each result is given a score of low, medium or high depending on the percentage change from the reference case. As the table clearly shows, the Spanish energy communities have a much better outcome in terms of cost reduction, emissions reduction and grid impact. In Norway, the best load configuration, both in terms of energy community benefit and grid impact, is the commercial energy community. This is mainly due to a high SCR, and relatively low grid impact. In Spain, the mixed energy community gives the highest grid benefit, since maximum import is not increased and maximum export is relatively low. In terms of energy community benefit, the residential energy community has the highest overall benefit due to emission reduction and cost reduction, although it has a relatively low SCR.

4.4. *Sensitivity analyses*

Three sensitivity analyses are performed: First, we investigate the ratio of commercial and residential loads in the mixed load configuration. Second, we vary selected input parameters to the optimisation model. Third, the optimisation model was run without certain technologies present.

4.4.1. *Changing mixed load ratio*

The mixed loads had a ratio of commercial loads equal to 0.5 in the original results. In Table 15, we compare the energy community costs and maximum import from the grid for different ratios. The maximum import shows a clear trend for both countries: a low share of commercial loads (and therefore a high share of residential loads) gives a high maximum import. This can be explained by the annualised investment costs for PV and battery system, which in general is higher when the ratio is low, meaning that a larger battery is required to increase self-consumption. The op. costs, on the other hand, do not show the same picture, and it seems more arbitrary which load ratio gives the best outcome. The SCR also increases with increasing share of commercial load profiles. Overall, these results indicate, for both countries, that a higher share of commercial load profiles lead to higher self-consumption rate, lower maximum import, lower battery sizes, but not necessarily lower operating costs.

4.4.2. *Changing optimisation input parameters*

A sensitivity analysis was conducted to assess how the input parameters affect the optimisation results for the energy community. The sensitivity analysis is a local, one-at-a-time analysis, meaning that one parameter is changed, while keeping the other parameters fixed [42].

Table 16 shows the results for the residential load configuration. The results are given in percentage change from the original optimisation results presented in Section 4.3. For Norway, maximum import is sensitive to the battery percentile and PV factor. Both these parameters impact the size or use of the battery, and thereby also the demand peaks from charging the battery. The load shifting percentage also has an impact on the maximum import, since a higher load shifting potential lets the model shift load to specific hours when the spot price is low. Emissions, on the other hand, show marginal sensitivity to any of the parameters (<4% change). Finally, it can be observed that all results are linearly correlated to the PV factor.

The costs are sensitive to the spot price level and grid tariff for both countries. The PV factor has a much higher impact on costs in Spain, compared to Norway. Also, almost all parameters present a relevant effect on the total emissions in Spain, which cannot be seen for Norway. Another difference between the countries is that the maximum import in Spain appears to be unaffected by any of the parameters, in contrast to Norway. It is interesting that the increase in spot price level does not impact the SCR in any of the countries. This suggests that the model is already mostly optimising based on the spot price level, given that the grid tariff is uniform.

The sensitivity results for commercial and mixed loads support the same overall conclusions, with some slight differences. For commercial loads in Norway, the maximum import is mostly impacted by PV factor and the spot price level. For commercial loads in Spain, the maximum export is more sensitive to the load shifting percentage. For mixed load configuration, the results for Norway are quite similar to the residential loads. In Spain, the main difference from the other load configurations is that maximum import is hardly affected by any parameter.

4.4.3. *Technology impact*

Since energy communities might not have implemented all different technologies, we here investigate how the costs, emissions and grid

Table 15
Costs and maximum import for different commercial load ratios in mixed load configuration.

Ratio	Norway				Spain			
	Op. cost [€]	Max. import [kWh/h]	SCR [%]	Inv. cost [€]	Op. cost [€]	Max. import [kWh/h]	SCR [%]	Inv. cost [€]
0.1	9669	58	81	4441	3208	36	80	4480
0.3	11,801	56	87	3976	6591	34	93	3549
0.5	9785	48	88	3956	7451	35	95	3336
0.7	9259	42	90	3724	5913	33	92	3646
0.9	9484	41	91	3646	6350	32	94	3452

Table 16
Sensitivity analysis for residential loads in % of original results.

Parameter[1]	Norway						Spain				
	Value	op. cost	max. imp.	max. exp.	tot. em.	SCR	op. cost	max. imp.	max. exp.	tot. em.	SCR
Battery percentile [–]	25	1	−34	0	3	−12	5	−4	0	15	−9
	50	0	−14	0	1	−6	2	−4	0	7	−4
PV factor [–]	1	6	−10	−24	4	7	37	−4	−24	22	9
	1.5	−6	10	23	−3	−7	−35	5	25	−18	−8
Spot price level [–]	1.5	26	0	0	0	0	19	0	0	−1	0
	2	52	0	0	0	0	38	0	0	−3	1
Grid tariff [€/kWh]	0.03	−16	0	0	2	−7	−18	0	0	11	−7
	0.06	16	0	0	0	1	17	0	0	−3	2
Load shifting percentage [%]	30	0	4	−1	−1	2	−3	2	−2	−7	4
	40	−1	9	−2	−1	4	−6	4	−4	−14	7

[1] Original values: battery percentile 75, PV factor 1.25, spot price level 1, grid tariff 0.0448 €/kWh, load shifting percentage 20%.

Table 17
Cases.

Case	PV generation	Battery	Shiftable loads
ref.	–	–	–
opt.	✓	✓	✓
onlyPV	✓	–	–
onlyShift	–	–	✓
PVbattery	✓	✓	–
PVshift	✓	–	✓

import change if we remove certain technologies from the optimisation. Table 17 gives an overview of the different cases.

Total costs follow the same trend in Spain, irrespective of load configuration, as seen in Fig. 10. *onlyPV* and *PVshift* have the lowest costs, followed by *PVbattery* and *opt*, while *onlyShift* and *ref* have the highest costs. In Norway, on the other hand, lower costs compared to the reference case are only obtained for cases *onlyPV*, *onlyShift* and *PVshift*. The trend is similar in Norway, although the cost reduction is not as high as for Spain. We can therefore conclude that PV generation is the main driver for reducing costs for both countries and all load configurations. The flexibility resources, shiftable loads and battery system, only lead to a marginal further reduction of costs. Considering the high cost of battery system technologies, compared to load shifting, which only requires a home energy management system, these results indicate that the cost reduction achieved through batteries is not significant enough to justify their adoption within the energy community, if the motivation is to reduce costs.

Fig. 11 shows that commercial and mixed load configurations obtain lower CO_2 emissions in *PVshift* than in *PVbattery*, for both countries. Hence, energy communities with PV generation and shiftable loads experience higher emission reductions compared to those with PV systems and batteries. This might seem contradictory — logically, a battery of 62–91 kWh should be able to provide more flexibility than load shifting maximum 20% of 33.3 kWh/h, which amounts to 6.65 kWh/h. This can be explained by the tariff design. When the cost components in the optimisation model are based on a uniform, volumetric grid tariff with a varying spot price, the optimisation model often chooses to use the battery for energy arbitrage. This strategy does not necessarily coincide with low/high CO_2 emissions, and therefore the battery does not necessarily contribute to reducing the CO_2 emissions as much as it could. In contrast, the residential configuration has the lowest CO_2 emissions for *PVbattery*. Load shifting (*onlyShift*) has almost no impact on total costs or CO_2 emissions, as can be seen in Fig. 10 and Fig. 11. Load shifting must be combined with PV generation (*PVshift*) to have a visible impact on costs and CO_2 emissions.

Fig. 12 shows that maximum import is almost equal for all cases and load configurations, with the following exceptions: *opt.* and *PVbattery*, the cases with a battery, lead to a significant increase for residential and mixed load configurations in Norway. Consequently, it becomes evident that the battery is responsible for the increase in import, due to spot price arbitrage. It is interesting that the commercial loads do not experience the same increase in maximum import. This is connected to the limited utilisation of the battery system, as demonstrated in Table 10, where the spot price variation is not significant enough for the optimisation model to choose to use the battery for arbitrage.

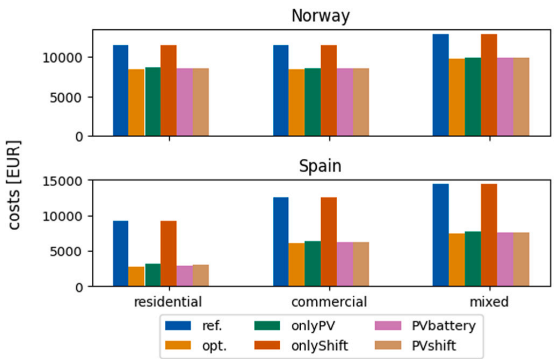

Fig. 10. Total cost comparison for all cases.

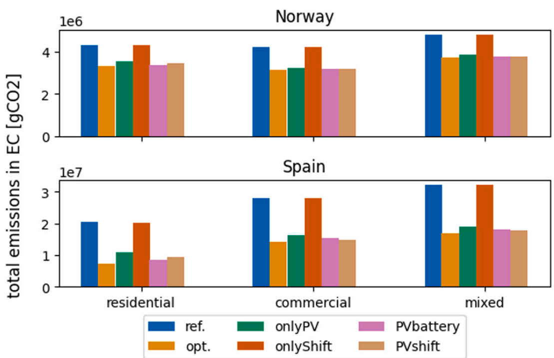

Fig. 11. CO_2 emissions comparison for all cases.

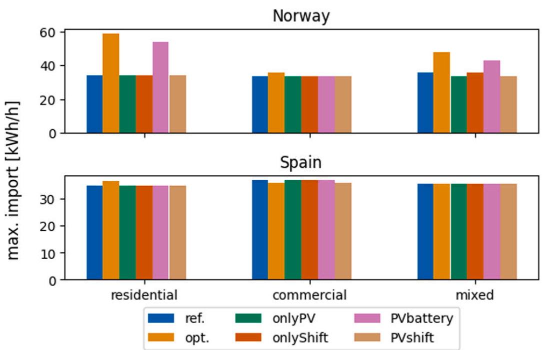

Fig. 12. Maximum import for all cases.

4.5. Assumptions and simplifications

In the course of this study, several assumptions were made to ensure equitable comparisons across cases involving two countries and distinct setups. The purpose of this section is to elaborate on these assumptions, providing clarity for the interpretation of the results.

The choice of grid tariffs is a central assumption in an optimisation model that minimises costs. One option considered was to use country-specific grid tariffs, which would make it difficult to compare the two countries and the technologies present in the energy community. Since the main focus of this article is not to compare grid tariffs, we chose to adopt a more straightforward approach in modelling grid tariffs, to enhance the interpretability of the optimisation results. A different grid tariff would certainly have led to different results. In Spain, it is not common to have contracts that follow the spot market price, but rather a time-of-use tariff. We would expect that such a tariff would lead to the flexibility resources being used to target the hours of low tariffs and avoid the hours of higher tariffs. If we had applied a grid tariff structure based on monthly peak demand charges, a common practice in Norway, we would have observed a more substantial decrease in maximum imports when utilising the flexibility resources. This would stand in contrast to the results obtained, where the battery is actually causing new load spikes, and stresses the need for accurate grid tariffs to give the right incentives to energy communities with flexibility resources.

The load profiles of shops and offices in Norway are synthetic profiles, as measured data for these building types was not publicly accessible. A random noise signal was added to these synthetic profiles to represent a more realistic load profile.

Furthermore, aggregated net metering is assumed in this study. Considering members of the energy community to be optimising individually, instead of centrally, would also lead to different results, depending on the PV generation installed at each member and the load shifting potential. This would also require an assumption concerning how the battery energy should be divided between all members, raising concerns about equity in the process.

5. Conclusion

The aim of this article was to investigate the energy community benefits and grid impact for different member configurations. Our methodology was based on running an optimisation model for one year of energy community operation for three different load configurations: residential, commercial and mixed for case studies in Norway and Spain.

The most grid-friendly load configurations were commercial loads in Norway and mixed loads in Spain. Residential loads were the least grid-friendly for both countries, due to the low correlation between load and PV generation, and therefore the need for a large battery. Maximum import increased by 3% and 74% for residential Spanish and Norwegian energy communities, respectively. The sensitivity analysis revealed that the ratio of commercial and residential load profiles in the mixed load configuration had a significant impact on the results, where a high ratio of commercial loads in general gave higher SCR and lower maximum import, but not necessarily lower costs.

PV generation emerged as a key technology for cost reduction across all load configurations in both countries. Additionally, the sensitivity analysis shed light on the comparable efficacy of load shifting and battery storage systems, emphasising that load shifting may be a more economically viable alternative. The sensitivity analysis also identified the impact of spot price levels on operational costs, particularly in Spain, and the substantial influence of battery size on maximum import in Norway.

The largest energy community benefits were obtained for commercial loads in Norway and residential loads in Spain. Both the operational costs and emissions reductions differed significantly between the countries. The Norwegian commercial loads had a 26% cost reduction and a 24% emissions reduction, while Spanish residential loads had a 70% cost reduction and a 64% emissions reduction. Although the operational costs for the residential energy community were reduced, the maximum import increased, showing that a cost optimal operation for energy communities can lead to a negative grid impact.

In light of these insights, future work could consider investigating power flow dynamics within the distribution grid and assessing their broader impact on other customers. This will lead to a more nuanced understanding of the dynamics between energy community benefits and grid impacts, ultimately paving the way for more informed and effective grid integration of energy communities. Another avenue for future research lies in investigating the distribution of operational costs and investment costs among the members of the community. The equitable allocation of financial responsibilities within energy communities can offer valuable insights into their sustainable development and management.

CRediT authorship contribution statement

Kjersti Berg: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Alejandro Hernandez-Matheus:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Mònica Aragüés-Peñalba:** Writing – review & editing, Supervision, Conceptualization. **Eduard Bullich-Massagué:** Supervision, Conceptualization. **Hossein Farahmand:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

The authors would like to thank Harald T. Walnum, Synne K. Lien, Karen B. Lindberg and Igor Sartori for access to and discussions regarding the PROFet tool. We also thank Ida Fuchs for discussions regarding PV modelling and Marte F. Dynge for proofreading. This work was supported by the project consortium of the research project FINE (Flexible Integration of Local Energy Communities into the Norwegian Electricity Distribution System), financed by the Research Council of Norway [project number 308833].

Table B.18
Validation of random sampling of residential loads, Norway.

	Ref. (no technologies)			Optimisation					
	Cost [€]	Max. imp. [kWh/h]	Tot. em. [kgCO_2]	Cost [€]	Max. imp. [kWh/h]	Max. exp. [kWh/h]	Battery size [kWh]	Tot. em. [kgCO_2]	SCR [%]
Mean	11,822	37	4,423	8,717	56	26	117	3,375	80
SD	861	3	324	815	4	2	10	299	3
CV	7.29%	8.15%	7.30%	9.34%	7.34%	5.95%	8.59%	8.86%	3.51%
Orig. result	11,452	34	4,305	8,441	59	27	131	3,317	76
z-score	−0.43	−0.74	−0.36	−0.34	0.68	0.71	1.40	−0.19	−1.55

Table B.19
Validation of random sampling of residential loads, Spain.

	Ref. (no technologies)			Optimisation					
	Cost [€]	Max. imp. [kWh/h]	Tot. em. [kgCO_2]	Cost [€]	Max. imp. [kWh/h]	Max. exp. [kWh/h]	Battery size [kWh]	Tot. em. [kgCO_2]	SCR [%]
Mean	11,899	34	26,502	5145	34	21	97	12,303	86
SD	1898	1	4249	1652	3	3	21	3412	6
CV	15.95%	2.22%	16.03%	32.11%	8.25%	14.37%	21.17%	27.74%	6.80%
Orig. result	9192	35	20,393	2760	36	26	127	7342	78
z-score	−1.43	0.90	−1.44	−1.44	0.54	1.86	1.46	−1.45	−1.25

Appendix A. Load profiles input data

A.1. Norway

The Norwegian dataset originates from a survey of households in different regions of Norway [34]. It contains hourly electricity consumption in kWh, in addition to information regarding e.g. heating, electric vehicles, and PV systems. To narrow the scope and amount of profiles, the dataset was filtered based on the following characteristics:

- Location and year: Oslo metropolitan area, 2021
- Heating options include heat pumps, electric ovens and floor heating. Alternative heating methods like district heating were excluded from consideration.
- PV generation and EVs discarded.

When filtering the dataset based on these characteristics, we were left with 423 households, with the following residence types: 246 apartment blocks, 77 townhouses or chain houses, 64 detached houses, 20 semi-detached houses and 16 others.

The synthetic load profiles for offices and shops were created using the PROFet tool [26,27]. The tool takes the input of year, location, heating type and square meters, and uses temperature data to estimate the electricity consumption. The input given to the tool for creating profiles for office and shop was: the year 2021, location Oslo, heating type electric, and floor area 225 m^2 for commercial load configuration. Since the synthetic profiles given by the tool are smooth, random, uniform noise of ± 5% was added to the profile to symbolise a more realistic consumption pattern.

A.2. Spain

The electricity consumption profiles for Spain were taken from [25]. The dataset comprises hourly electricity consumption for 499 customers in Spain in 2019, alongside corresponding temperature values based on the location of each customer's postcode. The consumption profiles are categorised into 68 distinct types of customers, ranging from households, schools and shops, to industries, among others. The dataset was filtered by separating the profiles for households, offices and shops. Furthermore, we excluded profiles with consumption peaks: higher than 18 kW for households and higher than 20 kW for shops and offices. This was done to ensure that the aggregated load profiles would not exceed the peak load limit.

Appendix B. Load profiles cross-validation

In this section, we present an analysis performed to evaluate the variation in the results of the optimisation, considering that the load profiles are chosen randomly from a larger dataset. This has been done by repeating the random selection of the load profiles available in the data set for the residential load configuration case 10 times. The results are shown in Tables B.18 and B.19, for Spain and Norway, respectively. The tables report the mean, standard deviation (SD), coefficient of variation (CV), and z-score [43]. The z-score is used to calculate the difference between these results compared to the original results, which are presented in Section 4 ("orig. result"). The results are considered representative if the z-score is within ±2 [44].

From Table B.19, we can observe that there is a greater variation in the results for Spain. This might be due to the large number of profiles available for Spain. However, the results reported in Section 4 are consistent with the results obtained in this validation, as confirmed by a maximum z-score of 1.86 in the maximum export value. In the case of Norway, as seen in Table B.18, there is less variation, which can be attributed to a smaller dataset. Again, following the z-score values with an absolute maximum of 1.55, the values reported in Section 4 align with these results.

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Paper VII: Quantifying the benefits of shared battery in a DSO-Energy community cooperation

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Cite as:
Berg, Kjersti, Rubi Rana, and Hossein Farahmand. "Quantifying the Benefits of Shared Battery in a DSO-Energy Community Cooperation." Applied Energy 343 (August 1, 2023): 121105. https://doi.org/10.1016/j.apenergy.2023.121105.

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Applied Energy 343 (2023) 121105

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Quantifying the benefits of shared battery in a DSO-energy community cooperation

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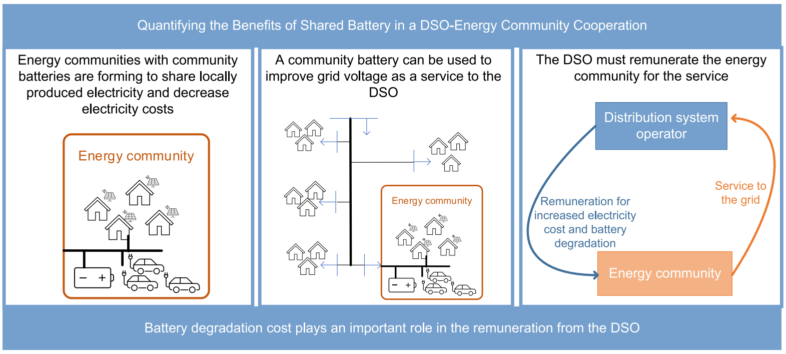
GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Energy community
Distribution grid service
Battery degradation
Community battery
Power flow analysis

ABSTRACT

Local energy communities are forming as a way for prosumers and consumers to invest in distributed renewable energy sources, community storage and share electricity. Meanwhile, several distribution grids have voltage problems at certain hours of the year. Local energy communities consisting of generation and storage units might be valuable flexible assets that the distribution system operator (DSO) can make use of. This article aims to study how a battery in an energy community can provide services to the distribution grid, by creating a linear optimisation model which includes power flow constraints and a battery degradation model. First, we investigate how the battery operation of an energy community impacts the voltage in the nearby buses. We find that when including the degradation model, the voltage limits are violated much less than when not including the degradation model. Next, we investigate how the battery operation differs when the energy community cooperates with an active DSO to share the battery use, and quantify how much the DSO should remunerate the energy community. We find that the energy community should get 15 € per year due to an increase in electricity and degradation costs, which equals an increase of 0.12%, compared to when the community is not providing a service. Finally, a sensitivity analysis is performed to determine which parameters are more important to consider. We find that voltage violations in the grid are sensitive to the battery replacement cost, electric vehicle charging peak and the average spot price, while the remuneration from the DSO is sensitive to the battery replacement cost. For small battery sizes and a low power-to-energy ratio, the community is not able to improve the voltage at all hours of the year.

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https://doi.org/10.1016/j.apenergy.2023.121105
Received 12 January 2023; Received in revised form 21 March 2023; Accepted 6 April 2023
Available online 5 May 2023
0306-2619/

Nomenclature

Parameters

δ	Cycle depth [%]
η	Battery charge and discharge efficiency [–]
$\Phi(\delta)$	Cycle depth stress function of battery [%]
$C^{B,rep}$	Replacement cost of battery [€/kWh]
C_t^{spot}	Electricity spot price in hour t [€/kWh]
C^{tar}	Volumetric grid tariff [€/kWh]
E^B	Energy capacity of battery [kWh]
$P_{j,t}^D$	Active power demand at bus j in hour t [kWh/h]
$P_{j,t}^{PV}$	PV production at bus j in hour t [kWh/h]
$Q_{j,t}^D$	Reactive power demand at bus j in hour t [kVArh/h]
R^{PE}	Power-to-energy ratio of battery [–]
R_{ij}	Resistance of line between bus i and j [Ω]
X_{ij}	Reactance of line between bus i and j [Ω]

Indices and sets

B	Set of buses where voltage constraint should be enforced
i, j	bus
S	Number of segments
s	degradation segment
T	Last hour of year
t	hour

Variables

C_s^{deg}	Battery degradation cost for segment s [€]
$p_{s,t}^{ch,seg}$	Battery charging for segment s in hour t [kWh/h]
p_t^{ch}	Battery charging in hour t [kWh/h]
$p_{s,t}^{disch,seg}$	Battery discharging for segment s in hour t [kWh/h]
p_t^{disch}	Battery discharging in hour t [kWh/h]
p_t^{exp}	Export to grid from EC bus in hour t [kWh/h]
$p_{ij,t}$	Active power flow between bus i and bus j in hour t [kWh/h]
$q_{ij,t}$	Reactive power flow between bus i and bus j in hour t [kVArh/h]
$soc_{s,t}^{seg}$	Battery state of charge for segment s in hour t [kWh]
soc_t	Battery state of charge in hour t [kWh]
$v_{i,t}$	Voltage at bus i in hour t [pu]

1. Introduction

The electricity distribution grid is changing as distributed energy resources are increasing in popularity and households are becoming active prosumers. A way for prosumers to organise and share electricity is by forming energy communities. As described in EU directives regarding Citizen and Renewable energy communities [1,2], the members of an energy community should be active, and the main objective of the community should not be to make profit, but rather to provide environmental, economic or social benefits for its members. A primary aspect of energy communities is collective assets such as storage systems, which the literature has demonstrated are more cost-effective than individual storage units [3,4].

Studies on energy communities have shown that photovoltaic (PV) panels and batteries are popular technologies in energy communities [5,6], as installation costs continue to decline. An increasing number of households in Norway are currently investing in PV panels owing to the increase in electricity prices over the previous year, as the electricity costs in Norway have historically been relatively low. Furthermore, the Norwegian Energy Regulatory Authority (NVE-RME) has proposed to change the regulation regarding sharing of electricity within properties [7], enabling houses and apartments located at the same property to share electricity generation up to 500 kW. With this proposition, sharing of electricity will also be possible in Norway, potentially leading to the formation of more energy communities. Additionally, since 2022, housing cooperatives in Norway are obliged to install electric vehicle (EV) chargers if requested by the residents [8].

The Norwegian distribution grid has many rural areas and long distances due to sparsely populated areas (Norway has a population density of 14 inhabitants/km^2). Rural feeders tend to have a high resistive characteristic, and in some cases, problems with over- or under-voltages breaching the limits of +/- 10% of nominal voltage (EN50160 standard) [9]. In some cases, the voltage is violated even though the households connected to the feeder are not exceeding their allowed import or export. In these cases, the distribution system operator (DSO) is responsible for improving the voltage quality, traditionally by upgrading lines and/or transformers. Furthermore, since the majority of household electricity use in Norway is due to electric heating [10], voltage limits are usually violated in only a few hours of the year when the outdoor temperature is especially low. In these hours, an active DSO could acquire flexibility services from households instead of reinforcing the grid, or at least to defer the grid reinforcement. Studies have investigated how grid-connected batteries operated by a DSO can improve the voltage [11–13]. However, EU legislation states that "Distribution system operators shall not own, develop, manage or operate energy storage facilities" [2]. Moreover, it would require the DSO to invest in an asset which is utilised only for some hours of the year. In this article, we investigate how an existing battery system owned by an energy community can improve the distribution grid voltage by providing a service to the DSO.

Energy communities can be an effective way for the DSO to acquire flexibility in hours where there are voltage problems. Flexible resources in energy communities can be manifold, from energy storage systems like hot water tanks to demand side responses such as shiftable loads or EV charging [14]. Both hot water tanks and shiftable loads are dependent on household demand, while EVs are stochastic in nature due to their mobility. Hence, their flexibility potential in a given hour is uncertain. Therefore, in this study, we focus on stationary battery storage, which has the advantage of being available at all hours.

Recently, power systems research has shown an increased interest in battery degradation due to the increased deployment of lithium-ion batteries [15–17]. Cyclic battery degradation depends on multiple factors, such as C-rate, temperature, depth-of-discharge, and average state-of-charge (SOC) [18]. Detailed degradation models are often non-linear and lead to a high computational burden when combined with optimisation models [19]. Therefore, many optimisation studies in power systems neglect battery degradation [5] or use linear power-energy models [19]. Such models often use a constraint-based approach where for instance, power, number of cycles per day, depth of discharge, and/or maximum and minimum SOC are constrained, leading to non-optimal solutions [20]. In the context of energy communities, examples of studies which include such constraints are [21–23]. If cyclic degradation is disregarded in optimisation models that minimise cost, the battery often charges and discharges heavily to perform energy arbitrage, which in practise would lead to a much lower lifetime [24,25]. One way to account for the cyclic degradation, while keeping the optimisation model linear, is to add a degradation cost in the objective function [19]. In this article, we investigate how an energy community and a DSO can cooperate to improve the voltage profile of a distribution

Table 1
Relevant literature on distribution grid impact from energy communities.

Ref.	Grid impact	Service to DSO	Battery	Battery degradation model	Power flow analysis
[4]	✓	✓	community	✓	✓
[40]	✓	✓	community	✓	X
[39]	✓	✓	community	X	X
[38]	✓	✓	community	X	✓
[21]	✓	X	community	X[a]	X
[32]	✓	X	X	X	X
[22]	✓	X	individual	X[a]	✓
[23]	✓	X[b]	individual	X[a]	✓
[31]	✓	✓[c]	X	X	✓

[a]has limits on SOC.
[b]service to reserve market.
[c]includes network constraints in market clearing.

grid - and how much the DSO should remunerate the energy community for this service. If the change in battery operation contributes to battery degradation, it should be accounted for when calculating how much the DSO should remunerate the energy community for providing the grid service.

1.1. Related literature

According to [5,26], there is limited literature focusing on how energy communities and PV-battery systems affect the distribution grid. Until now, most studies on energy communities have primarily focused on the sizing and siting of PV and battery systems [21,27–29], market designs [22,30,31], or the difference between individual and shared assets [3,32–37]. Few of these studies [21,22,32] have investigated how energy communities impact the grid, but not specifically focused on how the energy community operation can be changed to provide a grid service. One exception is [31], where a peer-to-peer market is cleared with grid constraints. Other studies, such as [23], do not investigate how the community can provide a local service, but rather services to the balancing reserve markets while considering congestions in the distribution grid.

A limited number of studies [4,38–40] have investigated how an energy community can improve the distribution grid voltage in cooperation with the DSO. Two ownership models of a community battery were compared in [40], where they found that the economic and environmental performance was slightly worse when there was a shared ownership of the battery between an aggregator and a DSO, compared to single ownership by the aggregator, but the differences were small. This study included a degradation model for the battery but did not consider power flow equations. Ref. [38] found that a community performing peak shaving helped reduce grid loading by up to 58%, compared to when the community was minimising its costs. The costs increased by only 0.3%. The battery model did not, however, include degradation.

Ref. [39] investigated the operation of flexible assets in energy communities and found that a grid-friendly strategy achieved a peak-power reduction of up to 55%. They also found that the cost difference between maximising economic benefits and the grid-friendly strategy was very low and therefore concluded that energy communities might be a cost-effective way to defer future grid reinforcements. They neglected both a degradation model for the battery and power flow equations. Ref. [4] studied how an energy community of 200 households could improve the voltage in the distribution grid, including degradation modelling. The battery operation was heuristic-based for self-consumption maximisation, and the main aim of the article was to investigate how to distribute energy use of shared assets among the community members. When comparing the annual bills of the community with and without grid constraints, they found an increase of 1874 £.

1.2. Contributions

To summarise the relevant literature and compare it to this article, Table 1 presents whether the references consider grid impact, service to the DSO, community battery, battery degradation model or power flow constraints. The primary objective of this article is to quantify the benefits of using community-owned battery storage for an energy community and a DSO. The electricity and degradation costs for the energy community are estimated by running an optimisation model with and without voltage constraints. This study examines a whole year, allowing a broader spectrum of analysis due to seasonal variations of load and PV in weeks, days and hours. Hence, the approach described here can give insights to both operation and planning of energy communities. A sensitivity analysis is performed to identify which parameters have the prominent impact on the remuneration from the DSO. In summary, the main contributions of this paper include:

- The paper presents a linear optimisation model which minimises the electricity and degradation costs for an energy community. The optimisation model includes linear battery degradation equations, which ensures that degradation costs are accounted for while maintaining a low complexity of the optimisation problem. The case studies show how the community-owned battery is used differently when voltage constraints are considered.
- The proposed model provides new insights for quantifying how much the DSO should remunerate the energy community for the voltage service.

1.3. Outline of article

The outline of this article is as follows: First, Section 2 explains the linear optimisation model created for this work. Section 3 explains the various input of the Norwegian case study used to showcase the model. Section 4 shows and discusses the main results from the case study, highlighting the impact of the degradation model and the service to the DSO. Finally, Section 5 concludes the article.

2. Method

Fig. 1 shows an overview of the input to and output from the optimisation model. The model takes the following input: hourly active and reactive load for each bus, hourly normalised PV production in each bus and the size of the PV system, and the hourly electricity spot price. Furthermore, the size and the power-to-energy (P2E) ratio of the community battery system must be specified, along with the grid tariff for the energy community. The battery degradation cost and the number of degradation segments are also given as an input as further explained in Section 2.3. Finally, the grid topology and resistance (R) and reactance (X) of the grid must be specified. The optimisation model then minimises the costs of the energy community, due to power flow and battery constraints. The model also includes optional constraints

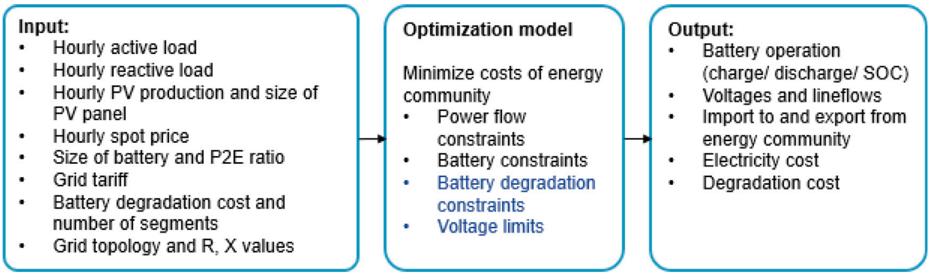


Fig. 1. Overview of input to and output from the optimisation model. The battery degradation and voltage constraints are marked in blue as they are not included in some of the cases.

for battery degradation and voltage limits, depending on the case, which will be further explained in Section 3. The model outputs the battery operation, the voltage and line flow of the grid, the import to and export from the energy community, the electricity costs of the community and the degradation cost of the battery.

2.1. Optimisation model

The optimisation model is shown in (1a)–(1t), see the nomenclature for an explanation of the variables and parameters. Perfect foresight is assumed, and the model is deterministic. (1a) is the objective of the model, which is to minimise operational costs related to electricity for the energy community and degradation cost of the battery. Import of electricity has a spot price, value-added tax (VAT) and a grid tariff, while it is assumed that the community can sell electricity for the spot price (as is the regulation in Norway).

Since the original AC power flow equations result in non-convex optimisation problems, the equations are often linearised or relaxed (through for instance semidefinite or second-order-cone programming) [41,42]. One common way to linearise is using the linear DistFlow (LinDistFlow) equations made for radial distribution grids [43]. The LinDistFlow equations assume that the line losses are negligible and have been shown to model power networks with satisfactory accuracy [44,45]. Constraints (1b)–(1g) cover the LinDistFlow constraints. (1b) describes the electricity produced and consumed in the bus of the energy community, while (1c) describes the same, but for the remaining buses. Note that since the objective requires separate variables for import and export, the line connected to the energy community (EC) is split into an import variable, $p_{ij,t}$ for j=EC bus, and an export variable, p_t^{exp}. This also requires a separate constraint depending on if the line in question is connected to the energy community (1d). (1e) describes the reactive power produced and consumed in each bus. (1f) describes the voltage dependence on the line resistance and reactance, where (1g) covers the EC bus.

Constraints (1h)–(1l) are constraints for the battery operation. (1h)–(1j) relate the SOC with the previous hour and the amount of electricity charged and discharged. The SOC of the final hour is set equal to the first hour. (1k)–(1l) restrict the charge and discharge to be lower than the battery inverter capacity, which is determined by the P2E ratio of the battery system, R^{PE}.

Constraints (1m)–(1q) for cyclic battery degradation are added as described in [46]. Each battery segment, s, has a cost which makes it more expensive the more segments the battery discharges through. This cost is added to the objective function to penalise heavy use of the battery. It ensures that the battery does not do arbitrage on very small price variations or discharge with high power, which would cause more harm to the battery in terms of a lower lifetime than benefit in terms of electricity cost savings. This model is chosen since it is piecewise linear.

Finally, (1r)–(1t) show the non-negativity constraints (see Box I).

Table 2
Case overview.

Case	Battery degradation cost included in objective function?	Voltage requirement included?
No battery	X	X
EC	✓	X
EC no deg.	X	X
EC+DSO	✓	✓
EC+DSO no deg.	X	✓

2.2. Energy community providing service to DSO

For cases where the battery is also utilised to provide a service to the DSO, the following constraint is included:

$$\underline{V}_i^2 \leq v_{i,t} \leq \overline{V}_i^2 \qquad i \in B, \forall t \tag{2}$$

where B is the set of buses where this voltage requirement must be fulfilled.

2.3. Battery degradation model

The battery degradation cost is found from [46]:

$$C_s^{deg} = \frac{C^{B,rep}}{\eta}(\Delta\Phi(\delta_s)) \tag{3}$$

where $C^{B,rep}$ is the replacement cost of the battery in €/kWh and $\Delta\Phi(\delta_s)$ is the stress due to the cycle depth δ_s of segment s in %.

3. Case

This section explains the Norwegian case study used to showcase the optimisation model. Four cases are run, as shown in Table 2. Case No battery is used as a reference case where the battery size is set to 0. In case EC (energy community), the battery is used to minimise the energy community's costs without enforcing constraint (2). Case EC no deg. is similar to case EC, however the degradation cost, $\sum_s C_s^{deg} p_{s,t}^{disch}$, is removed from the objective function. In case EC+DSO, the battery is now used to minimise costs for the energy community and to improve the voltage, hence constraint (2) is now included. Case EC+DSO no deg. is similar to case EC+DSO, however, the degradation cost is not considered in the objective function.

3.1. Input

Table 3 shows the input parameters. The following subsections describe the grid, household demand, PV production, spot prices and degradation cost input.

Objective:

$$\min \quad \sum_t \Big[(C_t^{spot} + C^{tar}) p_{ECline,t}^{imp} - C_t^{spot} p_t^{exp} + \sum_s C_s^{deg} p_{s,t}^{disch,seg} \Big] \qquad (1a)$$

Power flow constraints:

$$p_{ij,t} - p_t^{exp} = \sum_{k:j\to k} p_{jk,t} + P_{j,t}^D - P_{j,t}^{PV} + p_t^{ch} - p_t^{disch} \qquad j = \text{EC bus}, \forall t \quad (1b)$$

$$p_{ij,t} = \sum_{k:j\to k} p_{jk,t} + P_{j,t}^D \qquad \forall j \neq \text{EC bus}, t \quad (1c)$$

$$p_{ij,t} = \sum_{k:j\to k} p_{jk,t} - p_t^{exp} + P_{j,t}^D \qquad \forall k = \text{EC bus}, t \quad (1d)$$

$$q_{ij,t} = \sum_{k:j\to k} q_{jk,t} + Q_{j,t}^D \qquad \forall j, t \quad (1e)$$

$$v_{j,t} = v_{i,t} - 2(R_{ij} p_{ij,t} + X_{ij} q_{ij,t}) \qquad \forall j \neq \text{EC bus}, t \quad (1f)$$

$$v_{j,t} = v_{i,t} - 2\big[R_{ij}(p_{ij,t} - p_t^{exp}) + X_{ij} q_{ij,t}\big] \qquad j = \text{EC bus}, \forall t \quad (1g)$$

Battery constraints:

$$soc_t = soc_{t-1} + \eta p_t^{ch} - \frac{1}{\eta} p_t^{disch} \qquad \forall t > 0 \quad (1h)$$

$$soc_t = soc_T + \eta p_t^{ch} - \frac{1}{\eta} p_t^{disch} \qquad \forall t = 0 \quad (1i)$$

$$soc_t \leq E^B \qquad \forall t \quad (1j)$$

$$p_t^{ch} \leq E^B R^{PE} \qquad \forall t \quad (1k)$$

$$p_t^{disch} \leq E^B R^{PE} \qquad \forall t \quad (1l)$$

Battery degradation constraints:

$$p_t^{ch} = \sum_s p_{s,t}^{ch,seg} \qquad \forall t \ (1m)$$

$$p_t^{disch} = \sum_s p_{s,t}^{disch,seg} \qquad \forall t \ (1n)$$

$$soc_{s,t}^{seg} \leq E^B / S \qquad \forall s, t \quad (1o)$$

$$soc_{s,t}^{seg} = soc_{s,t-1}^{seg} + \eta p_{s,t}^{ch,seg} - \frac{1}{\eta} p_{s,t}^{disch,seg} \qquad \forall s, t > 0 \quad (1p)$$

$$soc_{s,t}^{seg} = soc_{s,T}^{seg} + \eta p_{s,t}^{ch,seg} - \frac{1}{\eta} p_{s,t}^{disch,seg} \qquad \forall s, t = 0 \quad (1q)$$

Non-negativity constraints:

$$p_t^{exp}, p_{ECline,t}, p_t^{ch}, p_t^{disch}, soc_t \geq 0 \qquad \forall t \quad (1r)$$

$$v_{i,t} \geq 0 \qquad \forall i, t \quad (1s)$$

$$p_{s,t}^{ch,seg}, p_{s,t}^{disch,seg}, soc_{s,t}^{seg} \geq 0 \qquad \forall s, t \quad (1t)$$

Box I.

Table 3
Input parameters.

Parameter	Value	Unit
Battery efficiency, η	0.95	–
Battery replacement cost, $C^{B,rep}$	200	€/kWh
Battery size, e^B	120	kWh
PV size	8	kWp
No. degradation segments	8	–
Cosphi	0.99	–
EC bus	16	–
Grid tariff, C^{tar}	0.041	€/kWh
Value added tax (VAT)	0.25	–
P2E ratio, R^{PE}	0.5	–
Average spot price	0.05	€/kWh
Voltage limits, $\underline{V}_b$, $\overline{V}_b$	0.92, 1.08	pu
Buses where voltage limit is enforced, B	16, 17	–

3.1.1. Modified CIGRE LV distribution network with energy community

A modified version of the residential part of the CIGRE European LV distribution network [47] is shown in Fig. 2. There are loads connected to buses 0, 10, 14, 15, 16 and 17. The energy community is connected to bus 16, with household load, PV production, shared EV chargers and a shared community battery. The R/X values and length of lines can be found in [47]. To make the case study more similar to the Norwegian rural distribution grids, the length of all the lines has been multiplied with a factor of 1.9.

In cases EC+DSO and EC+DSO no deg., lower and upper voltage limits of 0.92 pu and 1.08 pu are used for buses 16 and 17 in (2).

3.1.2. Household demand, EV charging demand and PV production

Household demand of all load buses is based on hourly normalised data from 100 Norwegian households in 2015 [48]. Loads of the CIGRE grid are populated by adding random profiles to each load bus, before scaling them up to meet loads of the CIGRE European LV distribution

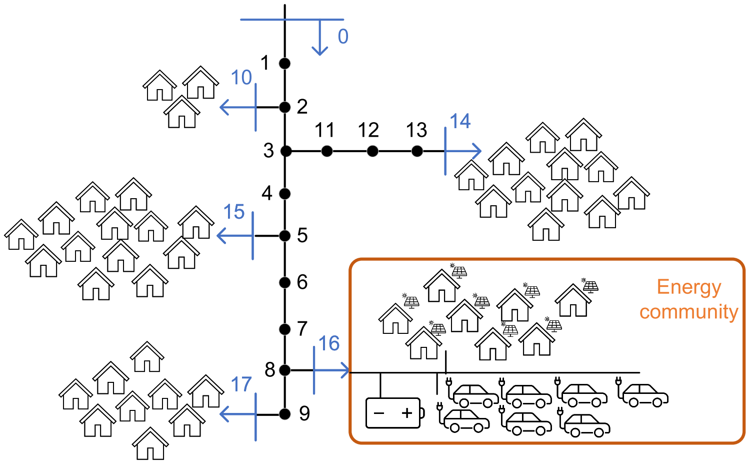


Fig. 2. Modified residential CIGRE European LV distribution network.

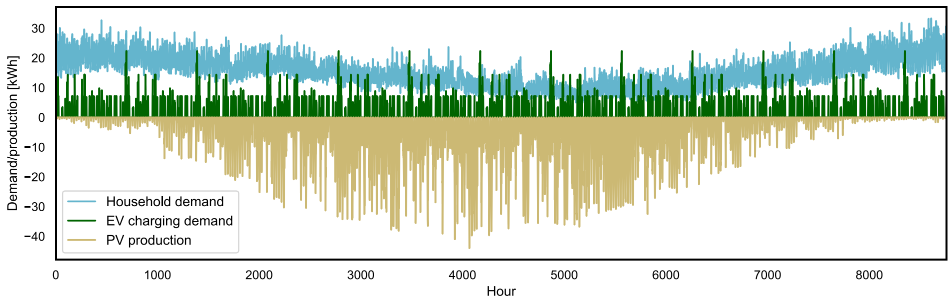


Fig. 3. Demand and production at EC bus.

Table 4
Max. load and no. of households at buses.

Bus	10	14	15	16	17
Max. load [kWh/h]	14.25	49.4	52.25	33.25	44.65
No. of households	3	12	13	8	10

network. Maximum load and number of households per load bus can be seen in Table 4. The aggregated load for each bus is shown in Fig. A.11.

The EV charging data is taken from a dataset on residential electric vehicle chargers for Norwegian apartment buildings [49]. The data used is the synthetic load profile of 7.2 kW common chargers from *Dataset 3b_Hourly EV loads - Aggregated shared*. Since the dataset starts 10 January 2019 and the number of shared chargers increased throughout the year, two modifications have been made to the dataset so that it is consistent with the other data in the case study: only data for seven and eight chargers are used, and the weekdays are shifted to correspond to the weekdays of 2015. Hence, the days in the dataset between 30 May and 24 June 2019 are used and repeated throughout the year.

The PV panels have the specifications from [50], and an assumed efficiency of 0.95. The power output from the PV system is calculated from measured irradiance and temperature data for Mære, Norway, as explained in more detail in [48]. The household demand, EV charging demand and PV production at the EC bus (16) can be seen in Fig. 3.

3.1.3. Spot price and grid tariff

The spot price from price zone NO3 for 2015 is used and scaled to match the predicted average spot price for Norway 2030 of 0.050 €/kWh [51]. The resulting spot price can be seen in Fig. 4 (excluding VAT). The energy-based grid tariff, C^{tar}, is set to 0.04126 €/kWh from the historical tariff of the Norwegian DSO Tensio TN [52].

3.1.4. Degradation cost

The cycle depth stress function of a lithium-ion nickel manganese cobalt (NMC) battery is used to calculate the degradation cost [46,53]:

$$\Phi(\delta) = (5.24 \cdot 10^{-4})\delta^{2.03} \tag{4}$$

Using (3) along with a battery replacement cost of 200 €/kWh [54] and eight segments, the degradation cost segments are calculated to be between 0.013 and 0.2095 €/kWh as shown in Table 5.

3.2. Loss calculation

Since the LinDistFlow equations do not account for losses, a load flow analysis is done in pandapower post-optimisation. The hourly values for demand, generation, battery charge and discharge are given as input for all cases, and the resulting line losses are reported.

3.3. Sensitivity

To analyse the impact of different parameters on the results, the optimisation is run for different inputs of PV size, battery size, P2E ratio, max. EV charging, the average spot price level and the battery replacement cost. The input is shown in Table 6.

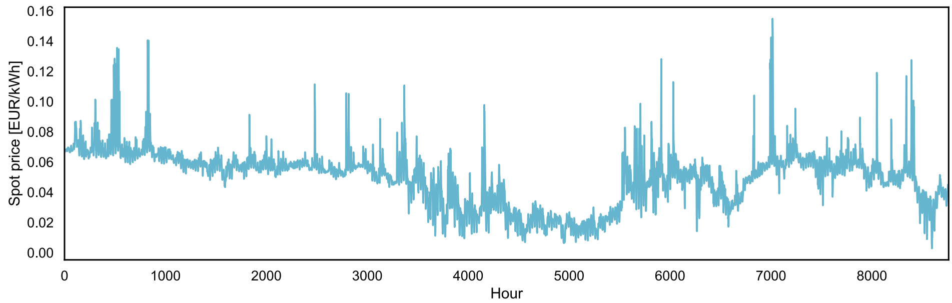


Fig. 4. Electricity spot price for NO3 from 2015, scaled to an average level of 0.050 €/kWh [51].

Table 5
Degradation cost segments.

Segment, s	1	2	3	4	5	6	7	8
C_s^{deg} [€/kWh]	0.0130	0.0400	0.0676	0.0956	0.1238	0.1522	0.1808	0.2095

Table 6
Sensitivity input.

PV size [kWp]	Battery size [kWh]	P2E ratio	EV max. charging [kWh/h]	Average spot price [€/kWh]	Battery replacement cost [€/kWh]
6.48	96	0.1	17.9	0.040	100
7.2	108	0.3	20.1	0.045	150
8	120	0.5	22.3	0.050	200
8.8	132	0.7	24.6	0.055	250
9.68	144	0.9	26.8	0.060	300

4. Results and discussion

The optimisation model is run for the given case study for 8760 h. In this section, we first illustrate how the degradation model affects the battery operation and voltage violations. Second, we illustrate how the battery operation changes when the community coordinates with the DSO to keep within voltage limits. Third, we summarise the results for the whole year and show how this service impacts the costs and battery use for the community. Finally, we investigate how sensitive the results are with respect to the input parameters before limitations of the study are addressed.

4.1. Degradation model effect on battery operation

Fig. 5 shows the results for one week in January for cases EC and EC no deg. The top graph shows the residual demand for the EC bus, with and without the battery. The middle graph shows the battery charge, discharge and SOC, while the lower graph shows the voltage at buses 16 and 17, which are the two buses where the voltage requirement must be fulfilled. In Fig. 5(a), it can be seen that the battery is used in five of the seven days even though there is no surplus energy due to low irradiance in winter. Hence, the battery is doing arbitrage on the spot price without considering the stress on the battery, and this leads to several drops in voltage below the voltage limit. When the degradation model is included, in Fig. 5(b), the battery is used a lot less, since the variation in spot price is not high enough compared to the degradation cost.

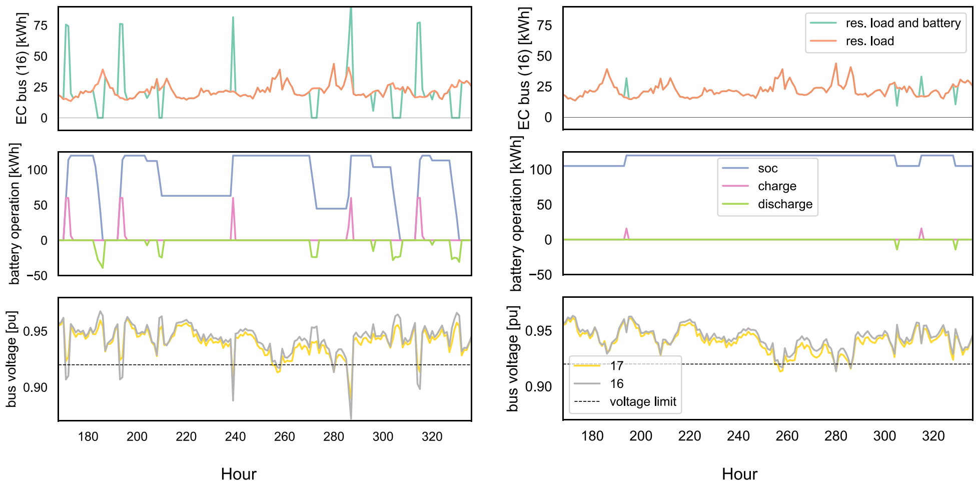
Fig. 6 shows the results for one week in June for cases EC and EC no deg. In Fig. 6(a) it can be seen that the battery is charged to 100% almost every day of the week due to a surplus of PV production. As a result, the voltage is quite stable except for two-three hours where the battery suddenly discharges or charges a lot, causing a spike in the voltage. In Fig. 6(b), when the degradation model is included, a lot of the self-produced energy from the PV generation is actually exported because it is more profitable to spare the battery than to charge from PV generation due to low spot price. Due to the lower usage of the battery, the voltage varies more throughout the week but avoids the sudden drops and spikes in voltage. Note also that the voltage is nowhere near the maximum voltage limit of 1.08 pu, due to a high load in the grid also in summer (ref. Fig. A.11).

4.2. Energy community coordinating with DSO

Fig. 7 illustrates the difference between cases EC (a) and EC+DSO (b), for the last three weeks in December. Note that these two cases both include the degradation model. From Fig. 7(a), we observe that the voltage is below the limit for several hours and that the battery is being used for energy arbitrage since there is no surplus energy from the PV. In case EC+DSO, the battery keeps the voltage at buses 16 and 17 above the voltage limit at all hours, which requires only a slightly different battery operation. Interestingly, one of the voltage drops that should be avoided in Fig. 7(a) (at approx. hour 8600) is created by the battery, because it is charging at maximum capacity (60 kWh/h). In Fig. 7(b), we observe that the battery limits the charging to avoid the voltage from dropping below 0.92 pu. In other words, the battery does not only remove voltage problems which occur due to high load, but it also avoids *causing* a voltage problem in the grid.

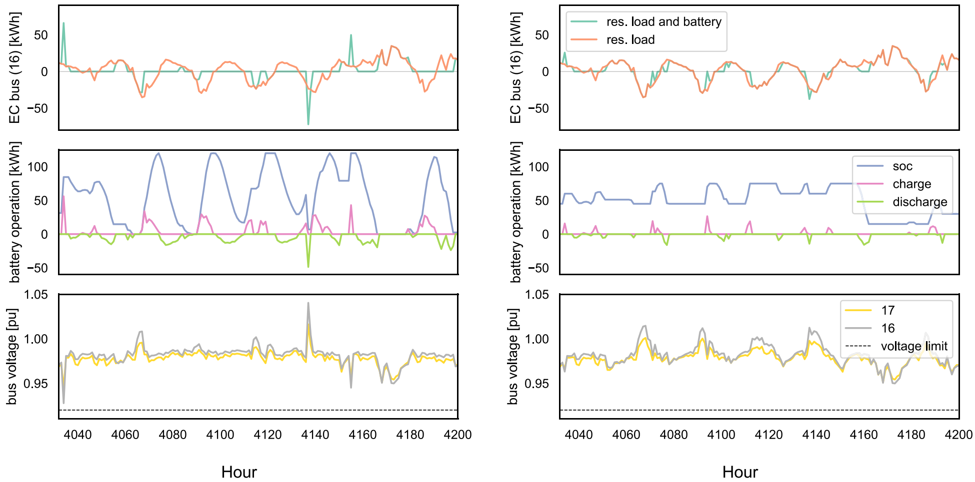
4.3. Yearly results of cases

Fig. 8 shows the voltages at buses 16 and 17 for cases EC no deg., EC and EC+DSO. Here we can observe that when not including the degradation model (upper graph), the battery is often charging at the same time as the voltage is below the limit. This occurs less when the degradation model is included (middle graph), indicating that many of the voltage problems in the upper graph are caused by the battery. There are, however, also many hours where the voltage is below 0.92 pu and the battery is not charging. Finally, the lower graph shows how the battery operation is changed to keep the voltages within the voltage limit.



(a) EC no deg. (b) EC

Fig. 5. One week in January, comparing cases EC and EC no deg.



(a) EC no deg (b) EC

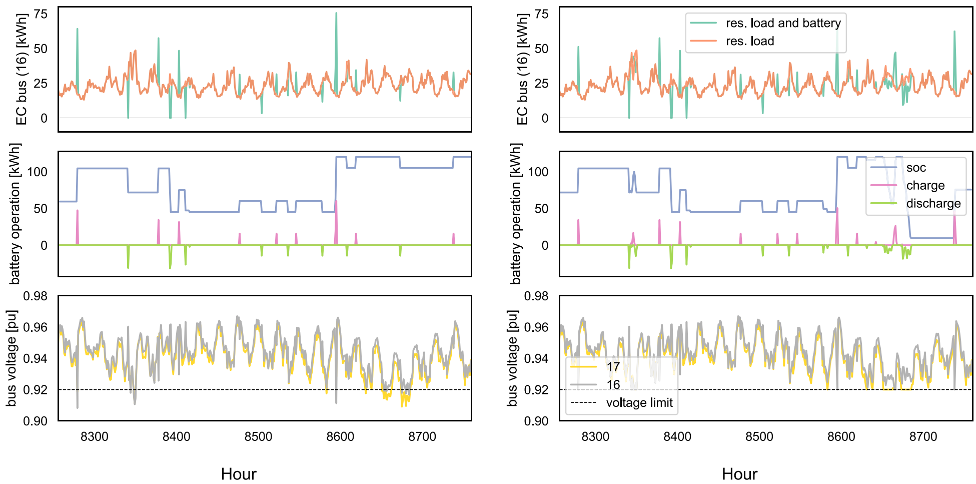
Fig. 6. One week in June, comparing cases EC and EC no deg.

Table 7 compares the electricity and degradation costs for all cases, both with and without the degradation model. Note that cases EC no deg. and EC+DSO no deg. correspond to the column named no degradation. Comparing the reference case with case EC, the electricity cost decreases by 267 € due to battery use, while the degradation cost increases by 121 €. Comparing cases EC and EC+DSO, the electricity cost increases by 5 €, and the degradation cost increases by 10 €. In other words, the total remuneration needed from the DSO to cover the additional costs for the energy community is 15 € per year. From the technical results in Table 8, we observe that the voltage violations at bus 17 is 38 h both in the reference case and in case EC. At bus 16, however, the voltage violations increase due to the battery operation, in addition to a lower minimum voltage.

Comparing cases EC and EC no deg., the electricity cost reduces by 343 €, but the degradation cost increases by 2299 €. This is connected to the battery usage shown in Table 8, where we observe that the battery is used substantially more in case EC no deg. (3371 vs 1370 h). Not considering degradation also leads to a lower minimum voltage of 0.872 pu due to the battery operation. Also, the voltage is violated 184 h at bus 16, compared to 25 h when degradation is considered. At bus 17, the voltage is violated 76 h, compared to 38 h. This increase in voltage violations is created solely from the battery operation, as we can compare with the reference case. All voltage violations occur in winter (November-February) in case EC, and the maximum voltage limit of 1.08 pu is not violated in any of the cases. Finally, we can observe from Table 7 that case EC+DSO no deg. has a lower degradation cost compared to case EC no deg. The reason for this is that the battery must limit its charging and discharging when the voltage restriction is included, which also leads to a lower degradation.

4.4. Impact on distribution grid losses

Since the LinDistFlow equations neglect line losses, a power flow has been run in pandapower post-optimisation to determine the losses in the distribution grid. From Table 9 we can see that the battery decreases the losses in the grid by 51 kWh, when comparing case EC



(a) EC

(b) EC+DSO

Fig. 7. Last three weeks in December, comparing cases EC and EC+DSO.

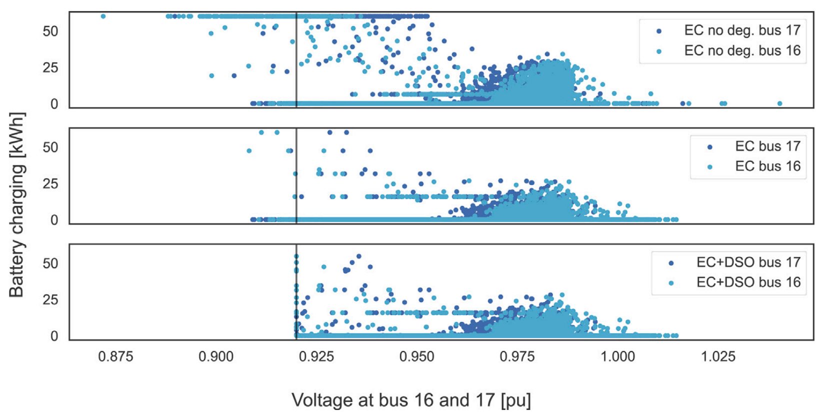


Fig. 8. Battery charging vs. voltages for cases EC no deg., EC and EC+DSO.

with case no battery. In case EC+DSO, when the energy community is providing a service to the DSO, the losses are further decreased by 8 kWh. Comparing cases EC and EC no deg., we see that the losses increase by 859 kWh when not accounting for degradation. Hence, including degradation does not only contribute to an improved voltage profile but also reduces losses in the grid.

4.5. *Sensitivity analysis*

In this section, we demonstrate the sensitivity of the results to varying input data. The reader is referred back to Table 6 to see the different sensitivity inputs, and all sensitivity results can be found in Tables B.10 and B.11.

4.5.1. *Voltage violations*

Fig. 9 shows the hours of voltage violation at buses 16 and 17 together with the lowest voltage for the different sensitivity input. Compared to bus 16, the voltage violations are always higher at bus 17, with 35 h as the lowest and 42 h as the highest. The most sensitive parameter is the EV charging peak, where the number of voltage violations ranges from 35 to 41 at bus 17. A higher EV charging peak leads to more voltage violations, and the charging profile of the EV is responsible for the majority of the voltage violations. The minimum voltage is, however, quite stable at 0.908 pu.

The average spot price of 0.06 €/kWh leads to a higher number of voltage violations compared to lower spot prices, due to more arbitrage from the battery. However, as the graph shows, it is not necessarily true that a lower average spot price will result in fewer voltage violations. Similarly, a higher battery replacement cost does not necessarily lead to a decrease in voltage violations, although that is the trend. The lowest battery replacement cost leads to the highest number of voltage violations and the voltage violations decrease until a cost of 250 €/kWh. The lowest voltage decreases for higher average spot prices but is quite stable around 0.909 pu. A battery replacement cost of 100 €/kWh gives the lowest voltage reported, at 0.894 pu.

Furthermore, the PV size has no impact on the voltage violations or the lowest voltage. This result is case-specific and is due to the fact that household demand in Norway is high in winter, while the solar irradiance is low (see Fig. 3). When the size of the battery is increased, there is a higher charging capacity, which results in an increase in the number of voltage violations (the P2E ratio is fixed at 0.5 when varying

Table 7
Yearly costs for energy community [€].

Case	With degradation		No degradation	
	Electricity cost	Degradation cost	Electricity cost	Degradation cost
No battery (ref.)	12 801	0		
EC	12 534	121	12 191	2420
EC+DSO	12 539	131	12 195	2401
Difference EC and EC+DSO	5	10	4	−19

Table 8
Yearly technical results for battery and network.

Case	With degradation			No degradation		
	Battery hours	Hours of voltage violation at bus 16, 17	Lowest voltage [pu][a]	Battery hours	Hours of voltage violation at bus 16, 17	Lowest voltage [pu][a]
No battery (ref.)	0	19, 38	0.909			
EC	1370	25, 38	0.908	3371	184, 76	0.872
EC+DSO	1432	0, 0	0.92	3441	0, 0	0.92

[a]Lowest voltage means the minimum voltage at bus 16 or 17.

Table 9
Yearly total losses for the CIGRE LV grid obtained post-optimisation [kWh].

Case	With degradation	No degradation
No battery (ref.)	32,128	
EC	32,077	32,936
EC+DSO	32,069	32,725
Difference EC and EC+DSO	−8	−211

the battery size, so the charging capacity increases with the battery size). Consequently, the lowest voltage drops to 0.90 pu for the largest battery. The same logic follows when looking at the P2E ratio: a higher ratio gives more voltage violations since the battery can charge with a higher power, and the voltage drops here are as severe as for the lowest battery replacement cost.

4.5.2. Remuneration from DSO

Fig. 10 shows the difference in cost between cases EC and EC+DSO, which can be interpreted as the remuneration that the DSO must pay to the community for providing this service.

The most sensitive parameter is the battery replacement cost, ranging from 9 to 21 €. We also observe that the ratio between the electricity and degradation cost is changing for the different replacement costs. A higher EV charging peak also gives a higher remuneration, which is solely due to an increase in degradation cost. A larger battery gives a lower remuneration, but it differs whether it is due to lower degradation cost or electricity cost. In general, a larger battery gives lower electricity cost, both for case EC and EC+DSO.

The average spot price always gives a remuneration of approx. 14 €, but it can be seen that the ratio between degradation and electricity cost changes for the different spot prices. This is due to the trade-off in the optimisation model: energy arbitrage or degradation of the battery. When the spot price is high, the battery is willing to accept a higher degradation cost due to higher savings in electricity cost.

For battery sizes of 96 and 108 kWh, and a P2E ratio of 0.1, the battery system is not able to provide the service to the DSO at all hours, and the optimisation model gives no solution. Input parameters of PV size and P2E ratio (except for a ratio of 0.1) have a very small impact on remuneration.

4.6. Limitations of study

In this study, we only consider a volumetric tariff, not demand charges or other tariffs that give incentives to lower the peak demand. This would have added an additional term in the objective function, which would lower the peak consumption and probably lead to fewer voltage violations.

A time resolution of one hour averages the PV production, household demand and EV charging, and therefore probably understates the charging and discharging capacity needed from the battery system. We expect that a higher resolution for PV production, household demand and EV charging demand would give more voltage violations due to

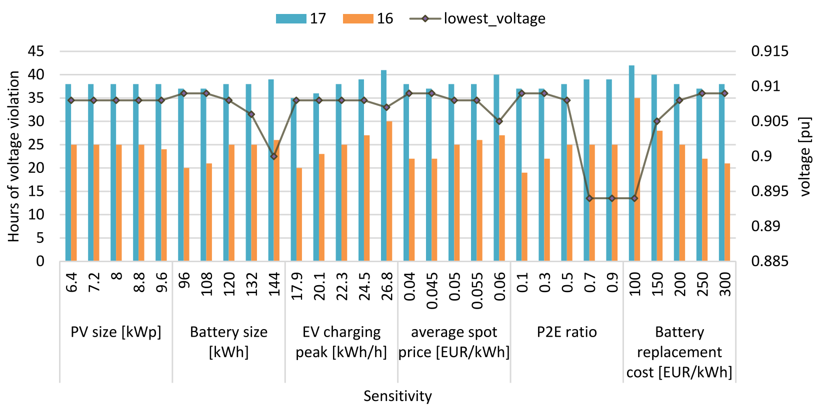


Fig. 9. Number of hours where the voltage limit is violated and minimum voltage for sensitivity analysis in case EC.

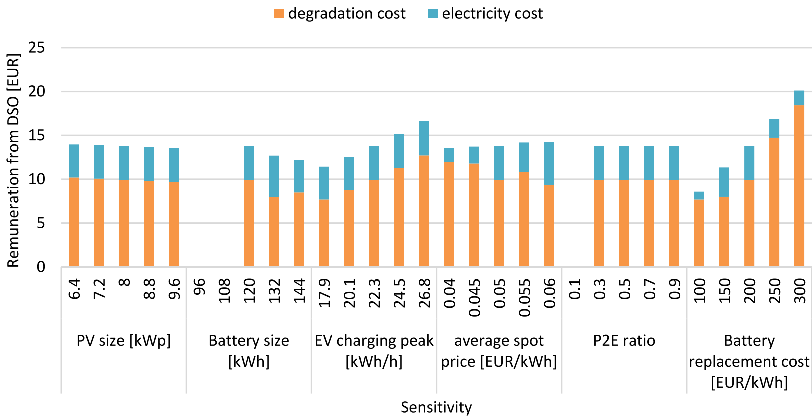


Fig. 10. Difference in yearly costs for cases EC and EC+DSO (in other words, the remuneration needed from the DSO to cover the costs for the community).

higher peaks in import and export. This would again lead to the need for a higher P2E ratio, and perhaps energy capacity, of the battery system to resolve the voltage problems in the grid in case EC+DSO. Higher and more frequent peaks would lead to more charging and discharging from the battery, which again would give a higher battery degradation cost.

Furthermore, we have assumed a perfect foresight model, which lets the battery operate with perfect information about the consumption, production and, thereby, the voltage in the grid. The sensitivity analysis compensates for the lack of uncertainty in our model, which has captured the effects of different levels of spot prices, EV charging peaks and PV size. However, the sensitivity analysis uses the same profiles/trends and only changes the level of the profile. The future spot price is expected to be more variable than the historical records, affecting our results. A more variable spot price could lead to a more significant difference in electricity costs for cases EC and EC+DSO, meaning that the remuneration from the DSO would increase.

Finally, an energy community can consist of flexibility assets other than battery energy storage, such as hot water tanks or load shifting, which could impact the voltage violations and the remuneration from the DSO. This kind of flexibility would also be less costly than a stationary battery but has the limitation of not always being available, as mentioned in Section 1.

5. Conclusion

The primary objective of this article was to study how an energy community and a DSO can coordinate to improve the voltage profile in the distribution grid. This was done by using a realistic model of community battery operation, taking into account battery degradation.

From our results and the sensitivity analysis performed, we observed that battery operation does affect both the voltage of the bus where it is connected and neighbouring buses. For the case study we investigated, the battery did actually cause some voltage problems due to arbitrage, mostly in the bus where the energy community was connected. This result is of importance for customers who are connected to the same bus as an energy community, as the community might actually create voltage problems for itself and other customers connected to the same bus. From Table 8, we see that the degradation model has a great impact on the voltage violations. When the battery is more restrictive on charging and discharging to diminish the battery degradation, it also leads to fewer spikes in voltage. Additionally, the losses in the grid are reduced when the battery provides the grid service. In other words: a battery-friendly operation is also a grid-friendly operation. The number of hours of voltage violations increased by 636% at the community bus and 100% at the neighbouring bus (17) when degradation was not considered, compared to when it was considered.

Moreover, our results show that the cost difference for the community, and thereby the remuneration needed from the DSO, was very low. It amounted to 15 € per year, which equals 0.12%. This result is similar to those reported by [4,38–40]. Ref. [38] reported a cost increase of 0.3% when doing peak shaving (note battery degradation was not considered), and [4] reported a cost increase of 1.6% when including grid constraints. The sensitivity analysis showed a range of 9–21 € in remuneration per year, which equals 0.07–0.17%, where the battery replacement cost was the most sensitive parameter.

The sensitivity analysis also showed that for some energy community configurations, the battery size or the inverter capacity was too low to perform the service throughout the whole year. Another interesting finding is that the battery is not always solving a voltage problem, it is sometimes merely avoiding creating a voltage problem. As shown in Fig. 10, the degradation cost had the major part in the remuneration from the DSO. If degradation cost would not be considered, the energy community would be remunerated less than their real cost of providing this service.

The case studied in this article was made with Norwegian data, and the results must be interpreted with this in mind. Since Norwegian households use electricity for space and water heating, their peak electricity consumption is in winter, which is also when the irradiance is the lowest. In summer, when the irradiance is the highest, the consumption is much lower. This stands in contrast to Southern European countries where households use more electricity in summer due to cooling [55]. The sensitivity analysis showed that increasing the PV size did not reduce voltage violations and that it had little impact on the remuneration from the DSO. Also, there were no over-voltage challenges, most likely due to the low share of PV in the grid. These results could be very different for countries with different profiles for household electricity demand and PV generation.

The practical agreement between the DSO and the energy community has not been addressed in this study. However, a more practical interpretation of our results is that an energy community with a stationary battery can coordinate with the DSO to improve the distribution grid voltage, without the need for a very large remuneration. Moreover, if this were put into effect, we would suggest that the community and DSO collaborate together to ensure that the battery characteristics (its energy and power capacity) would be sufficient to address the voltage problems in the grid.

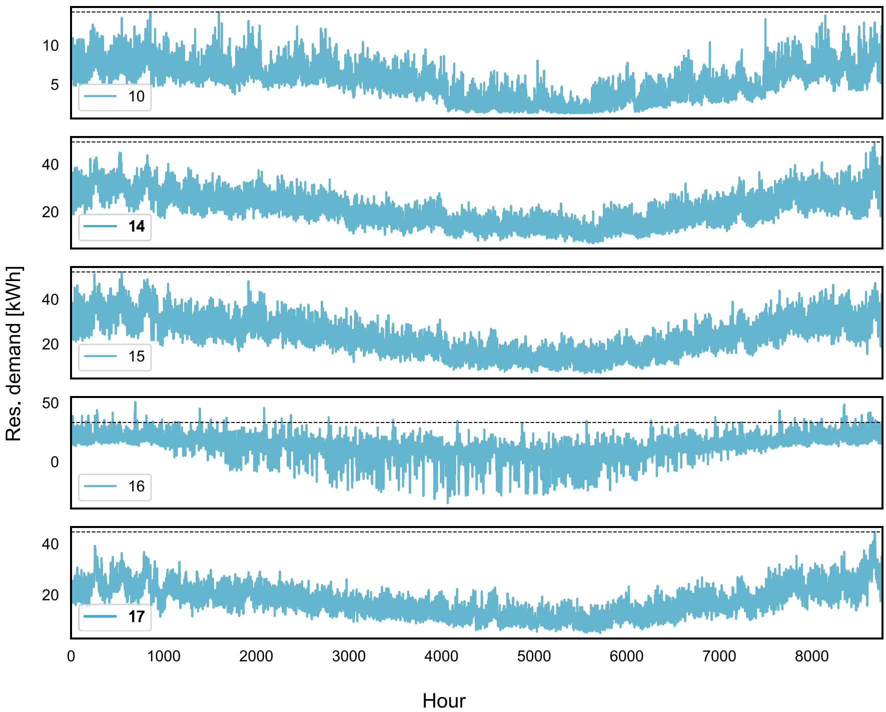


Fig. A.11. Demand per bus. Stippled line shows the load specified by the CIGRE European LV distribution network [47].

Table B.10
Sensitivity analysis costs [€].

Case		EC		EC+DSO	
		electricity cost	deg. cost	electricity cost	deg. cost
PV size [kWp]	6.4	13 082	101	13 086	111
	7.2	12 802	112	12 807	122
	8	12 534	121	12 539	131
	8.8	12 278	130	12 283	140
	9.6	12 032	137	12 037	147
Battery size [kWh]	96	12 569	108		
	108	12 552	114		
	120	12 534	121	12 539	131
	132	12 519	127	12 524	135
	144	12 504	132	12 509	141
EV charging peak [kWh/h]	17.9	12 255	121	12 260	129
	20.1	12 394	121	12 399	130
	22.3	12 534	121	12 539	131
	24.5	12 674	121	12 679	132
	26.8	12 814	121	12 819	134
Average spot price [€/kWh]	0.04	11 014	105	11 016	117
	0.045	11 778	110	11 780	122
	0.05	12 534	121	12 539	131
	0.055	13 296	127	13 300	138
	0.06	14 051	137	14 057	146
P2E ratio	0.1	12 551	110		
	0.3	12 534	121	12 539	131
	0.5	12 534	121	12 539	131
	0.7	12 534	121	12 539	131
	0.9	12 534	121	12 539	131
Battery replacement cost [€/kWh]	100	12 430	138	12 431	146
	150	12 502	119	12 506	127
	200	12 534	121	12 539	131
	250	12 585	94	12 588	109
	300	12 612	84	12 614	102

Table B.11
Sensitivity analysis technical results case EC.

		Battery hours	Voltage violation hours at bus 16, 17	Lowest voltage [pu]
PV size [kWp]	6.4	1217	25, 38	0.908
	7.2	1326	25, 38	0.908
	8	1370	25, 38	0.908
	8.8	1449	25, 38	0.908
	9.6	1482	24, 38	0.908
Battery size [kWh]	96	1271	20, 37	0.909
	108	1327	21, 37	0.909
	120	1370	25, 38	0.908
	132	1411	25, 38	0.906
	144	1458	26, 39	0.9
EV charging peak [kWh/h]	17.9	1385	20, 35	0.908
	20.1	1378	23, 36	0.908
	22.3	1370	25, 38	0.908
	24.5	1363	27, 39	0.908
	26.8	1359	30, 41	0.907
Average spot price [€/kWh]	0.04	1296	22, 38	0.909
	0.045	1327	22, 37	0.909
	0.05	1370	25, 38	0.908
	0.055	1396	26, 38	0.908
	0.06	1436	27, 40	0.905
P2E ratio	0.1	1541	19, 37	0.909
	0.3	1374	22, 37	0.909
	0.5	1370	25, 38	0.908
	0.7	1367	25, 39	0.894
	0.9	1367	25, 39	0.894
Battery replacement cost [€/kWh]	100	1797	35, 42	0.894
	150	1509	28, 40	0.905
	200	1370	25, 38	0.908
	250	1163	22, 37	0.909
	300	1065	21, 38	0.909

CRediT authorship contribution statement

Kjersti Berg: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Visualization. **Rubi Rana:** Methodology, Software, Validation, Writing – review & editing. **Hossein Farahmand:** Conceptualization, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data used in the article is published in Data in Brief.

Acknowledgements

The authors would like to thank Sigurd Bjarghov for discussions regarding this work. This work was supported by the project consortium of the research project FINE (Flexible Integration of Local Energy Communities into the Norwegian Electricity Distribution System), financed by the Research Council of Norway [project number 308833].

Appendix A. Input data

See Fig. A.11.

Appendix B. Sensitivity analysis results

See Tables B.10 and B.11.

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Appendices

Appendix A: Additional sensitivity analysis for Paper VI

A.1 Self-consumption rate

Figure A.1 shows the self-consumption rate for the energy communities in **Paper VI**. It shows that when load shifting is combined with PV generation ($PVshift$) it obtains approximately the same self-consumption as PV generation with a battery ($PVbattery$).

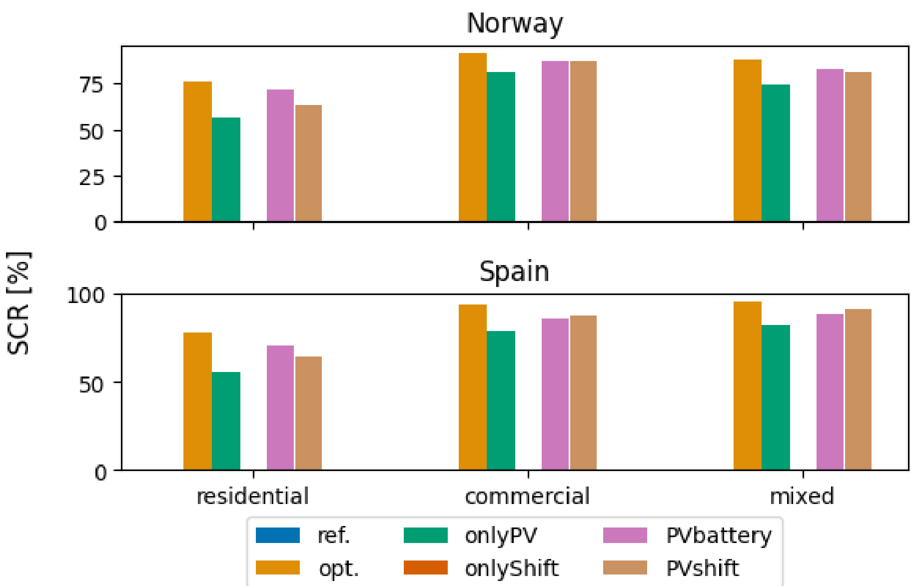

Figure A.1: Comparing the self-consumption rate for various technologies in the energy community.

A.2 Maximum export

Figure A.2 shows the maximum export for the energy communities in **Paper VI**. It shows that when there is only PV generation ($onlyPV$), or PV generation and battery (*PVbattery*), the export is the highest. Export is slightly lowered when load shifting is included.

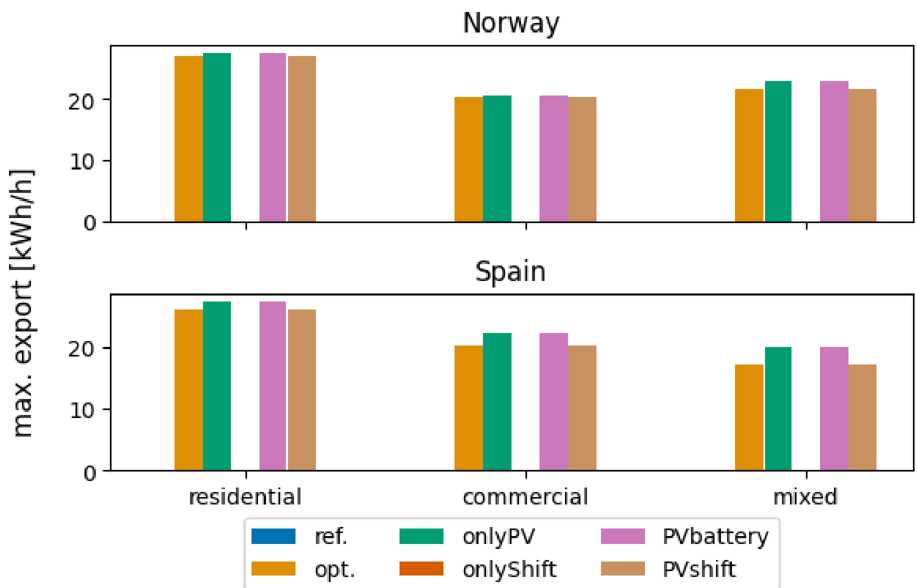

Figure A.2: Comparing the maximum export for various technologies in the energy community.