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Impacts of Neighbourhood Energy Systems on European Decarbonization Pathways

Doctoral thesis

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Norwegian University of Science and Technology
Thesis for the Degree of
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Management

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If you work hard enough,
you can replace depression with
exhaustion.

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Summary

The European Union (EU) aims to be climate neutral by 2050, which implies a major transformation for existing energy systems to reduce greenhouse gas (GHG) emissions. Driven both by climate targets and a dramatic drop in costs for wind and solar technologies, electricity production from variable renewable energy sources (VRES) is likely to dominate the European electricity market within the next few decades. Understanding the impacts and consequences of large shares of VRES is a common research topic of today spanning widely across academic disciplines. Much of existing research focus on the supply side of electricity markets, and there is an increasing need to also explore developments on the demand side. Buildings in neighbourhoods account for about 40% of final energy use in Europe and are traditionally consumers of electricity and heat. More recently, neighbourhoods are increasingly able to produce their own electricity and provide comfort and services ever more flexibly and energy efficiently. The relationship between the future energy system and neighbourhoods in the future building sector is increasingly important as the two sectors overlap, yet their sectoral relationship is still not completely understood.

This thesis explores transition pathways towards a decarbonized European energy system with a focus on distributed energy resources (DERs) in neighbourhoods. The overarching research questions are: (1) how are DERs in neighbourhoods impacted by the decarbonization pathways of the surrounding energy system? and (2) how do DERs in neighbourhoods impact the decarbonization pathways of the surrounding energy system?

The first part of this thesis takes a bottom-up perspective on the neighbourhood level, which includes developing and using mathematical programming models to explore how electricity billing structures for neighbourhood stakeholders can incentivize efficient utilization of DERs as electricity loads are changing. The second part of this thesis takes a top-down perspective on the European level, which includes developing and using multi-horizon stochastic programming to analyze investments in the European electricity and heat system while considering variable and uncertain operations on a country aggregated level.

Findings imply that existing billing practices in neighbourhoods ought to be revised such that local DERs are incentivized to efficiently utilize grid infrastructure when electricity loads are changing. This includes facilitating end-user price signals to be more dynamic and less dependent on individual metering. Further findings imply that the development of DERs in neighbourhoods significantly impacts the capacity expansion pathway for the future energy system at national and European level. Given fulfilment of EU decarbonization policy, neighbourhood energy systems compete with low-carbon sources in the surrounding energy system, and a wide deployment of DERs are found to increase cost-efficiency on the transition towards a decarbonized energy system.

Abbreviations

CCS	Carbon Capture and Storage
DER	Distributed Energy Resource
DSO	Distribution System Operator
EMPIRE	The European Model for Power (system) Investments with (high shares of) Renewable Energy
ENTSO-E	The European Network of Transmission System Operators
ETS	Emission Trading System
EU	European Union
FME ZEN	The Research Centre on Zero Emission Neighbourhoods in Smart Cities
GHG	GreenHouse Gas
GUSTO	enerGy commUnity SysTem mOdelling
KKT	Karush-Kuhn-Tucker
MP	Mathematical Program
nZEB	Nearly Zero-Energy Building
PV	Photovoltaic
RQ	Research Question
VRES	Variable Renewable Energy Sources
ZEN	Zero Emission Neighbourhood
ZENIT	Zero Emission Neighborhood Investment Tool

Contents

List of papers

I **S. Backe**, G. Kara, and A. Tomasgard (2020). Comparing individual and coordinated demand response with dynamic and static power grid tariffs. *Energy*, vol. 201, p. 117619.[1]

II M. Askeland, **S. Backe**, S. Bjarghov, and M. Korpås (2021). Helping end-users help each other: Coordinating development and operation of distributed resources through local power markets and grid tariffs. *Energy Economics*, vol. 94, p. 105065.[2]

III **S. Backe**, M. Korpås, and A. Tomasgard (2021). Heat and electric vehicle flexibility in the European power system: A case study of Norwegian energy communities. *International Journal of Electrical Power & Energy Systems*, vol. 125, p. 106479.[3]

IV **S. Backe**, D. Pinel, M. Askeland, K. B. Lindberg, M. Korpås, and A. Tomasgard. Emission reduction in the European power system: exploring the link between the EU ETS and net-zero emission neighbourhoods. *Submitted manuscript.*[4]

V **S. Backe**, S. Zwickl-Bernhard, D. Schwabeneder, H. Auer, M. Korpås, and A. Tomasgard. Impact of Energy Communities on the European Electricity and Heat System Decarbonization Pathway: Comparing local and global flexibility responses. *Submitted manuscript.*[5]

[1] **SB: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Visualization, Data curation, Writing - original draft, Writing - review & editing.** GK: Conceptualization, Writing - original draft, Writing - review & editing. AT: Conceptualization, Funding acquisition, Supervision, Writing - review & editing.

[2] MA: Conceptualization, Methodology, Software, Validation, Investigation, Visualization, Writing - original draft, Writing - review & editing. **SBa: Conceptualization, Methodology, Writing - review & editing.** SBj: Conceptualization, Writing - review & editing. MK: Conceptualization, Methodology, Funding acquisition, Supervision, Writing - review & editing.

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[5] **SB: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft preparation, Writing – review & editing, Visualization, Project administration.** SZB+DS: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft preparation, Writing – review & editing, Visualization. HA+MK+AT: Conceptualization, Funding acquisition, Supervision, Writing - review & editing.

Other relevant publications during PhD project:

- **S. Backe**, P. C. del Granado, A. Tomasgard, D. Pinel, M. Korpås, and K. B. Lindberg. (2018). Towards Zero Emission Neighbourhoods: Implications for the Power System. In *15th International Conference on the European Energy Market (EEM)*, pp. 1-6, https://doi.org/10.1109/EEM.2018.8469976
- M. Askeland, **S. Backe**, and K. B. Lindberg (2019). Zero energy at the neighbourhood scale: Regulatory challenges regarding billing practices in Norway. In *IOP Conference Series: Earth and Environmental Science (EES)*, vol. 352(1), p. 012006, https://doi.org/10.1088/1755-1315/352/1/012006.
- **S. Backe**, Å. L. Sørensen, D. Pinel, J. Clauß, and C. Lausselet (2019). Opportunities for Local Energy Supply in Norway: A Case Study of a University Campus Site. In *IOP Conference Series: Earth and Environmental Science (EES)*, vol. 352(1), p. 012039, https://doi.org/10.1088/1755-1315/352/1/012039.
- S. Schønfeldt Karlsen, **S. Backe**, and M. Hamdy (2019). Effect Of Grid Tariffs On Demand-side Management In All-electric Buildings In Norway. In *Proceedings of the International Building Performance Simulation Association (IBPSA)*, https://doi.org/10.26868/25222708.2019.210535.
- S. Bjarghov, M. Askeland, and **S. Backe** (2020). Peer-to-peer trading under subscribed capacity tariffs - an equilibrium approach. In *17th International Conference on the European Energy Market (EEM)*, pp. 1-6, https://doi.org/10.1109/EEM49802.2020.9221966.
- M. Askeland, **S. Backe**, S. Bjarghov, K. B. Lindberg, M. Korpås. (2021). Activating the potential of decentralized flexibility and energy resources to increase the EV hosting capacity: A case study of a multi-stakeholder local electricity system in Norway. *Smart Energy*, In Press, https://doi.org/10.1016/j.segy.2021.100034.

1 Introduction

In December 2015, the Paris Agreement was adopted by nearly all the world's nations to limit global warming to well below 2°C [1]. Developing net-zero emission energy systems are essential to meet the Paris Agreement [2, 3], and measures include (a) increasing energy efficiency, (b) increasing the share of low-carbon energy sources and (c) electrifying energy use [4]. In the European Union (EU), nearly 80% of total greenhouse gas emissions (GHG) emissions are energy related [5]. Despite decreasing primary energy demand, electrification of society will strongly increase electricity demand in Europe towards 2050 [6, 7].

Since 2005, the EU successfully set up its European-wide emission trading system (ETS): a 'cap-and-trade' system where a quota is set on the maximum allowed emissions within the scope of the system, and installations within the system are required to have allowances to emit [8]. The EU ETS covers 40% of European GHG emissions, including emissions from large-scale electricity and heat production. To be in line with the Paris Agreement, the EU ETS cap towards 2030 and beyond must decrease faster than currently planned [9].

As raised by Sovacool [10], an important question in the energy transition is how long it will take. Climate policy in the EU, like the EU ETS, has been found to clearly pursue emission reductions by sector with given deadlines, as well as more renewable energy [11]. However, targets for the needed degree of restructuring the organization of the power system are not clearly stated [12]. The challenge of mitigating climate change has triggered significant attention towards *sustainability transition* in research: 'a fundamental transformation towards more sustainable modes of production and consumption' [13], where the focus shifts from growth of renewables to large-scale integration of these resources. Successful integration of renewables requires grid infrastructure and complementary technologies, e.g., energy storage, flexible energy resources, sector coupling, and short-term fuel switching [14, 15], as well as corresponding changes in market structure and business models [16]. To facilitate a cost-effective development of the growing electricity sector, roll-out of advanced metering infrastructure and more dynamic pricing of electricity are being adopted [17, 18], including the design of cost reflective electricity network tariffs [19].

Sustainability in urban areas is a global trend [20], and it has developed from primarily focusing on urban ecology and 'eco-cities' [21] towards increasingly integrating 'smart city' concepts [22], including local renewable energy sources [23] and local flexibility markets [24]. Indicator frameworks for sustainable cities [25] focus on aspects like economy, energy, waste, and GHG emissions. A popular indicator framework is based on the concept of nearly zero-energy buildings (nZEB) [26, 27]. The Energy Performance of Buildings Directive 2018/844 [28] defines nZEB as a building that requires a very low amount of energy that should be covered by on-site or nearby renewable energy [29]. The 'zero' in the 'zero energy'-concept is reached when the net energy exchange between the building and the surrounding energy system is cancelled out over a measuring period, typically one year [30]. The 'zero energy'-concept has been extended to the neighbourhood level [31] and adapted towards a 'zero emission'-concept through the Norwegian research centre on Zero Emission Buildings [32]. In a Zero Emission Neighbourhood (ZEN), GHG emissions for a neighbourhood are compensated by local renewable energy [33], and the compensation is assumed to avoid GHG emissions based on GHG emission factors [34, 35]. Neighbourhood emissions are mostly due to the buildings' embodied and operational energy [36].

In 2014, 29% of electricity in the EU was consumed by households, and an additional 30% was consumed by the service sector [37]. Together, the household sector and the service sector mainly represent the building sector. Although buildings still dominate electricity use [37], the building sector is rarely modeled with detail when analyzing the electricity sector. The EU aims to transition towards a climate neutral economy by 2050 requiring a $93-99\%$ [11] emission reduction of the electricity sector compared to 1990. It is still unclear how bridging the development of neighbourhoods and the electricity sector can support European decarbonization.

This thesis is written in the PhD program 'Industrial Economics and Technology Management' at the Norwegian University of Science and Technology as part of the Research Centre on Zero Emission Neighbourhoods in Smart Cities (FME ZEN)[1]. Through FME ZEN, the PhD project is part of interdisciplinary research to better understand how neighbourhoods can contribute to net-zero GHG emissions. This PhD project applies mathematical programming to study how technical, political, and economic parameters affect decision making when developing neighbourhoods as part of future energy systems in compliance with the Paris Agreement. The geographical scope of the thesis is European, and countries are represented on a national level with increased details for Norway.

Two system perspectives are explored and linked in this thesis: the European perspective and the neighbourhood perspective. Papers I and II explore the neighbourhood perspective, Paper III explore mainly the European perspective, while Papers IV and V link the neighbourhood perspective and the European perspective. Further, Paper I analyzes operational decisions, and Papers II–V explore long-term investment decisions while considering short-term operations.

[1]'The Research Centre on Zero Emission Neighbourhoods in Smart Cities' is funded by the Research Council of Norway as a 'Centre for Environment-friendly Energy Research (FME)', along with funding from public and private partners.

The remaining thesis is structured as follows: Chapter 2 presents related research and the research questions explored in this thesis, and Chapter 3 presents, links, and discusses the contributions of the five papers. Finally, Chapter 4 presents concluding remarks, discusses limitations, and points towards further work. The five papers supporting the thesis follow Chapter 4.

2 Background

This chapter links the content of this thesis with existing literature. Section 2.1 introduces the overarching methodology used throughout the thesis, namely mathematical programming. Section 2.2 presents relevant research on decarbonization of large-scale energy systems. Section 2.3 presents relevant research exploring sustainable neighbourhoods and energy communities, and Section 2.4 presents relevant research on energy flexibility and market mechanisms in future smart grids. Finally, Section 2.5 presents the research questions explored in this thesis.

2.1 Mathematical programming

Mathematical programming, or mathematical optimization, is a quantitative decision making approach that arose during World War II, and it deals with: '*the efficient use of limited resources to meet desired objectives*' [38]. Note that the word 'programming' in this context refers less to the process of writing computer programs and more to the process of decision making and scheduling. A mathematical program (MP) is a collection of equations and inequalities, as well as an objective function, that represents a decision problem. The equations and inequalities of the MP are constraints, and the objective function quantifies key indicators, e.g., costs or social welfare, that are minimized or maximized subject to the constraints. An MP with only linear expressions is classified as a linear program. The input data to an MP represents quantitative information about the decision problem, e.g., decisions costs, resource limitations, minimum requirements, quantitative relationships between decisions, etc.

The solution to an MP indicates optimal decisions towards a desired objective under two main assumptions: (1) the mathematical formulation of the MP represents the 'actual' problem and (2) the input data to the MP represents 'true' information of the problem. When a complex decision problem is systematically quantified, the two aforementioned assumptions are increasingly questionable. Nevertheless, MPs are useful when studying complex decision problems, although the link between the MP and the decision problem it represents is important to clarify and discuss when applying mathematical programming.

With increasingly large and complex MPs, it is also increasingly hard to prove that a feasible MP solution is optimal [39]. Thus, the fundamental challenge of mathematical programming is to balance *accuracy*, i.e., how well the MP represents the problem, with *solvability*, i.e., how long it takes to find feasible solutions and to prove optimality.

Many researchers use MPs to study decision making under uncertainty. One way to consider uncertainty is to perform sensitivity analyzes of an MP by resolving it with varying input data. This is referred to as deterministic programming when all decisions are made given a single scenario with perfect information. An alternative approach is stochastic programming [40, 41], where the MP's decisions are categorized by consecutive points in time when uncertain information is revealed. Decisions in the first stage represent here-and-now decisions made under uncertainty, while decisions in the following stage(s) represent wait-and-see decisions: reactive decisions after some uncertainty is revealed. In the scenario formulation of a stochastic program, outcomes of the uncertain information are represented in several discrete scenarios within one MP instance. First stage decisions must be consistent across all scenarios within the instance, while decisions in following stages are adapted to each specific scenario.

Linear programs are solvable in polynomial time [42] using commercial solvers. Note that stochastic programs can be linear programs. Some decision problems require non-linear expressions or discrete decisions in MPs, which could make them (very) much harder to solve. Increased computational power supports the computational challenge of complex MPs, but sufficient MP complexity could make it practically impossible to solve with exact methods [39].

When considering long-term horizons subject to uncertainty, multi-stage stochastic programming is useful [43]. However, solving scenario formulations of multi-stage stochastic programs can be very computationally challenging. A more recent development within stochastic programming presented by Kaut et al. [44] is called multi-horizon stochastic programming, and it allows the representation of uncertainty in long-term models with reduced computational challenge. The main idea within multi-horizon stochastic programming is to decouple uncertainty across multiple horizons within the same problem, for example decoupling long-term and short-term uncertainty. Multi-horizon stochastic programming can be used when the strategic long-term decisions do not depend on single operational scenarios, but on the collection of operational scenarios.

In this thesis, two-stage stochastic programming [45] is used in all papers but Paper II, while multi-horizon stochastic programming [44] is used in Papers III–V. All papers apply MPs that are solvable with exact methods in reasonable time (minutes to hours) given the indicated computational power.

2.2 Energy system decarbonization pathways

Mathematical programming is often used to study electricity markets as they have become more competitive since the 1990s [46]. In particular, capacity expansion modelling [47] is used to support when and where different types of new transmission, generation, and storage capacity should be developed in future scenarios, while respecting techno-economic constraints. Market equilibrium models are used to study the impacts of imperfect competition in deregulated electricity markets [48]. Murphy and Smeers [49] expand capacity expansion models to consider imperfect competition in electricity markets.

Many studies explore how to mitigate climate change by analyzing the energy system development in compliance with the Paris Agreement. For the EU, needed emission reductions by sector in five-year periods towards 2050 are quantified by the European Commission in [11] implying nearly zero carbon emissions from the European power sector by 2040. Rogelj et al. [50] find that zero carbon electricity is likely needed by mid-century in a 1.5°C scenario, and they highlight the need to decrease emissions from many sectors, including the building sector. Blesl et al. [51] find that political considerations ultimately shape the future structure of a decarbonized electricity system.

Mendelevitch et al. [52] present the development of the European electricity system since World War II: From being dominated by coal and nuclear power until the 1990s, to a growth in fossil gas and renewable energy sources driven by climate policy and competitive electricity markets through the 2000s. Recently, European climate targets have been set to 55% reduction of GHG emissions by 2030 compared to 1990 [9]. In 2021, the International Energy Agency [53] published a comprehensive study on how to transition towards a net zero energy system by 2050, and they controversially found that no new exploration of fossil fuels can be made to reach the target. There are limited—but multiple—existing electricity generation alternatives that complies with current climate targets, and the three main categories of technologies are: renewable energy, nuclear energy, and carbon capture and storage (CCS) [52].

The fossil fuel sector is still a large part of the European energy market, and one way to remain so while fulfilling climate targets is through CCS [54]. Although technologically feasible, CCS remains to be commercialised: Mendelevitch et al. [52] present an overview over failed CCS projects across Europe through the 2010s along with the only two large scale European CCS projects in operation. Leung et al. [55] highlight that the main barrier for CCS deployment is lacking investment incentives and business cases. In this thesis, CCS is not considered an investment option in the capacity expansion modelling.

Most recent capacity expansion studies agree that cost-efficient decarbonization of

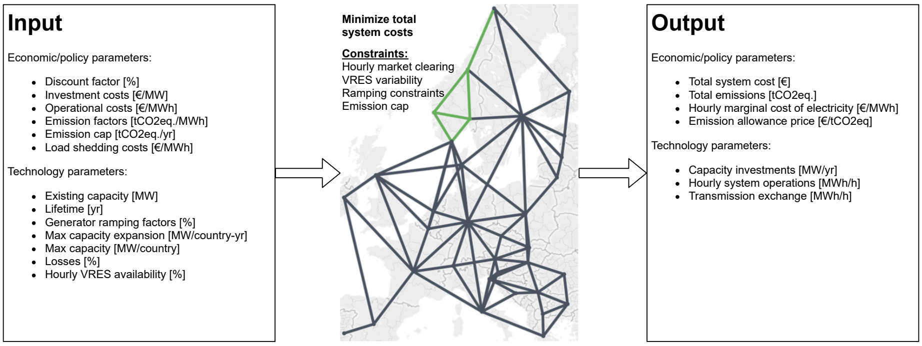

Figure 2.1: Overview of EMPIRE and its inputs and outputs.

electricity systems means that renewable energy sources will dominate electricity production by 2050, a large share of which will be variable renewable energy sources (VRES), in particular solar photovoltaics (PV) and wind power [56, 57, 7]. Creutzig et al. [58] explore how solar PV have been consistently underestimated, and they find that updated projections could mean that 30 to 50% of global electricity by 2050 is provided by solar PV. Traber and Kemfert [59] raise the paradox that wind power increases need for flexibility, but the market impact of more wind power simultaneously decreases incentives to invest in flexibility. Woo et al. [60] find that although wind power decreases the average spot price, the spot price variance increases, which means risk management is of growing importance. Aaslid et al. [61] find that electrical energy storage can decrease the price variations in VRES dominated systems.

When modeling the transition towards a future energy system with high shares of VRES, long-term models must represent sufficient short-term temporal details for VRES operations [62, 63, 64, 65]. With high shares of VRES, it is not only important to represent the short-term *variability* of VRES, but also the *uncertainty* of the VRES variability. Seljom and Tomasgard [66] show how short-term uncertainty is crucial to avoid capacity inadequacy in long-term planning.

Some capacity expansion models consider both investments and operations, but only single or myopic investment periods, e.g., Balmorel [67]. Other models consider multiple investment periods and short-term operations, e.g., Switch [68], TIMES [69], PyPSA [70], and GENeSYS-MOD [7]. The E2M2 model [71] considers uncertain VRES variability, but does not consider multiple investment periods. Figure 2.1 presents an overview of the European Model for Power system Investments with Renewable Energy (EMPIRE)[1] [73]. EMPIRE consolidates three key model characteristics: multiple long-term investment horizons, short-term representative operational periods, and short-term uncertainty. Therefore,

[1] An open version of the EMPIRE model is available from [72].

EMPIRE is a good tool to gain insights on the link between long-term strategic decisions and short-term operational decisions subject to operational uncertainty on the transition towards a decarbonized European power system. EMPIRE is a multi-horizon stochastic programming model [44] developed through the 2010s [74, 73, 75], and it is a capacity expansion model where long-term decisions are dependent on multiple short-term scenarios with varying VRES availability and load profiles. The benefit of the multi-horizon structure is reduced computational challenge while still providing endogenous uncertainty through the assumption of independence between long-term decisions and single short-term scenarios. EMPIRE preserves statistical correlations and properties for VRES and load data.

Chang et al. [65] highlight the need to consider cross-sectoral synergies when modelling the energy transition. Hansen et al. [76] identify increasing attention towards 100% renewable energy systems, and they highlight a need to link local and global levels. Bloess et al. [77] review modelling tools that analyze power-to-heat solutions for VRES integration in electricity markets, and they find mathematical programming to be a highly applied methodology in this context. Mehigan et al. [78] do not find that there is a single modelling tool to deal with all the complexity of distributed generation within the large-scale electricity system, and they suggest soft-linking models to determine the balance between centralized and decentralized resources. McCollum et al. [79] find that investments will increase towards demand-side energy efficiency, as well as storage, transmission, and distribution of electricity. Gils [80] presents theoretical potential for demand response in Europe and finds that flexible loads are available in all sectors, including the building sector.

2.3 Neighbourhoods in the energy transition

In November 2016, the European Commission published eight legislative measures entitled the ‘Winter Package’ [81], highlighting the need to facilitate active demand-side participation in future European power markets. According to Article 17 in the European Electricity Directive [81], prosumers[2] should be able to participate in organized markets alongside conventional generators in a non-discriminatory way, potentially through aggregators [82]. Parag and Sovacool [83] identify emerging market designs to integrate prosumers into competitive electricity markets, including prosumer grid integration, peer-to-peer markets, and prosumer community groups. Through decentralization and democratization of energy systems, prosumers are increasingly empowered in renewable energy co-operatives with distributed energy resources (DERs) [84]. The term DER is a common name for any distributed energy asset that could adapt its interaction with the energy system. Some examples of DERs in neighbourhoods include

[2]Prosumers are defined as consumers producing their own energy or providing energy flexibility, e.g., demand response, energy storage, load shifting, peak shaving, etc.

space heating devices, hot water tanks, and electric vehicles.

Capacity expansion models, like those mentioned in Section 2.2, are used to analyze energy system design at the building level. Milan et al. [85] develop an MP to study least costly designs of 100% renewable residential energy systems, and they find that PV and heat pumps are the best technology choices. Lindberg et al. [34] develop an MP to study the least costly technology mix for different levels of Zero Emission Buildings, and they find that operational carbon emissions are most cost-effectively reduced by replacing heat pumps with bio boilers for heating. Cano et al. [86] develop a multi-stage stochastic program using conditional value-at-risk [87] to analyze energy system design for a building under uncertainty, and they find that modeling uncertainty and risk significantly impacts total costs.

In northern European climates, energy use in buildings is dominated by space heating and sanitary hot water [88]. Lund et al. [89] study the role of district heating in future renewable energy systems for Denmark, and they find that a mix of district heating and individual heat pumps is preferred. Patteeuw et al. [90] study how flexible use of heat pumps can reduce costs and carbon emissions, and they highlight the superior performance of direct load control to consistently signal when flexibility should be dispatched.

The roll-out of electric vehicles creates opportunities and challenges in neighbourhoods [91]. Clement-Nyns et al. [92] show how uncoordinated charging of electric vehicles can lead to increased power losses and voltage deviations, and they use mathematical programming to show how coordinated charging and peak shaving can decrease the problems. Sørensen et al. [93] analyze the potential for flexible charging of electric vehicles in a large housing cooperative in Norway, and they identify a high potential for flexibility when private parking spots have charging infrastructure.

Buildings and neighourhoods are increasingly adopting medium-scale electricity production and DERs in smart and sustainable energy communities [94, 95], and these energy communities are analyzed and developed widely across Europe, e.g., in Switzerland [96], the Netherlands [97], Denmark [98], Spain [99], Austria [100], Italy [101], and Norway [102, 103]. Inês et al. [104] find that legal frameworks in the EU are increasingly providing opportunities for collective prosumers in several European countries. Seljom et al. [105] study how an extensive implementation of Zero Energy Buildings with PV could impact the development of the Scandinavian electricity and heat system, and they find that the Zero Energy Buildings substitute some development of combined heat and power, non-flexible hydropower, and wind power. Pinel et al. [106] study the cost optimal design of a Zero Emission Neighbourhood (ZEN), and they highlight large investments in solar PV. Zwickl-Bernhard and Auer [107] study how to best utilize local renewable energy sources in an urban neighbourhood, and they highlight a promising potential for geothermal sources.

2.4 Flexibility and the smart grid

One of the main challenges of electricity systems is the constant need for a short-term supply-demand balance, which raises the need for flexible resources that can adapt to the variable electricity demand. Storage of electricity has historically been limited and expensive [108], so dispatchable electricity plants, along with large-scale pumped hydroelectric storage [109], have traditionally been the dominant providers of flexibility in electricity systems. More recently, batteries are gaining relevance as storage technologies in electricity systems [110]. Over the last 30 years, the development of lithium-ion batteries has caused extensive cost reductions with its wide application, particularly in the fast growing electric vehicle market, and lithium-ion battery costs are expected to drop further towards 2030 [111].

To decarbonize electricity system as presented in Section 2.2, there is a limited opportunity for dispatchable electricity plants that produce GHG emissions to continue as flexibility providers. Jafari et al. [112] find that decarbonization of the power system is less expensive with battery storage, however, they also identify a decreasing marginal value of adding more battery capacity. Denholm and Mai [113] show how energy storage can avoid curtailment of surplus renewable electricity in a system with 55% VRES. Lund and Kempton [114] show how batteries in electric vehicles can allow more VRES with less curtailment.

At the distribution level, electricity systems are transforming from manual and centralized operations towards responsive and decentralized coordination in the 'smart grid' [115]. Key enabling technologies of the smart grid is advanced metering infrastructure [116] and the energy internet [117] that allows more insight for efficient system operation and development.

Lüth et al. [118] show how battery flexibility provides benefits at the distribution level within a local electricity market. The flexibility service from batteries can also be partly provided by other flexible DERs, e.g., electric vehicles [119] and thermal mass in buildings [120]. There are many incentive measures and market designs that directly or indirectly shape the scheduling and dispatch of DERs [121]. Many researchers are studying the potential for energy flexibility in buildings and neighbourhoods [122, 123]. Barbato and Capone [124] review methods that optimize dispatch of flexible electricity assets in the residential sector, and they find that mathematical programming is commonly used to analyze how end-users can minimize their electricity costs in response to different price signals.

A significant part of the electricity bills faced by buildings covers grid costs. Brown et al. [125] explore how grid tariff design can ensure economic efficiency, and they also highlight that fairness and gradualism are important when designing grid tariffs. Bjørndal et al. [126] analyze different incentive structures for efficient flexibility dispatch, and they find that a redesign of grid tariffs is cheaper than direct payment to flexibility providers. With advanced metering infrastructure, buildings are technologically able to respond to frequent price signals and become flexible energy users [127]. Schittekatte et al. [128] find that grid tariffs ought to be revised when more and more consumers respond to price signals. Kirkerud et al. [129] find that different grid tariff designs incentivizes significantly different operation of electric boilers.

In 2017, the Norwegian energy regulator sent out a hearing [130] proposing a capacity-based grid tariff for all electricity customers, including households. One of the proposed tariff schemes is based on capacity subscription, which was introduced by Doorman [131]. The idea is that customers subscribe to a certain level of simultaneous electricity use and pay a volumetric penalty when using more electricity than their subscription. Bjarghov and Doorman [132] analyze a dynamic version of the subscribed capacity tariff and finds it to be an attractive option when flexible DERs can be utilized. Sæle and Bremdal [133] find that a capacity-based grid tariff increases the electricity bill for Norwegian customers with PV panels unless they also become flexible electricity users.

The efficient utilization of DERs requires price signals faced by electricity users to incentivize when and where flexible DERs should be dispatched. Traditionally, retail prices faced by residential electricity users are volumetric and static over large geographical areas and long time horizons. When households are faced with time varying electricity prices, Thorsnes et al. [134] find some cost-reducing responses during winter season from an experiment in New Zealand. Further, local electricity markets provide promising schemes to enable prosumers to contribute with valuable services in future electricity systems [135]. So far, research has demonstrated that the residential sector has an impact on the aggregated peak load in the interconnected European power system [136] and that buildings are able to facilitate more efficient operation of the power system by responding to price signals [134, 137, 138, 123].

2.5 Research questions

This thesis explores the role of neighbourhoods within the decarbonizing heat and electricity system in a European context. Its contribution is mainly empirical in its development and application of mathematical programming frameworks to analyze the role of DERs in neighbourhoods within the energy transition. The thesis addresses the research gap raised by Allan et al. [139], who identify a lack of research addressing how the increased use of DERs impact economics at larger scales. Following the advise of Mehigan et al. [78], we soft-link different models in Paper IV and V to better represent DERs in large-scale energy systems.

There are two main research questions (RQs) with specific sub-questions linked to the literature above:

- **RQ1: How does the energy transition impact DERs in neighbourhoods?**
  - How do neighbourhoods respond to grid tariff signals designed to incentivize efficient use of DERs so that flexible electricity loads are well distributed? (Paper I)
  - How does decarbonization of the European electricity system and national heat systems impact the cost-optimal design of ZENs across Europe? (Paper IV)
  - How is the dispatch of DERs in neighbourhoods impacted when they are utilized towards a European objective versus a local objective? (Paper V)
- **RQ2: How do DERs in neighbourhoods impact the energy transition?**
  - How can local electricity trading, designed to support efficient use of DERs in neighbourhoods, impact distribution grid investments? (Paper II)
  - How are investments on the European level impacted when long-term planning of DERs in buildings is coordinated with long-term planning of the European electricity system? (Paper III–V)
  - How does a European-wide development of ZEN impact emission reductions from the heat and electricity sectors? (Paper IV)

RQ1 is explored by analyzing how DERs in neighbourhoods can facilitate decarbonizing electricity systems in growth, while RQ2 is explored by analyzing how the European electricity system are impacted with a large-scale roll-out of DERs in neighbourhoods. In providing answers to both RQ1 and RQ2, this thesis explores how the integration between the building sector and the energy sector impacts the transition towards a low-carbon society.

3 Contributions

In the following, Section 3.1 presents a summary of each paper and its contribution to the research community, and Section 3.2 discusses and links the results from the five papers following Chapter 4 in light of the RQs presented in Section 2.5.

3.1 Papers

3.1.1 Paper I: Comparing individual and coordinated demand response with dynamic and static power grid tariffs

Authors: Stian Backe, Güray Kara, Asgeir Tomasgard

Published by Elsevier in Energy, vol 201 (2020): 117619.

With more electricity users becoming flexible, there is a growing opportunity to respond to electricity price signals. In this paper, we develop a cost-minimizing linear program to compare resulting price signals and electricity loads for two neighbourhoods faced with four different grid tariff schemes.

The main contributions of Paper I are:

- The development of a two-stage stochastic program to analyze capacity-based grid tariffs.
- Insights on the difference between implementing a static versus dynamic grid tariff scheme.
- Insights on the difference between a grid tariff based on individual customer loads versus the combined load of several customers.

Table 3.1 summarizes the attributes of the model[1] developed and used in Paper I. It is a linear program that models how flexible DERs are operated to minimize electricity costs in response to different grid tariff designs. The purpose of the

[1]The model, including the MP implementation and all input data in Paper I, is open-source and downloadable from [140].

model is to compare resulting costs and cost-optimal DER responses under different grid tariff designs. All grid tariff designs are versions of capacity subscription tariffs [132]. The assumptions in the model are that end-users have perfect information, and that they act economically rationally towards minimizing their electricity bills. We also assume that the end-users can reliably deliver flexibility from all DERs over the entire modelling horizon. Flexibility dispatch is subject to electricity losses and limited by installed capacity in the model.

Table 3.1: Key model attributes of the linear MP in Paper I.

Model Attribute	Description
Name	-
Paper	I
Implementation	Python/Pyomo [141]
Solver	Gurobi
Spatial scope	Neighbourhood, aggregated by customer.
Temporal scope	Representative year, hourly resolution.
Objective	Minimize the summed electricity bills of prosumers.
Input	Hourly electricity prices, hourly electricity loads, electric vehicle demand, tariff rates, operational losses, installed DER capacity.
Output	Subscribed grid capacity, resulting electricity loads, operational schedule for DERs.

The model is solved for four versions of capacity subscription tariffs in instances with otherwise equivalent input data. Two electricity customers are modelled for each version. The versions represent whether the customers are billed together or separately or whether their subscription is adjusted weekly or annually. All versions are considered for one year with hourly resolution. Input data consists of tariff rates as proposed by the Norwegian Regulator [130]. We use historical electricity prices in the model from a Norwegian price zone with hourly resolution, and electricity load profiles are measured load from a pilot in FME ZEN (Campus Evenstad). We assume three flexible assets available at both customers: An electric battery, flexible electric vehicle charging, and a curtailable load. We assume no cost of providing flexibility other than diffusion losses.

Results show that 5–6% cost savings are achieved in response to grid tariffs adjusted weekly, while 3% cost savings are achieved for grid tariffs adjusted annually. Further, only grid tariffs adjusted weekly cause the annual peak load to decrease. When customers are billed together, their combined peak load is reduced by 15%, while separate billing cause 3% reduction in combined peak load. To promote the efficient development of electricity grids, grid tariffs should be adjusted within a year and have a price signal dependent on potential bottlenecks in the grid.

My contributions to Paper I include: conceptualizing the problem, developing and formulating the model, collecting and processing data, implementing and solving the model, and processing and visualizing the results. Together with my co-authors, I have discussed the case study and the results. Finally, I have been the main author of the manuscript when writing the original draft and when reviewing and editing.

3.1.2 Paper II: Helping end-users help each other: Coordinating development and operation of distributed resources through local power markets and grid tariffs

Authors: Magnus Askeland, Stian Backe, Sigurd Bjarghov, Magnus Korpås

Published by Elsevier in Energy Economics, vol 94 (2021): 105065.

There are several mechanisms that can be established to incentivize efficient development of electricity systems. In this paper, we develop a game-theoretic framework to study grid tariffs and local electricity markets to compare resulting investments and operations in a neighbourhood in three instances.

The main contributions of Paper II are:

- The development of a game-theoretic framework for grid tariff design under local market mechanisms.
- A case study demonstrating that a local market can reduce the need for grid capacity.
- Insights into the long-term and short-term effects of establishing a local electricity market.

Table 3.2 summarizes the attributes of the modelling framework developed and used in Paper II. The modelling framework is a game-theoretic setup inspired by Schittekatte et al. [128], and consists of several linear programs and their Karush-Kuhn-Tucker (KKT) conditions [142]. The linear programs represent different agents that all have cost-minimizing objectives, including several prosumers and their distribution system operator (DSO). The modelling framework explores the balance between prosumer trading and grid tariff rates, and its purpose is to study the effect of prosumer trading on investments and operational decisions by prosumers and the DSO. The grid tariffs faced by the prosumers consist of an energy-based part to cover operational costs and a capacity-based part to cover investment costs. The assumptions in the modelling framework are that the prosumers pursue their own self-interest with imperfect information, while the DSO minimizes costs with perfect information. Like in Paper I, flexibility can be reliably delivered with all flexible DERs subject to losses and capacity constraints.

Table 3.2: Key model attributes of the bilevel MP in Paper II.

Model Attribute	Description
Name	-
Paper	II
Implementation	GAMS [143]
Solver	CPLEX and PATH [143]
Spatial scope	Neighbourhood, aggregated by customer and distribution system.
Temporal scope	Representative weeks, hourly resolution.
Objective	Minimize investment and operational costs of DSO and prosumers.
Input	Hourly electricity prices, hourly electricity loads, electric vehicle demand, investment options, costs, operational losses, resource limits, existing capacity.
Output	Tariff rates, resulting electricity loads, investments, local trading price, schedule for trades and operations.

The modelling framework is solved in three different instances. The first instance is solved as combined linear program of all agents. The second and third instances are solved as bilevel optimization problems [144]: The upper level is the linear program minimizing DSO costs, while the lower level is a mixed complementarity problem [145] minimizing costs for each prosumer given that they act in their own self-interest. The difference between the second and third instance is whether prosumers can trade with each other or not. All instances are solved for representative weeks in four different seasons. We simulate electricity profiles based on the total floor area of a neighbourhood using the method presented by Lindberg et al. [146]. The neighbourhood in the case study is assumed to represent a pilot in FME ZEN (Ydalir) with a school, kindergarten, and residential buildings. Endogenous technologies include solar PV, battery, electric vehicle charging, and grid dimensioning. Costs are inspired by open data from the Danish Energy Agency.

Results show that the needed grid capacity is 20% lower with a local market compared to without a local market. This is because a local market can effectively reduce the coincident peak load of a neighbourhood, even when the grid tariff is based on individual load. Further, total investments in solar PV are 4 times higher with a local market than without, which is because solar surplus from larger installations can be traded locally at better terms than externally.

Although the study identifies multiple benefits of local electricity markets, its success will depend on the actual responses by electricity users in the neighbourhood and the DSO, which remains to be tested.

My contributions to Paper II include: conceptualizing the problem, discussing the methodology, and developing the modelling framework. Together with my co-authors, I have discussed the case study, the results, and their implications. I have contributed to finalize the manuscript, in particular when reviewing and editing.

3.1.3 Paper III: Heat and electric vehicle flexibility in the European power system: A case study of Norwegian energy communities

Authors: Stian Backe, Magnus Korpås, Asgeir Tomasgard

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The European electricity system is decarbonizing, while buildings in neighbourhoods still dominate electricity demand. In this paper, we develop the multi-horizon stochastic programming model EMPIRE to analyze the impact of nationally aggregated neighbourhoods on the European power system.

The main contributions of Paper III are:

- The development of a model consolidating stochastic and integrated power system capacity expansion to explicitly represent neighbourhoods in a large-scale electricity market.
- A case study demonstrating the benefits of a coordinated development of Norwegian neighbourhoods and the European power system.
- Insights into the effects of linking development and operation of small-scale and large-scale electricity and heat assets.

Table 3.3 summarizes the attributes of EMPIRE developed and used in Paper III. The development of EMPIRE in this thesis consolidates multiple investment periods, uncertainty in short-term operations, and short-term interactions between electricity and heat markets to represent neighbourhoods. The model represents the European electricity system as a network of nodes and arcs, where nodes represent national heat and electricity markets and arcs represent international transmission exchange. The objective is to minimize total system costs subject to market clearing constraints with hourly resolution, short-term technical limitations, assumed future economic conditions, and climate policy. The main purpose of the model is to study least cost investment pathways in the European electricity and heat system (transmission, generation, storage) towards 2060 while satisfying EU climate targets, and it is specifically developed and used in this thesis to understand how neighbourhood energy systems impact the least cost investment pathway. The assumption in the model is perfect competition within the European electricity and heat market. All market decisions related to investments and operational dispatch are linear, which means that power flows are simplified, and that we ignore lumpy investments. Thermal electricity and heat generators are subject to inter-hourly up-ramping limitations, and VRES are subject to uncertain short-term capacity factors with an hourly resolution.

Table 3.3: Key model attributes of the multi-horizon MP in Paper III, IV, and V.

Model Attribute	Description
Name	EMPIRE
Paper	III, IV, and V
Implementation	Python/Pyomo [141]
Solver	Gurobi and Xpress
Spatial scope	Europe, aggregated by country.
Temporal scope	Representative weeks, hourly resolution.
Objective	Minimize investment and operational costs in the European heat and electricity market in five-year steps towards 2060.
Input	Hourly electricity loads, hourly building heat demand, electric vehicle demand, hourly capacity factor for VRES, investment options, costs, operational losses, resource limits, existing capacity (transmission, generation, storage), annual CO_2 cap (alternatively CO_2 price).
Output	Capacity investments (transmission, generation and storage), hourly cross-border transmission operations, hourly heat and electricity asset operations (generation and storage), hourly heat and electricity price, annual CO_2 emissions and price, electrification of building heat.

In Paper III, the EMPIRE model is solved in two different instances to compare European capacity expansion when neighbourhood energy systems in Norway is developed with a European perspective or not. The first instance represents the case where investment decisions for Norwegian neighbourhoods are not explicitly represented, whereas the second instance represents the case where investment decisions in Norwegian neighbourhoods are made in coordination with the European electricity system. Data input is open-source data from the European Network of Transmission System Operators (ENTSO-E) for the electricity system, including hourly electricity load profiles[2] and initial net generation/storage capacities by country. VRES data is from renewables.ninja [147, 148] and ENTSO-E. Costs are from De Vita et al. [149] and the Danish Energy Agency. Climate policy follows the emission reduction pathway laid out for the power sector by the European Commission [11].

Results show that total system costs is reduced by 0.38% when investment decisions for Norwegian neighbourhoods are endogenous. Note that the two instances only differ by about 1% of European electricity demand being defined as heating demand in Norway. Further, heat pumps and combined heat and power in Norway replace some investments in onshore and offshore wind power, and Norwegian electricity exports increase by 8%. The increase in Norwegian electricity exports do not lead to more investments in transmission capacity; on the contrary, 500 MW less transmission capacity is developed between Norway and Sweden. Charging capacity expansion for electric vehicles in Norway are also reduced by 3% when investment decisions for heating in Norwegian neighbourhoods are endogenous.

My contributions to Paper III include: conceptualizing the problem, developing new constraints and features in EMPIRE, collecting and processing new input data for the modelling framework, re-implementing and solving EMPIRE in Python, and processing and visualizing the results. Together with my co-authors, I have discussed the case study and the results. I have been the main author of the manuscript when writing the original draft and when reviewing and editing.

3.1.4 Paper IV: Emission reduction in the European power system: exploring the link between the EU ETS and net-zero emission neighbourhoods

Authors: Stian Backe, Dimitri Pinel, Magnus Askeland, Karen Byskov Lindberg, Magnus Korpås, and Asgeir Tomasgard

Submitted to an international journal and is currently being peer-reviewed.

Climate policy is driving development at different scales within the electricity and heat system, both at the European level and at the neighbourhood level. In this paper, we link two capacity expansion models to analyze the interaction between the European emission trading system (ETS) and Zero Emission Neighbourhoods (ZEN).

[2]Electricity load profiles are scaled in line with [57] to represent future time periods.

The main contributions of Paper IV are:

- The development of a modelling framework that links investments and policies at the European level with the neighbourhood level.
- Insights into how ZENs across Europe is impacted by the European electricity system decarbonizing.
- Insights into how the surrounding electricity and heat system is impacted by ZENs across Europe.

Table 3.4 summarizes the attributes of the Zero Emission Neighborhood Investment Tool (ZENIT) which is linked with EMPIRE (Table 3.3) in Paper IV. The ZENIT model is presented in Pinel et al. [35], and it is a mixed integer linear program that models investment decisions, as well as hourly operational decisions, to find the least costly neighbourhood electricity and heat system design that meets the ZEN requirements. The purpose of the model is to compare how different ZEN requirements and CO_2 accounting methods impact ZEN design. The assumptions in the model is that the neighbourhood, not individual building owners, makes decisions given perfect information for the same representative weeks as in EMPIRE. Losses and efficiencies are considered for different technology options with hourly resolution.

In Paper IV, ZENIT is solved for 20 European countries, including five subregions in Norway, and three future investment periods using EMPIRE results regarding hourly electricity prices and CO_2 intensities. Because both EMPIRE and ZENIT use the same representative weeks to represent operations, the data results from EMPIRE are directly used as input to ZENIT. The ZENIT results are then used to produce an endogenous investment option in EMPIRE, and EMPIRE is solved with the option to invest in ZEN in the respective countries and future investment periods. Other data input to ZENIT is mostly from the Danish Energy Agency, see also [150]. Climate policy follows the emission reduction pathway laid out for the power sector by the European Commission [11], and the EU ETS representation in EMPIRE does not include emissions from small-scale gas boilers.

Results show that when the European electricity system decarbonizes, driven by the EU ETS, developing ZEN generally requires more local electricity production. However, the cost of developing ZEN is reduced by 20% on average between 2030 and 2050 mainly driven by technology development, in particular bio-based solid-oxide fuel cells. As an endogenous investment option, ZENs are widely developed across Europe around 2050, and produce on average 12% of European electricity and 9% of European heat by 2060. The ZENs cause 17% less electricity from nuclear and 2% less electricity from wind. After ZENs are developed, the endogenous CO_2 price is reduced, which means that ZENs reduce the cost of

Table 3.4: Key model attributes of the MP linked with EMPIRE in Paper IV.

Model Attribute	Description
Name	ZENIT
Paper	IV
Implementation	Python/Pyomo [141]
Solver	Gurobi
Spatial scope	Neighbourhood.
Temporal scope	Representative weeks, hourly resolution.
Objective	Minimize investment and operational costs for a neighbourhood to become a ZEN.
Input	Hourly electricity loads, hourly building heat demand, hourly capacity factor for VRES, investment options, costs, operational losses and efficiencies, resource limits, CO_2 intensity for fuels and electricity from the grid, hourly electricity price.
Output	Capacity investments (generation and storage), hourly heat and electricity asset operations (generation and storage), annual CO_2 emissions, electrification of building heat.

achieving climate targets in line with the visions of the European Commission [11].

My contributions to Paper IV include: conceptualizing the problem, developing the modelling linking framework, collecting and processing data for the modelling linking exercise, solving EMPIRE, and processing and visualizing the results. Together with my co-authors, I have discussed the case study and the results. Finally, together with Dimitri Pinel, I have been the main author of the manuscript when writing the original draft and when reviewing and editing.

3.1.5 Paper V: Impact of Energy Communities on the European Electricity and Heat System Decarbonization Pathway: Comparing local and global flexibility responses

Authors: Stian Backe, Sebastian Zwickl-Bernhard, Daniel Schwabeneder, Hans Auer, Magnus Korpås, and Asgeir Tomasgard

Submitted to an international journal and is currently being peer-reviewed.

The growing development of energy communities across Europe will impact their surrounding electricity and heat systems, and resources within the energy communities can be utilized towards different objectives. In this paper, we use link two capacity expansion models to analyze how the European electricity and heat system is impacted by the exogenous development of energy communities, and how flexible resources within the energy communities are used towards local versus European cost minimization.

The main contributions of Paper V are:

- The development of a modelling framework that links investments and operations at the European level with different settlement patterns at the neighbourhood level.
- Insights into how energy communities across Europe impact investments and operations in the decarbonizing European electricity system.
- Insights into how distributed flexibility options can be aggregated in large-scale models and its effect on results.

Table 3.5 summarizes the attributes of the enerGy commUnity SysTem mOdeling (GUSTO)[3] which is linked with EMPIRE in Paper V. The GUSTO model is presented in Zwickl-Bernhard and Auer [107], and it is a mixed integer linear program that models investments and operations in a neighbourhood energy system similar to ZENIT. The main difference between GUSTO and ZENIT is that GUSTO does not include a ZEN requirement or any CO_2 accounting, except for a CO_2 price. The purpose of GUSTO is to study investments and operational decisions for electricity, heat, and cooling systems in energy communities under different economic conditions. The assumptions in the model include perfect information for an energy community for a single representative year. Like ZENIT, losses and efficiencies are considered for different technologies on an hourly basis.

In Paper V, GUSTO is solved for six European countries, including five subregions in Norway; four neighbourhood typologies (settlement patterns); and three investment periods. In each solve, GUSTO uses mean electricity and CO_2 prices for future investment periods from EMPIRE to create input. GUSTO results regarding hourly electricity and heat operations are used to modify load profiles in EMPIRE to reflect an exogenous development of energy communities. Further data input to GUSTO can be found in [151], e.g., standard electricity and heating demand profiles on the building level from [152, 153, 154]. Climate policy follows the emission reduction pathway laid out for the power sector by the European Commission [11].

Results show that the roll-out of energy communities in the selected European countries decrease total system cost and centralized capacity expansion by less

[3] The GUSTO model is open-source and available from [151].

Table 3.5: Key model attributes of the MP linked with EMPIRE in Paper V.

Model Attribute	Description
Name	GUSTO
Paper	V
Implementation	Python/Pyomo [141]
Solver	Gurobi
Spatial scope	Neighbourhood.
Temporal scope	Representative year, hourly resolution.
Objective	Minimize investment and operational costs for an energy community.
Input	Hourly electricity loads, hourly building heat demand, hourly capacity factor for VRES, investment options, costs, operational losses and efficiencies, resource limits, CO_2 price, hourly electricity and heat price.
Output	Capacity investments (generation and storage), hourly heat and electricity asset operations (generation and storage), electrification of building heat.

than 1%. The energy communities cause a lower heat demand and higher electricity demand during winter seasons, as well as lower electricity and heat demand during summer seasons. On the European level, this causes a shift of investments from onshore to offshore wind. When distributed flexibility options within energy communities are available for dispatch at the European level, investments in batteries at the European level are reduced by 2%. At the local level, energy community flexibility is utilized mainly for absorption of solar PV, while at the European level, flexibility is utilized more towards the absorption of wind.

My contributions to Paper V include: conceptualizing the problem, developing the modelling linking framework, collecting and processing data for the modelling linking exercise, solving EMPIRE, and processing and visualizing the results. Together with my co-authors, I have discussed the case study and the results. Finally, I have been the main author of the manuscript when writing the original draft and when reviewing and editing.

3.2 Results and discussion

3.2.1 RQ1: How does the energy transition impact DERs in neighbourhoods?

As the electricity system that surrounds neighbourhoods meets more demand with less CO_2 intensity, there is a need for new resources/services within the electricity system. This thesis finds that neighbourhoods and cost-efficiently supply some of these resources/services given advanced metering infrastructure and regulatory frameworks that allow neighbourhoods to actively participate in electricity markets. Some of the resources/services in neighbourhoods that are studied in this thesis include: solar PV, bio-based electricity/heat generation, heat pumps, batteries, hot water storage, and flexible charging of electric vehicles.

In Paper I and II, we study the ability of capacity-based grid tariffs (Paper I and II) and local electricity trading (Paper II) to incentivize lower coincident electricity peak loads in neighbourhoods. Both Paper I and II find that, given flexible DERs and some incentive to schedule them, the coincident peak loads in the neighbourhood are successfully lowered. Both papers also find that price signal coordination among neighbourhood stakeholders is important: Paper I finds that individual billing is less efficient than combined billing to lower coincident peak loads in neighbourhoods, and Paper II finds that allowing electricity trading between stakeholders in the neighbourhood is more cost-efficient than not. Further, Paper I finds that adjusting price signals (tariff rates) more frequently than annually is needed to signal seasonal variations for the value of flexibility: load reduction ought to be incentivized when it is needed, but not incentivized when it is not needed.

Flexible DERs in neighbourhoods could be used for different purposes, and the objective of lowering the coincident peak load could be in competition with the objective of becoming a ZEN or balancing VRES load. In Paper IV, we study how electricity and heat system design in ZEN changes as the surrounding electricity system decarbonizes, and we find that neighbourhoods must produce more electricity to become ZEN as the energy transition progresses. In Paper V, we study the difference between pursuing local cost minimization versus European cost minimization in terms of how DERs are scheduled, and we find that countries with large shares of wind power would benefit from using flexible DERs to partly balance wind load, which is sometimes in conflict with balancing local grid or PV loads.

Given the benefits of DERs in neighbourhoods identified in this thesis, the energy transition should lead to revised regulatory frameworks regarding electricity billing in neighbourhoods, as well as regulatory frameworks for aggregators as discussed by Burger et al. [155]. If so, neighbourhoods could decrease their electricity costs through smart scheduling of flexible DERs; however, electricity costs for stakeholders without flexible DERs could simultaneously increase. Although the models in this thesis focus on economic efficiency, fairness in electricity billing is also important to consider when revising regulatory frameworks as laid out by Brown et al. [125]. Further, given a conflict of interest between lowering peak loads and balancing VRES within and around neighbourhoods, it will be important that the price signals what to prioritize at different times. Nevertheless, this thesis identifies a significant economic value of flexible DERs in neighbourhoods towards 2050 and beyond. If potential complexity and disutility related to smart scheduling of flexible DERs does not outweigh its benefits, flexible DERs in neighbourhoods are increasingly relevant assets within the energy transition.

3.2.2 RQ2: How do DERs in neighbourhoods impact the energy transition?

As European neighbourhoods develop fully or partly autonomous electricity and heat systems, DERs in neighbourhoods become wide-spread and significant on a European level. This thesis finds that the development of DERs in neighbourhoods have a significant impact on the transition pathway towards 2060 for the surrounding European electricity and heat system, in particular large-scale investments, CO_2 prices, and emissions.

In Paper II, we study how electricity trading between prosumers in neighbourhoods could impact DSO grid investments, and we find that grid investments are avoided when electricity trading is allowed. The main reason for avoided grid investment is that the coincident peak load is reduced as trading between neighbourhood stakeholders incentivizes reduction of the aggregate neighbourhood load rather than their individual peak load.

Investments on the European level are also impacted by more DERs in neighbourhoods. In Paper III, we study the development of DERs in Norwegian neighbourhoods in coordination with the European electricity system, and we find that DER development in Norwegian neighbourhoods decrease investments in wind power and increase the export of hydro power from Norway. In Paper IV, we study the endogenous development of ZENs in several countries in the European electricity and heat system, and we find that ZENs are cost-efficient investment options from a European perspective around 2050. Paper IV further finds that ZENs mostly replace large-scale investments in nuclear power. In Paper V, we study the exogenous development of energy communities in several countries in the European electricity and heat system, and we find that they shift large-scale investment from onshore to offshore wind power. The shift towards offshore wind is likely driven by the energy communities developing heat pumps that cause increased electricity loads during winter, and offshore wind has a higher average capacity factor during winter than onshore wind. European cross-border transmission investments are not affected by DERs in neighbourhoods in Paper IV and V, which is likely because the neighbourhood DERs are developed after the maximum allowed transmission investments are done in both papers.

In Paper IV, European CO_2 prices, as well as unregulated European CO_2 emissions, are found to decrease in the long term when ZENs are developed. This is mainly because fossil gas heating around Europe is less developed and used when the more cost-competitive ZEN option is developed. Paper IV also finds that CO_2 prices could increase in the years before a zero emission investment option like ZEN is anticipated to become cost-efficient. In Paper V, the exogenous development of energy communities increases the CO_2 prices, which is again likely because energy communities increase electricity load in the winter. Note that Paper IV and V only compare future scenarios where European climate targets are met in line with the vision of the European Commission [11], also without DERs in neighbourhoods.

Papers II–V all find that the development and scheduling of DERs in neighbourhoods contribute to cost savings in the surrounding electricity and heat systems. We find that centralized investments in the European electricity system, especially wind and nuclear power, could be partly substituted by DERs in neighbourhoods.

4 Concluding remarks

Hamming [156] stated that: '*The purpose of (scientific) computing is insight, not numbers*', and Box [157] stated that: '*Essentially, all models are wrong, but some models are useful*'. In this thesis, very complex energy systems are represented in simplified mathematical frameworks. Thus, it is worth remembering the wise men's point: We are looking for *useful insights* on how techno-economic interactions drive decision-making. It is the qualitative interpretations of modelling output—in light of the models, what they represent, and their limitations—that yield the useful insights towards practical implications of the studies.

This thesis studies the impact of neighbourhood electricity and heat systems on European decarbonization pathways from the neighbourhood perspective (Paper I and II), the European perspective (Paper III), and the link between them (Paper IV and V). However, there are many scopes and layers between these perspectives that are not considered, including electricity grid infrastructure on a country level, infrastructure for district heating, and more sectors overlapping with the electricity system. Further, when modelling energy systems several decades into the future, all modelling input and assumptions are uncertain, and the modelling results are practically impossible to verify. Thus, the thesis focuses on comparing differences between several instances of the same modelling frameworks. The results are not intended to forecast the future, but rather to outline the differences between future pathways with and without DERs in neighbourhoods.

Energy systems in future neighbourhoods are studied in this thesis, however, it does not explicitly consider directly improving final energy demand in neighbourhoods, e.g., renovation. Future work should address accelerating renovation in Europe: 75% of today's buildings is considered energy inefficient, 85–95% of today's buildings will still exist in 2050, and current renovation rates in the EU are alarmingly low: around 1% per year [158]. Further, the step-wise emission reductions for the European electricity and heat system towards 2050 needs more investigation. By shifting allowed GHG emissions further into the future, the CO_2 price spikes in Paper IV might be avoided. However, a smoother transition from fossil to renewable energy also implies that more fossil capacity can be cost-efficiently developed and used further into the future, which could increase the problem of stranded assets as discussed by Bos and Gupta [159]. More work is needed to study the balance between strict decarbonization policy and economic efficiency in line with climate targets, both on the European level and on the neighbourhood level.

Bibliography

[1] Cara A. Horowitz. Paris Agreement. *International Legal Materials*, 55(4): 740–755, 2016. doi: 10.1017/S0020782900004253.

[2] Steven J Davis, Nathan S Lewis, Matthew Shaner, Sonia Aggarwal, Doug Arent, Inês L Azevedo, Sally M Benson, Thomas Bradley, Jack Brouwer, Yet-Ming Chiang, et al. Net-zero emissions energy systems. *Science*, 360 (6396), 2018.

[3] Myles Allen, Mustafa Babiker, Yang Chen, Heleen de Coninck, Sarah Connors, Renée van Diemen, Opha Pauline Dube, Kris Ebi, et al. Global Warming of 1.5 °C, an IPCC special report on the impacts of global warming of 1.5 °C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. *Prepared by Working Groups I, II and III of the Intergovernmental Panel on Climate Change*, 2018.

[4] James H Williams, Andrew DeBenedictis, Rebecca Ghanadan, Amber Mahone, Jack Moore, William R Morrow, Snuller Price, and Margaret S Torn. The Technology Path to Deep Greenhouse Gas Emissions Cuts by 2050: The Pivotal Role of Electricity. *Science*, 335(6064):53–59, 2012.

[5] European Environment Agency. CO2 intensity of electricity and heat generation. `https://www.eea.europa.eu/data-and-maps/indicators/co2-intensity-of-electricity-and`, 2021. Accessed: October 11, 2021.

[6] Pantelis Capros, Alessia De Vita, Nikolaos Tasios, Pelopidas Siskos, Maria Kannavou, Apostolos Petropoulos, Stavroula Evangelopoulou, Marilena Zampara, Dimitris Papadopoulos, Christos Nakos, et al. EU Reference Scenario 2016 - Energy, transport and GHG emissions Trends to 2050. *Luxembourg: Publications Office*, 2016.

[7] Hans Auer, Pedro Crespo del Granado, Pao-Yu Oei, Karlo Hainsch, Konstantin Löffler, Thorsten Burandt, Daniel Huppmann, and Ingeborg Grabaak. Development and modelling of different decarbonization scenarios of the European energy system until 2050 as a contribution to achieving the ambitious 1.5°C climate target—establishment of open source/data modelling in the European H2020 project openENTRANCE. *e & i Elektrotechnik und Informationstechnik*, pages 1–13, 2020.

[8] Yue-Jun Zhang and Yi-Ming Wei. An overview of current research on EU ETS: Evidence from its operating mechanism and economic effect. *Applied Energy*, 87(6):1804–1814, 2010.

[9] Aleksandar Zaklan, Jakob Wachsmuth, and Vicki Duscha. The EU ETS to 2030 and beyond: adjusting the cap in light of the 1.5°C target and current energy policies. *Climate Policy*, pages 1–14, 2021.

[10] Benjamin K Sovacool. How long will it take? conceptualizing the temporal dynamics of energy transitions. *Energy Research & Social Science*, 13:202–215, 2016.

[11] European Commission. A Clean Planet for all - A European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy. `https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52018DC0773`, November 2018. Accessed: October 11, 2021.

[12] Marie Byskov Lindberg, Jochen Markard, and Allan Dahl Andersen. Policies, actors and sustainability transition pathways: A study of the EU's energy policy mix. *Research policy*, 2018.

[13] Jochen Markard, Rob Raven, and Bernhard Truffer. Sustainability transitions: An emerging field of research and its prospects. *Research policy*, 41 (6):955–967, 2012.

[14] Peter D Lund, Juuso Lindgren, Jani Mikkola, and Jyri Salpakari. Review of energy system flexibility measures to enable high levels of variable renewable electricity. *Renewable and Sustainable Energy Reviews*, 45:785–807, 2015.

[15] Hans Auer and Reinhard Haas. On integrating large shares of variable renewables into the electricity system. *Energy*, 115:1592–1601, 2016.

[16] Jochen Markard. The next phase of the energy transition and its implications for research and policy. *Nature Energy*, page 1, 2018.

[17] Hassan Farhangi. The path of the smart grid. *IEEE power and energy magazine*, 8(1):18–28, 2009.

[18] Paul L. Joskow and Catherine D. Wolfram. Dynamic Pricing of Electricity. *American Economic Review*, 102(3):381–85, May 2012.

[19] Robert Passey, Navid Haghdadi, Anna Bruce, and Iain MacGill. Designing more cost reflective electricity network tariffs with demand charges. *Energy Policy*, 109:642–649, 2017.

[20] Martin De Jong, Simon Joss, Daan Schraven, Changjie Zhan, and Margot Weijnen. Sustainable–smart–resilient–low carbon–eco–knowledge cities; making sense of a multitude of concepts promoting sustainable urbanization. *Journal of Cleaner production*, 109:25–38, 2015.

[21] Mark Roseland. Dimensions of the eco-city. *Cities*, 14(4):197–202, 1997.

[22] Simon Elias Bibri and John Krogstie. Smart sustainable cities of the future: An extensive interdisciplinary literature review. *Sustainable cities and society*, 31:183–212, 2017.

[23] Rasmus Luthander, Joakim Widén, Daniel Nilsson, and Jenny Palm. Photovoltaic self-consumption in buildings: A review. *Applied energy*, 142: 80–94, 2015.

[24] Pol Olivella-Rosell, Eduard Bullich-Massagué, Mònica Aragüés-Peñalba, Andreas Sumper, Stig Ødegaard Ottesen, Josep-Andreu Vidal-Clos, and Roberto Villafáfila-Robles. Optimization problem for meeting distribution system operator requests in local flexibility markets with distributed energy resources. *Applied energy*, 210:881–895, 2018.

[25] Sieting Tan, Jin Yang, Jinyue Yan, Chewtin Lee, Haslenda Hashim, and Bin Chen. A holistic low carbon city indicator framework for sustainable development. *Applied Energy*, 185:1919–1930, 2017.

[26] Delia D'Agostino and Livio Mazzarella. What is a Nearly zero energy building? Overview, implementation and comparison of definitions. *Journal of Building Engineering*, 21:200–212, 2019.

[27] Anna Joanna Marszal, Per Heiselberg, Julien S Bourrelle, Eike Musall, Karsten Voss, Igor Sartori, and Assunta Napolitano. Zero Energy Building–A review of definitions and calculation methodologies. *Energy and buildings*, 43(4):971–979, 2011.

[28] European Commission. Directive (EU) 2018/844 of the European Parliament and of the Council of 30 May 2018 amending Directive 2010/31/EU on the energy performance of buildings and Directive 2012/27/EU on energy efficiency. *Official Journal of the European Union*, 2018.

[29] Eleonora Annunziata, Marco Frey, and Francesco Rizzi. Towards nearly zero-energy buildings: The state-of-art of national regulations in Europe. *Energy*, 57:125–133, 2013.

[30] Igor Sartori, Assunta Napolitano, Anna Joanna Marszal, Shanti Pless, Paul Torcellini, and Karsten Voss. Criteria for definition of net zero energy buildings. In *International Conference on Solar Heating, Cooling and Buildings (EuroSun 2010)*. EuroSun 2010, 2010.

[31] Silvia Bossi, Christoph Gollner, and Sarah Theierling. Towards 100 positive energy districts in europe: Preliminary data analysis of 61 european cases. *Energies*, 13(22):6083, 2020.

[32] Anne Grete Hestnes and Nancy Lea Eik-Nes. *Zero emission buildings*. Fagbokforlaget Bergen, 2017.

[33] Marianne Kjendseth Wiik, Selamawit Mamo Fufa, John Krogstie, Dirk Ahlers, Annemie Wyckmans, Patrick Driscoll, Helge Brattebø, and Arild Gustavsen. Zero Emission Neighbourhoods in Smart Cities: Definition, Key Performance Indicators and Assessment Criteria: Version 1.0. `https://fmezen.no/wp-content/uploads/2018/11/ZEN-Report-no-7-Bilingual.pdf`, 2018. Accessed: October 11, 2021.

[34] Karen Byskov Lindberg, Gerard Doorman, David Fischer, Magnus Korpås, Astrid Ånestad, and Igor Sartori. Methodology for optimal energy system design of Zero Energy Buildings using mixed-integer linear programming. *Energy and Buildings*, 127:194 – 205, 2016. ISSN 0378-7788.

[35] Dimitri Pinel, Magnus Korpås, and Karen B Lindberg. Impact of the CO2 factor of electricity and the external CO2 compensation price on zero emission neighborhoods' energy system design. *Building and Environment*, 187: 107418, 2021.

[36] Marianne Kjendseth Wiik, Selamawit Mamo Fufa, Torhildur Kristjansdottir, and Inger Andresen. Lessons learnt from embodied GHG emission calculations in zero emission buildings (ZEBs) from the Norwegian ZEB research centre. *Energy and Buildings*, 165:25–34, 2018.

[37] European Environment Agency. Overview of electricity production and use in Europe. `https://www.eea.europa.eu/data-and-maps/indicators/overview-of-the-electricity-production-2/assessment`, 2018. Accessed: October 11, 2021.

[38] S. M. Sinha. *Mathematical programming: theory and methods.* Elsevier, 2005.

[39] Daniel Pierre Bovet, Pierluigi Crescenzi, and D Bovet. *Introduction to the Theory of Complexity.* Prentice Hall London, 1994.

[40] George B Dantzig. Linear programming under uncertainty. *Management science*, 1(3-4):197–206, 1955.

[41] Peter Kall and Stein Wallace. *Stochastic programming.* Springer, 1994.

[42] Narendra Karmarkar. A new polynomial-time algorithm for linear programming. In *Proceedings of the sixteenth annual ACM symposium on Theory of computing*, pages 302–311, 1984.

[43] Kai Huang and Shabbir Ahmed. The value of multistage stochastic programming in capacity planning under uncertainty. *Operations Research*, 57 (4):893–904, 2009.

[44] Michal Kaut, Kjetil T Midthun, Adrian S Werner, Asgeir Tomasgard, Lars Hellemo, and Marte Fodstad. Multi-horizon stochastic programming. *Computational Management Science*, 11(1-2):179–193, 2014.

[45] John R Birge and Francois Louveaux. *Introduction to stochastic programming*. Springer Science & Business Media, 2011.

[46] Antonio J Conejo and Francisco J Prieto. Mathematical programming and electricity markets. *Top*, 9(1):1–22, 2001.

[47] Hanan Luss. Operations research and capacity expansion problems: A survey. *Operations research*, 30(5):907–947, 1982.

[48] Benjamin F Hobbs, Carolyn B Metzler, and J-S Pang. Strategic gaming analysis for electric power systems: An MPEC approach. *IEEE transactions on power systems*, 15(2):638–645, 2000.

[49] Frederic H Murphy and Yves Smeers. Generation capacity expansion in imperfectly competitive restructured electricity markets. *Operations research*, 53(4):646–661, 2005.

[50] Joeri Rogelj, Gunnar Luderer, Robert C Pietzcker, Elmar Kriegler, Michiel Schaeffer, Volker Krey, and Keywan Riahi. Energy system transformations for limiting end-of-century warming to below 1.5°C. *Nature Climate Change*, 5(6):519–527, 2015.

[51] Markus Blesl, Tom Kober, David Bruchof, and Ralf Kuder. Effects of climate and energy policy related measures and targets on the future structure of the European energy system in 2020 and beyond. *Energy Policy*, 38(10): 6278–6292, 2010.

[52] Roman Mendelevitch, Claudia Kemfert, Pao-Yu Oei, and Christian von Hirschhausen. *The Electricity Mix in the European Low-Carbon Transformation: Coal, Nuclear, and Renewables*, pages 241–282. Springer International Publishing, Cham, 2018. ISBN 978-3-319-95126-3.

[53] International Energy Agency. Net zero by 2050. IEA, Paris, `https://www.iea.org/reports/net-zero-by-2050`, 2021. Accessed: October 11, 2021.

[54] R. Stuart Haszeldine. Carbon capture and storage: how green can black be? *Science*, 325(5948):1647–1652, 2009.

[55] Dennis Y. C. Leung, Giorgio Caramanna, and M Mercedes Maroto-Valer. An overview of current status of carbon dioxide capture and storage technologies. *Renewable and Sustainable Energy Reviews*, 39:426–443, 2014.

[56] Volker Krey, Gunnar Luderer, Leon Clarke, and Elmar Kriegler. Getting from here to there–energy technology transformation pathways in the EMF27 scenarios. *Climatic change*, 123(3):369–382, 2014.

[57] Pantelis Capros, Maria Kannavou, Stavroula Evangelopoulou, Apostolos Petropoulos, Pelopidas Siskos, Nikolaos Tasios, Georgios Zazias, and Alessia DeVita. Outlook of the EU energy system up to 2050: The case

of scenarios prepared for European Commission's "Clean Energy for All Europeans" package using the PRIMES model. *Energy strategy reviews*, 22:255–263, 2018.

[58] Felix Creutzig, Peter Agoston, Jan Christoph Goldschmidt, Gunnar Luderer, Gregory Nemet, and Robert C Pietzcker. The underestimated potential of solar energy to mitigate climate change. *Nature Energy*, 2(9):1–9, 2017.

[59] Thure Traber and Claudia Kemfert. Gone with the wind?—Electricity market prices and incentives to invest in thermal power plants under increasing wind energy supply. *Energy Economics*, 33(2):249–256, 2011.

[60] Chi-Keung Woo, Ira Horowitz, Jack Moore, and Andres Pacheco. The impact of wind generation on the electricity spot-market price level and variance: The Texas experience. *Energy Policy*, 39(7):3939–3944, 2011.

[61] Per Aaslid, Magnus Korpås, Michael M Belsnes, and Olav B Fosso. Pricing electricity in constrained networks dominated by stochastic renewable generation and electric energy storage. *Electric Power Systems Research*, 197:107169, 2021.

[62] Stefan Pfenninger, Adam Hawkes, and James Keirstead. Energy systems modeling for twenty-first century energy challenges. *Renewable and Sustainable Energy Reviews*, 33:74–86, 2014.

[63] Hans-Kristian Ringkjøb, Peter M Haugan, and Ida Marie Solbrekke. A review of modelling tools for energy and electricity systems with large shares of variable renewables. *Renewable and Sustainable Energy Reviews*, 96:440–459, 2018.

[64] Seán Collins, John Paul Deane, Kris Poncelet, Evangelos Panos, Robert C Pietzcker, Erik Delarue, and Brian Pádraig Ó Gallachóir. Integrating short term variations of the power system into integrated energy system models: A methodological review. *Renewable and Sustainable Energy Reviews*, 76: 839–856, 2017.

[65] Miguel Chang, Jakob Zink Thellufsen, Behnam Zakeri, Bryn Pickering, Stefan Pfenninger, Henrik Lund, and Poul Alberg Østergaard. Trends in tools and approaches for modelling the energy transition. *Applied Energy*, 290:116731, 2021.

[66] Pernille Seljom and Asgeir Tomasgard. Short-term uncertainty in long-term energy system models—A case study of wind power in Denmark. *Energy Economics*, 49:157–167, 2015.

[67] Frauke Wiese, Rasmus Bramstoft, Hardi Koduvere, Amalia Pizarro Alonso, Olexandr Balyk, Jon Gustav Kirkerud, Åsa Grytli Tveten, Torjus Folsland

Bolkesjø, Marie Münster, and Hans Ravn. Balmorel open source energy system model. *Energy strategy reviews*, 20:26–34, 2018.

[68] Josiah Johnston, Rodrigo Henriquez-Auba, Benjamín Maluenda, and Matthias Fripp. Switch 2.0: a modern platform for planning high-renewable power systems. *SoftwareX*, 10:100251, 2019.

[69] Hans-Kristian Ringkjøb, Peter M Haugan, Pernille Seljom, Arne Lind, Fabian Wagner, and Sennai Mesfun. Short-term solar and wind variability in long-term energy system models-A European case study. *Energy*, 209: 118377, 2020.

[70] Tom Brown, Jonas Hörsch, and David Schlachtberger. PyPSA: Python for Power System Analysis. *Journal of Open Research Software*, 6(4), 2018.

[71] Derk J Swider and Christoph Weber. The costs of wind's intermittency in Germany: application of a stochastic electricity market model. *European Transactions on Electrical Power*, 17(2):151–172, 2007.

[72] Stian Backe. OpenEMPIRE: Stochastic linear program for investments in the European power system. `https://github.com/ntnuiotenergy/OpenEMPIRE`, 2021. Accessed: October 11, 2021.

[73] Christian Skar, GL Doorman, Gerardo A Pérez-Valdés, and Asgeir Tomasgard. A multi-horizon stochastic programming model for the European power system. `https://www.semanticscholar.org/paper/A-multi-horizon-stochastic-programming-model-for-Skar-Doorman/60e07af486807ee3b2426c70cfa5e6d54c8ed15e`, 2016. Accessed: October 11, 2021.

[74] Christian Skar, Gerard Doorman, and Asgeir Tomasgard. The future European power system under a climate policy regime. In *Energy Conference (ENERGYCON), 2014 IEEE International*, pages 318–325. IEEE, 2014.

[75] Héctor Marañón-Ledesma and Asgeir Tomasgard. Analyzing Demand Response in a Dynamic Capacity Expansion Model for the European Power Market. *Energies*, 12(15):2976, 2019.

[76] Kenneth Hansen, Christian Breyer, and Henrik Lund. Status and perspectives on 100% renewable energy systems. *Energy*, 175:471–480, 2019.

[77] Andreas Bloess, Wolf-Peter Schill, and Alexander Zerrahn. Power-to-heat for renewable energy integration: A review of technologies, modeling approaches, and flexibility potentials. *Applied Energy*, 212:1611–1626, 2018.

[78] Laura Mehigan, J. Paul Deane, Brian P. Ó. Gallachóir, and Valentin Bertsch. A review of the role of distributed generation (DG) in future electricity systems. *Energy*, 163:822–836, 2018.

[79] David L McCollum, Wenji Zhou, Christoph Bertram, Harmen-Sytze De Boer, Valentina Bosetti, Sebastian Busch, Jacques Després, Laurent Drouet, Johannes Emmerling, Marianne Fay, et al. Energy investment needs for fulfilling the Paris Agreement and achieving the Sustainable Development Goals. *Nature Energy*, 3(7):589–599, 2018.

[80] Hans Christian Gils. Assessment of the theoretical demand response potential in Europe. *Energy*, 67:1–18, 2014.

[81] Leigh Hancher and B. Marinus Winters. The EU Winter Package: Briefing paper. *Allen & Overy LLP*, February 2017.

[82] Stig Ødegaard Ottesen, Asgeir Tomasgard, and Stein-Erik Fleten. Multi market bidding strategies for demand side flexibility aggregators in electricity markets. *Energy*, 149:120–134, 2018.

[83] Yael Parag and Benjamin K Sovacool. Electricity market design for the prosumer era. *Nature energy*, 1(4):1–6, 2016.

[84] Rafael Leal-Arcas. A paradigm shift in the governance of sustainable development: Citizens' empowerment. *International markets regulation and the erosion of the European political and social model, Thomson Reuters*, 2019.

[85] Christian Milan, Carsten Bojesen, and Mads Pagh Nielsen. A cost optimization model for 100% renewable residential energy supply systems. *Energy*, 48(1):118–127, 2012.

[86] Emilio L Cano, Javier M Moguerza, and Antonio Alonso-Ayuso. A multi-stage stochastic optimization model for energy systems planning and risk management. *Energy and Buildings*, 110:49–56, 2016.

[87] R Tyrrell Rockafellar, Stanislav Uryasev, et al. Optimization of conditional value-at-risk. *Journal of risk*, 2:21–42, 2000.

[88] Constantinos A Balaras, Kalliopi Droutsa, Elena Dascalaki, and Simon Kontoyiannidis. Heating energy consumption and resulting environmental impact of european apartment buildings. *Energy and buildings*, 37(5):429–442, 2005.

[89] Henrik Lund, Bernd Möller, Brian Vad Mathiesen, and A Dyrelund. The role of district heating in future renewable energy systems. *Energy*, 35(3): 1381–1390, 2010.

[90] Dieter Patteeuw, Gregor P Henze, and Lieve Helsen. Comparison of load shifting incentives for low-energy buildings with heat pumps to attain grid flexibility benefits. *Applied energy*, 167:80–92, 2016.

[91] Siang Fui Tie and Chee Wei Tan. A review of energy sources and energy management system in electric vehicles. *Renewable and sustainable energy reviews*, 20:82–102, 2013.

[92] Kristien Clement-Nyns, Edwin Haesen, and Johan Driesen. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. *Power Systems, IEEE Transactions on*, 25(1):371–380, 2010.

[93] Åse Lekang Sørensen, Karen Byskov Lindberg, Igor Sartori, and Inger Andresen. Analysis of residential ev energy flexibility potential based on real-world charging reports and smart meter data. *Energy and Buildings*, 241: 110923, 2021.

[94] Binod Prasad Koirala, Elta Koliou, Jonas Friege, Rudi A Hakvoort, and Paulien M Herder. Energetic communities for community energy: A review of key issues and trends shaping integrated community energy systems. *Renewable and Sustainable Energy Reviews*, 56:722–744, 2016.

[95] Jens Lowitzsch, Christina E. Hoicka, and Felicia van Tulder. Renewable energy communities under the 2019 European Clean Energy Package–Governance model for the energy clusters of the future? *Renewable and Sustainable Energy Reviews*, 122:109489, 2020.

[96] Kristina Orehounig, Georgios Mavromatidis, Ralph Evins, Viktor Dorer, and Jan Carmeliet. Towards an energy sustainable community: An energy system analysis for a village in Switzerland. *Energy and Buildings*, 84: 277–286, 2014.

[97] Tineke van der Schoor and Bert Scholtens. Power to the people: Local community initiatives and the transition to sustainable energy. *Renewable and sustainable energy reviews*, 43:666–675, 2015.

[98] Jiawei Wang, Shi You, Yi Zong, and Chresten Træholt. EnergyLab Nordhavn: An integrated community energy system towards green heating and e-mobility. In *2017 IEEE Transportation Electrification Conference and Expo, Asia-Pacific (ITEC Asia-Pacific)*, pages 1–6. IEEE, 2017.

[99] Iñaki Heras-Saizarbitoria, Lucía Sáez, Erlantz Allur, and Jon Morandeira. The emergence of renewable energy cooperatives in Spain: A review. *Renewable and Sustainable Energy Reviews*, 94:1036–1043, 2018.

[100] Carolin Monsberger, Bernadette Fina, and Hans Auer. Profitability of Energy Supply Contracting and Energy Sharing Concepts in a Neighborhood Energy Community: Business Cases for Austria. *Energies*, 14(4):921, 2021.

[101] Luca Tricarico. Is community earning enough? Reflections on engagement processes and drivers in two Italian energy communities. *Energy Research & Social Science*, 72:101899, 2021.

[102] Hans-Kristian Ringkjøb, Peter M Haugan, and Astrid Nybø. Transitioning remote Arctic settlements to renewable energy systems–A modelling study of Longyearbyen, Svalbard. *Applied Energy*, 258:114079, 2020.

[103] Carine Lausselet, Kirsti Marie Lund, and Helge Brattebø. LCA and scenario analysis of a Norwegian net-zero GHG emission neighbourhood: The importance of mobility and surplus energy from PV technologies. *Building and Environment*, 189:107528, 2021.

[104] Campos Inês, Pontes Luz Guilherme, Marín-González Esther, Gährs Swantje, Hall Stephen, and Holstenkamp Lars. Regulatory challenges and opportunities for collective renewable energy prosumers in the EU. *Energy Policy*, 138:111212, 2020.

[105] Pernille Seljom, Karen Byskov Lindberg, Asgeir Tomasgard, Gerard Doorman, and Igor Sartori. The impact of Zero Energy Buildings on the Scandinavian energy system. *Energy*, 118:284–296, 2017.

[106] Dimitri Pinel, Magnus Korpås, and Karen Byskov Lindberg. Cost Optimal Design of Zero Emission Neighborhoods'(ZENs) Energy System Model Presentation and Case Study on Evenstad. In *Advances in Energy System Optimization Proceeding of the 2nd International Symposium on Energy System Optimization*. Springer Verlag, 2019.

[107] Sebastian Zwickl-Bernhard and Hans Auer. Open-source modeling of a low-carbon urban neighborhood with high shares of local renewable generation. *Applied Energy*, 282:116166, 2021.

[108] Steven Stoft. Power system economics. *Journal of Energy Literature*, 8: 94–99, 2002.

[109] Shafiqur Rehman, Luai M Al-Hadhrami, and Md. Mahbub Alam. Pumped hydro energy storage system: A technological review. *Renewable and Sustainable Energy Reviews*, 44:586–598, 2015.

[110] Bruce Dunn, Haresh Kamath, and Jean-Marie Tarascon. Electrical energy storage for the grid: a battery of choices. *Science*, 334(6058):928–935, 2011.

[111] Matthew Li, Jun Lu, Zhongwei Chen, and Khalil Amine. 30 years of lithium-ion batteries. *Advanced Materials*, 30(33):1800561, 2018.

[112] Mehdi Jafari, Magnus Korpås, and Audun Botterud. Power system decarbonization: Impacts of energy storage duration and interannual renewables variability. *Renewable Energy*, 156:1171–1185, 2020.

[113] Paul Denholm and Trieu Mai. Timescales of energy storage needed for reducing renewable energy curtailment. *Renewable energy*, 130:388–399, 2019.

[114] Henrik Lund and Willett Kempton. Integration of renewable energy into the transport and electricity sectors through v2g. *Energy policy*, 36(9): 3578–3587, 2008.

[115] Ali Ipakchi and Farrokh Albuyeh. Grid of the future. *IEEE power and energy magazine*, 7(2):52–62, 2009.

[116] Ramyar Rashed Mohassel, Alan Fung, Farah Mohammadi, and Kaamran Raahemifar. A survey on advanced metering infrastructure. *International Journal of Electrical Power & Energy Systems*, 63:473–484, 2014.

[117] Shi You and Hanmin Cai. Early Experience of the Energy Internet: A Review of Demonstrations and Pilot Applications in Europe. *Energy Internet*, pages 121–133, 2020.

[118] Alexandra Lüth, Jan Martin Zepter, Pedro Crespo del Granado, and Ruud Egging. Local electricity market designs for peer-to-peer trading: The role of battery flexibility. *Applied energy*, 229:1233–1243, 2018.

[119] David B Richardson. Electric vehicles and the electric grid: A review of modeling approaches, impacts, and renewable energy integration. *Renewable and Sustainable Energy Reviews*, 19:247–254, 2013.

[120] Jérôme Le Dréau and Per Heiselberg. Energy flexibility of residential buildings using short term heat storage in the thermal mass. *Energy*, 111:991–1002, 2016.

[121] Cherrelle Eid, Paul Codani, Yannick Perez, Javier Reneses, and Rudi Hakvoort. Managing electric flexibility from Distributed Energy Resources: A review of incentives for market design. *Renewable and Sustainable Energy Reviews*, 64:237–247, 2016.

[122] Søren Østergaard Jensen, Anna Marszal-Pomianowska, Roberto Lollini, Wilmer Pasut, Armin Knotzer, Peter Engelmann, Anne Stafford, and Glenn Reynders. IEA EBC annex 67 energy flexible buildings. *Energy and Buildings*, 155:25–34, 2017.

[123] Rune Grønborg Junker, Armin Ghasem Azar, Rui Amaral Lopes, Karen Byskov Lindberg, Glenn Reynders, Rishi Relan, and Henrik Madsen. Characterizing the energy flexibility of buildings and districts. *Applied Energy*, 225:175–182, 2018.

[124] Antimo Barbato and Antonio Capone. Optimization models and methods for demand-side management of residential users: A survey. *Energies*, 7 (9):5787–5824, 2014.

[125] Toby Brown, Ahmad Faruqui, and Lea Grausz. Efficient tariff structures for distribution network services. *Economic Analysis and Policy*, 48:139–149, 2015.

[126] Endre Bjørndal, Magnus Buvik, Eivind Gramme, Mette Bjørndal, and Christian Børke Nærup. End-User Flexibility in the Local Electricity Grid - Blurring the Vertical Separation of Market and Monopoly? In *52nd Hawaii International Conference on System Sciences*, pages 3560–3570. HICSS, 2019. ISBN 978-0-9981331-2-6.

[127] Vehbi C Gungor, Dilan Sahin, Taskin Kocak, Salih Ergut, Concettina Buccella, Carlo Cecati, and Gerhard P Hancke. Smart grid technologies: Communication technologies and standards. *IEEE transactions on Industrial informatics*, 7(4):529–539, 2011.

[128] Tim Schittekatte, Ilan Momber, and Leonardo Meeus. Future-proof tariff design: Recovering sunk grid costs in a world where consumers are pushing back. *Energy economics*, 70:484–498, 2018.

[129] Jon Gustav Kirkerud, Erik Trømborg, and Torjus Folsland Bolkesjø. Impacts of electricity grid tariffs on flexible use of electricity to heat generation. *Energy*, 115:1679–1687, 2016.

[130] Håvard Hansen, Torfinn Jonassen, Kari Løchen, and Velaug Mook. Høringsdokument nr 5-2017: Forslag til endring i forskrift om kontroll av nettvirksomhet. `http://publikasjoner.nve.no/hoeringsdokument/2017/hoeringsdokument2017_05.pdf`, 2017. Accessed: October 11, 2021.

[131] Gerard L Doorman. Capacity subscription: solving the peak demand challenge in electricity markets. *IEEE Transactions on Power Systems*, 20(1): 239–245, 2005.

[132] Sigurd Bjarghov and Gerard Doorman. Utilizing end-user flexibility for demand management under capacity subscription tariffs. In *2018 15th International Conference on the European Energy Market (EEM)*, pages 1–5. IEEE, 2018.

[133] Hanne Sæle and Bernt A Bremdal. Economic evaluation of the grid tariff for households with solar power installed. *CIRED-Open Access Proceedings Journal*, 2017(1):2707–2710, 2017.

[134] Paul Thorsnes, John Williams, and Rob Lawson. Consumer responses to time varying prices for electricity. *Energy Policy*, 49:552–561, 2012.

[135] Sigurd Bjarghov, Markus Löschenbrand, A.U.N. Ibn Saif, Raquel Alonso Pedrero, Christian Pfeiffer, Shafiuzzaman K Khadem, Marion Rabelhofer, Frida Revheim, and Hossein Farahmand. Developments and challenges in local electricity markets: A comprehensive review. *IEEE Access*, 9:58910–58943, 2021.

[136] Jacopo Torriti. The Risk of Residential Peak Electricity Demand: A Comparison of Five European Countries. *Energies*, 10(3):385, 2017.

[137] Ahmad Faruqui and Sanem Sergici. Household response to dynamic pricing of electricity: a survey of 15 experiments. *Journal of regulatory Economics*, 38(2):193–225, 2010.

[138] Stig Ødegaard Ottesen, Asgeir Tomasgard, and Stein-Erik Fleten. Prosumer bidding and scheduling in electricity markets. *Energy*, 94:828–843, 2016.

[139] Grant Allan, Igor Eromenko, Michelle Gilmartin, Ivana Kockar, and Peter McGregor. The economics of distributed energy generation: A literature review. *Renewable and Sustainable Energy Reviews*, 42:543–556, 2015.

[140] Stian Backe. Reproducible model to compare individual and coordinated demand response with dynamic and static power grid tariffs. Mendeley Data, 2020. v1.

[141] William E Hart, Carl D Laird, Jean-Paul Watson, David L Woodruff, Gabriel A Hackebeil, Bethany L Nicholson, and John D Siirola. *Pyomo-optimization modeling in python*, volume 67. Springer, 2012.

[142] William Karush. Minima of functions of several variables with inequalities as side constraints. *M. Sc. Dissertation. Dept. of Mathematics, Univ. of Chicago*, 1939.

[143] Michael C. Ferris and Todd S. Munson. Complementarity Problems in GAMS and the PATH Solver. *Journal of Economic Dynamics and Control*, 24(2):165–188, 2000.

[144] Stephan Dempe. *Foundations of bilevel programming.* Springer Science & Business Media, 2002.

[145] Stephen C Billups and Katta G Murty. Complementarity problems. *Journal of computational and Applied Mathematics*, 124(1-2):303–318, 2000.

[146] Karen Byskov Lindberg, Steffen J Bakker, and Igor Sartori. Modelling electric and heat load profiles of non-residential buildings for use in long-term aggregate load forecasts. *Utilities Policy*, 58:63–88, 2019.

[147] Stefan Pfenninger and Iain Staffell. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. *Energy*, 114:1251–1265, 2016.

[148] Iain Staffell and Stefan Pfenninger. Using bias-corrected reanalysis to simulate current and future wind power output. *Energy*, 114:1224–1239, 2016.

[149] Alessia De Vita, Izabela Kielichowska, Pavla Mandatowa, et al. Technology pathways in decarbonisation scenarios. `https://ec.europa.eu/energy/sites/ener/files/documents/2018_06_27_technology_pathways_-_finalreportmain2.pdf`, 2018. Accessed: October 11, 2021.

[150] Stian Backe, Dimitri Pinel, Magnus Askeland, Karen Byskov Lindberg, Magnus Korpås, and Asgeir Tomasgard. Zero Emission Neighbourhoods in the European Energy System. https://ntnuopen.ntnu.no/ntnu-xmlui/handle/11250/2730011, 2021. Accessed: October 11, 2021.

[151] Sebastian Zwickl-Bernhard. GUSTO: enerGy commUnity SysTem mOdeling. https://github.com/sebastianzwickl/GUSTO, 2021. Accessed: October 11, 2021.

[152] Bernd Schieferdecker, Christian Fünfgeld, Hermann Meier, and Thomas Adam. Repräsentative VDEW-lastprofile. VDEW-Materialien M-28/99, Frankfurt. https://www.bdew.de/media/documents/1999_Repraesentative-VDEW-Lastprofile.pdf, 1999. Accessed: October 11, 2021.

[153] Anna Kallert, Robert Egelkamp, and Dietrich Schmidt. High Resolution Heating Load Profiles for Simulation and Analysis of Small Scale Energy Systems. *Energy Procedia*, 149:122–131, 2018.

[154] Oliver Ruhnau, Lion Hirth, and Aaron Praktiknjo. Time series of heat demand and heat pump efficiency for energy system modeling. *Scientific data*, 6(1):1–10, 2019.

[155] Scott Burger, Jose Pablo Chaves-Ávila, Carlos Batlle, and Ignacio J Pérez-Arriaga. A review of the value of aggregators in electricity systems. *Renewable and Sustainable Energy Reviews*, 77:395–405, 2017.

[156] Richard Wesley Hamming. *Numerical Methods for Engineers and Scientists.* McGraw Hill. New York, 1962.

[157] George Edward Pelham Box. Science and statistics. *Journal of the American Statistical Association*, 71(356):791–799, 1976.

[158] Faidra Filippidou and Juan Pablo Jimenez Navarro. Achieving the cost-effective energy transformation of Europe's buildings. *Publications Office of the European Union*, EUR 29906 EN, JRC117739, 2019. URL https://doi.org/10.2760/278207.

[159] Kyra Bos and Joyeeta Gupta. Stranded assets and stranded resources: Implications for climate change mitigation and global sustainable development. *Energy Research & Social Science*, 56:101215, 2019.

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Comparing individual and coordinated demand response with dynamic and static power grid tariffs

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ABSTRACT

This paper investigates cost-optimal operation of flexible electricity assets with a capacity-based power grid tariff involving power subscription. The purpose of this research is to identify the characteristics of a subscribed capacity-based tariff that promotes efficient network development through demand response. Using historical load data, we compare two consumers with flexible assets being billed by their individual load versus their combined and coordinated loads in a two-stage stochastic program. The frequency of adjusting the subscribed capacity level (weekly versus annually) influences the effectiveness of the tariff in terms of reducing loads that dimension the grid. The results show that weekly subscription on average provides 5 – 6% cost savings, while annual subscription on average provides 3% cost savings. A combined annual peak load reduction of 15% occurs when the combined subscription level is adjusted weekly. We also find that when the subscription level is adjusted weekly, the load reduction is cost efficient even when capacity is not scarce, which ought to be avoided. Depending on where a bottleneck in the grid is located, the price signal should be based on the combined load of several consumers rather than individual loads if combined peak load shaving is to be cost-optimal.

1. Introduction

Successful mitigation of climate change will require decarbonization of the energy sector, increased production from variable renewable energy sources (RES), and electrification. Several of these measures are likely to be decentralized and require cross-sectoral thinking [1].

Flexibility in power systems relates to the ability to deal with variability in supply and demand. Demand-side flexibility through demand response has been proposed as being significant if assets can be coordinated and aggregated [2–6]. We will refer to consumers with demand-side flexibility as 'prosumers' because they both consume and produce energy services. Prosumers are seen as part of the solution to facilitate a large share of variable RES, making the demand-side more flexible through self-generation, market participation and active responses to price signals [7,8].

Several studies have been performed to analyze prosumer response to different grid tariffs [9–15]. However, to the authors' knowledge, no previous study compares dynamic intra-annual adjustment of tariff parameters with annually fixed parameters and simultaneously considers the difference between providing short-term price signals based on individual loads versus the combined load of several prosumers. To cover this gap, we propose a two-stage stochastic program where uncertainty is related to net load and spot prices with an hourly resolution for different prosumers. The novelty of this paper is using the two-stage stochastic programming framework to compare dynamically adjusting tariff parameters within a year versus statically fixing tariff parameters for a complete year. The paper also has the original contribution of comparing individual versus coordinated asset planning to analyze how effective different versions of a capacity-based grid tariff are in reducing load peaks in the grid. Based on our results, we address the implications for successful grid tariff design, i.e., a design that will trigger efficient utilization of the local flexible assets and reduce the highest loads.

The outline of the paper is as follows: Section 2 introduces the background regarding flexibility in energy systems and the purpose

Abbreviations: C1, Campus 1; C2, Campus 2; CA, Combined annual subscription scheme; CW, Combined weekly subscription scheme; DG, Distributed generation; DSO, Distribution system operator; IA, Individual annual subscription scheme; IW, Individual weekly subscription scheme; PV, Photovoltaic; RES, Renewable energy source.

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of grid tariffs. Section 3 presents the model developed to analyze subscribed capacity-based grid tariff schemes and the assumptions and input for our case study. Section 4 states our model results, while Section 5 discusses the implications of these results. Finally, Section 6 concludes our paper and suggests further research.

2. Background and literature

This section elaborates on the literature and previous studies related to our paper. The first part (Sections 2.1-2.3) explains the context of our study linking flexibility in power systems to grid tariff design, while the last part (Section 2.4) presents the reasoning behind the use of the two-stage stochastic program in this paper.

2.1. Flexibility services in power systems

Flexibility is a term used to characterize a service or property that is part of tangible assets [16]. Flexibility can be characterized along three dimensions based on the *Nordic Balancing Concept*: time, location, and resource type. Properties of the *time* dimension include activation (response) time, ramp-up or down rate, and the duration of the service. The *location* dimension describes how the service from an asset can be provided in geographical locations, e.g. individual unit (building), neighborhood, country, and cross-border. For example, services based on reactive and active power have different geographical relevance. The *type of resource* dimension describes the type of asset in the following classes: supply-side, demand-side, grid-side, and storage [17].

In our analysis, we focus on time horizons with hourly resolution, demand-side flexibility assets, the neighborhood level, and assume that all flexibility assets provide a firm service (there is no uncertainty related to delivery). We assume that the scheduling of flexible assets is driven by the prosumers' wish to minimize the total cost of energy consumption, including net trades in the spot market and the grid tariff paid. In addition, we investigate the effect of prosumer coordination by investigating what happens when an aggregator controls all the flexibility assets to minimize total costs. We do not discuss how to share the benefits of this, e.g. in a flexibility market [18], only the total effect.

2.2. Allocation of ancillary service costs and flexibility

In a power system, distribution of electricity by preserving power quality and maintaining adequate assets in the low voltage grid are the main tasks of a distribution system operator (DSO). The DSO is commonly regulated as a natural monopoly which is challenged by the development of a smart grid [19,20]. Full and timely recovery of network costs is important for the DSO's financial sustainability [21]. A successful tariff design should increase network efficiency in the short-term and signal efficient network capital development in the long-term [22,23].

The tariff design normally includes up to three elements: a fixed element, a volumetric (energy) element, and a capacity element. Volumetric elements generally do not incentivize demand-side flexibility services [24] as opposed to capacity elements that partly charge consumers based on the power use over a measuring period [23]. Due to an increase in distributed generation (DG), especially solar photovoltaics (PV), power systems with net-metering tariff designs are faced with the threat of a *utility death spiral* [25]. The threat appears when DG behind the meter triggers not just energy cost savings, but also tariff savings. Unless the DG reduces the DSO's costs, it creates a marginally higher cost for consumers without DG, which is demonstrated in Ref. [26] where a capacity element in the grid tariff increases the electricity costs up to 10% for consumers with high power outtake in Norway. A redesign of network tariffs is needed to avoid the allocation of grid payments away from DG owners [27].

Most current grid tariff designs in Europe are *static*, i.e., dependent on a single element (commonly energy) without any temporal rate variation [28]. In contrast, a *dynamic* tariff design will depend on several elements and/or be subject to temporal variation. Static tariff designs are practical, predictable, and good at achieving a single long-term objective, e.g. increasing energy efficiency. In theory, dynamic tariffs reflect the DSO's costs better and could create signals to trigger flexibility services by prosumers [29]. However, dynamic tariffs are harder to implement [21] and could cause political challenges related to an 'unfair' change in network costs for certain consumer groups [30].

The signal for flexibility need could be provided using market-based approaches, as proposed in e.g. Ref. [31–33]. An example of a market-based approach calling for flexibility can be found in Ref. [34] which proposes distribution locational marginal pricing. The idea of activating demand-side flexibility in both market-based solutions and through dynamic grid tariffs is to create price signals to trigger efficient flexibility responses. We analyze how market-based approaches could be similar to responding to a dynamic grid tariff. In Ref. [35], they analyzed different ways of creating incentives for prosumer flexibility, including tariff redesign and a direct payment to flexibility providers. They find that a redesign of network tariffs is up to 20% less costly than direct payment to flexibility providers. However [35], does not consider how the network tariffs should be redesigned.

2.3. Grid tariff design in Norway

Currently in Norway, grid tariffs for residential consumers have a fixed element and a volumetric element. The volumetric element is location dependent through a marginal loss factor, which reflects how far electricity generation is from a consumer [28]. The current Norwegian grid tariff design does not price high power outtakes for households [26], and it is shown that dynamic tariffs provide incentives for better utilization of the grid [36].

In this paper, we analyze the 'subscribed capacity' grid tariff scheme proposed by the Norwegian Regulator [37], where consumers subscribe to a capacity level. If their hourly load exceeds the subscribed level, a penalty is charged depending on the violation (see Fig. 1). As consumers pay both for the subscribed level and the penalty, they have incentives to subscribe to as low capacity as possible providing they can stay below it most of the time. We analyze four different versions of the subscribed capacity tariff scheme. In the first version, consumers have individual subscriptions that cannot be changed for a year (individual annual subscription). The second version is individual subscriptions where the consumers can adjust the subscription level on a weekly basis (individual weekly subscription). The third version is a combined capacity subscription on the total load of several consumers combined, and the subscription is fixed for one year (combined annual subscription). Finally, the fourth version is a combined subscription for several consumers that can be changed on a weekly basis (combined weekly subscription). By comparing these four versions of the subscribed capacity grid tariff, our contribution is to elaborate on the effect of providing inter-weekly rather than inter-annual tariff adjustment and coordinated rather than individual scheduling of flexibility assets. We study the effect on (1) the resulting cost savings and cost-optimized responses by prosumers minimizing their electricity bill and (2) the total peak load reduction for the grid. We assume the tariff rates are as presented in Ref. [37] (see Table 1). These rates are suggested by the Norwegian Regulator upon analyzing measured load data from 500 Norwegian consumers, and the rates are determined subject to the criteria that

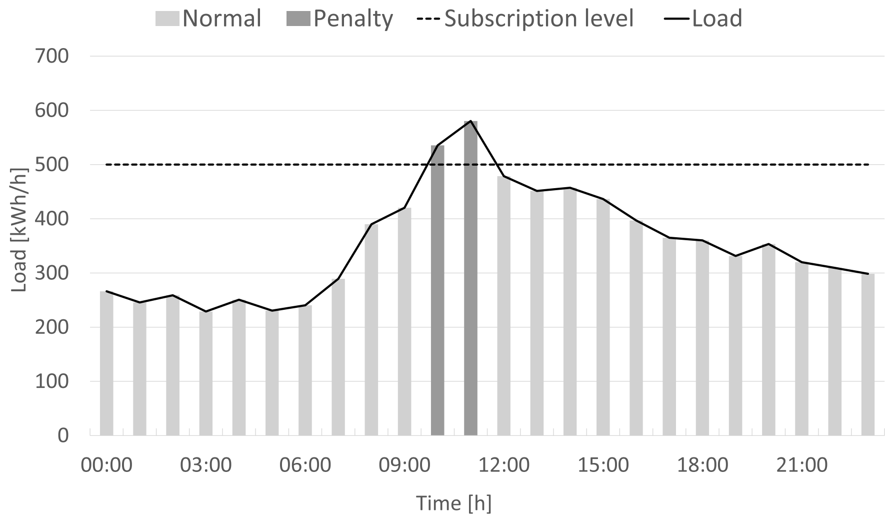


Fig. 1. Illustration of the 'subscribed capacity' grid tariff scheme. The illustration shows an example of measured hourly load over 24 h for the combined load of Campus 1 (C1) and Campus 2 (C2) and a combined subscription. The horizontal line represents the subscription level which causes a penalty charge for hours 11 and 12 (load exceeds subscribed level).

Table 1
Grid tariff rates provided as input in all our 52 instances. The rates are assumed to be as proposed by the Norwegian regulators [37] (see Section 2.3).

	c^{sub} [NOK/kW/year]	c^{norm} [NOK/kWh]	c^{pen}[NOK/kWh]
Rates	689	0.0500	1.00

the same annual income to the DSO is provided as with the current Norwegian gird tariff scheme.

2.4. Two-stage stochastic programming approach

Stochastic programming supports decision making under uncertainty [38]. In Ref. [39], a stochastic programming approach is used to analyze trading between prosumers under uncertainty; however, there are not multiple stages. Throughout different stages in stochastic programming, a decision maker ought to make decisions for short-term and long-term plans, where stages represent realization of uncertain outcomes. In our case, the short-term plans include operating flexible assets to minimize costs given a realization of prosumer load and day-ahead prices, and the long-term plan involves tuning the tariff parameters. We use two-stage stochastic programming to analyze the difference between long-term and short-term adjustment of the tariff parameters, where short-term adjustment of the tariff parameters is analyzed by solving deterministic versions of our two-stage stochastic program. Other examples of two-stage programming approaches for addressing uncertainty in energy management are [40–42].

3. The mathematical model

In this section, we present the model for the prosumer's cost-minimization problem. The model is a two-stage stochastic linear program [43] where the first-stage decisions include deciding the subscribed capacity level and the second-stage decisions include operating flexible assets. The complete nomenclature of the model can be found in Appendix A.

3.1. Time structure

The model considers one temporal scale with all operational time periods defined in the ordered set $\mathcal{T} = \{1, 2, \ldots, |\mathcal{T}|\}$. In every time step, decisions about how to operate a flexible asset is supported. Operational (second-stage) decisions can be different in all stochastic scenarios ω in the set of all scenarios Ω. Each stochastic scenario represents one realization of prosumer load and electricity spot prices for a time horizon. The flexible assets are located at different prosumers $p \in \mathcal{P}$, and the scenario independent first-stage decision is the subscribed capacity x_p^{I}.

The model includes flexible asset types $f \in \mathcal{F}$. If asset type f is located at prosumer p, it belongs to the set $\mathcal{F}_p \subseteq \mathcal{F}$. Any flexible asset type f is modelled as a conceptual storage. Depending on the asset type, it can be flexibly charged (prosumer demand can be increased, e.g. electric vehicle [44]); it can be flexibly discharged (prosumer demand can be decreased, e.g. curtailable loads [45]); or it can be both flexibly charged and discharged (e.g. battery [46]). Note that there is no resolving of uncertainty within a scenario as time passes, hence the storages are operated with perfect foresight within a scenario. For a static tariff where the subscribed capacity is decided for a year, each scenario may consist of all hours in a week with $\mathcal{T} = \{1, 2, \ldots, 168\}$. Scenarios can be sampled from historical data, and ideally, they represent seasonal variations over a year. If the scenarios represent all weeks of a year, we would have $\Omega = \{1, 2, \ldots, 52\}$. Note that each scenario is independent with no link or dependency between operations or storage levels in two subsequent scenarios.

3.2. Objective function

The objective function for an individual prosumer, z^{I}, minimizes the electricity bill by scheduling flexible assets subject to energy costs and a grid tariff:

$$\min z^{\mathrm{I}} = \sum_{p\in\mathscr{P}}\left(c^{\mathrm{sub}}x_p^{\mathrm{I}} + \sum_{\omega\in\Omega}\pi_\omega\sum_{t\in\mathscr{T}}\left(k^{\mathrm{I}}_{p,t,\omega} + c^{\mathrm{ret}}_{t,\omega}y^{\mathrm{load}}_{p,t,\omega}\right)\right), \quad (1)$$

where x_p^{I} are variables for the subscribed capacity level for prosumer p, the π_ω are scenario probabilities, and $k^{\mathrm{I}}_{p,t,\omega}$ are variables identifying the tariff cost depending on the prosumer's grid interaction in different scenarios. Resulting load profiles (import from the grid to the prosumer) are identified through the second-stage variables $y^{\mathrm{load}}_{p,t,\omega}$ and vary by scenario. The objective contains a time varying load dependent retail cost ($c^{\mathrm{ret}}_{t,\omega}$) and a fixed capacity dependent subscription cost (c^{sub}) for the capacity subscription.

For prosumer p, the tariff cost is identified through a two-step linear cost function depending on the subscribed capacity level x_p^{I} and the prosumer load $y^{\mathrm{load}}_{p,t,\omega}$:

$$c^{\mathrm{norm}}y^{\mathrm{load}}_{p,t,\omega} \le k^{\mathrm{I}}_{p,t,\omega}, p\in\mathscr{P}, t\in\mathscr{T}, \omega\in\Omega, \quad (2)$$

$$c^{\mathrm{pen}}\left(y^{\mathrm{load}}_{p,t,\omega} - x_p^{\mathrm{tariff}}\right) + c^{\mathrm{norm}}y^{\mathrm{load}}_{p,t,\omega} \le k^{\mathrm{I}}_{p,t,\omega}, p\in\mathscr{P}, t\in\mathscr{T}, \omega\in\Omega, \quad (3)$$

where c^{norm} and c^{pen} are load dependent prices for loads below and above the subscribed capacity, respectively. Constraints (2) make sure that the tariff has a lower bound of load multiplied by the cost below the subscribed capacity, whereas constraints (3) ensure that the tariff cost is increased when load exceeds the subscribed capacity to the penalty cost multiplied by the load.

3.3. Constraints

The original load before scheduling of the flexible assets (expected net demand) for electricity at prosumer p at time t in scenario ω is denoted $\xi^{\mathrm{load}}_{p,t,\omega}$. The total import from the grid to prosumers is identified in the following constraints:

$$y^{\mathrm{load}}_{p,t,\omega} = \xi^{\mathrm{load}}_{p,t,\omega} + \sum_{f\in\mathscr{F}_p}\left(w^{\mathrm{charge}}_{p,f,t,\omega} - \varepsilon_f^{\mathrm{discharge}}w^{\mathrm{discharge}}_{p,f,t,\omega}\right),$$
$$p\in\mathscr{P}, t\in\mathscr{T}, \omega\in\Omega, \quad (4)$$

where $w^{\mathrm{charge}}_{p,f,t,\omega}$ is charging of flexible asset type f at prosumer p while $w^{\mathrm{discharge}}_{p,f,t,\omega}$ is discharging. Constraints (4) ensure that prosumer p at time t will have a resulting load equal to the original load plus the charged and discharged energy from all the flexible assets at the prosumer. Note that losses $\varepsilon_f^{\mathrm{discharge}}$ are only considered for discharged energy in (4).

In time period t, $w^{\mathrm{storage}}_{p,f,t,\omega}$ is the available energy in flexible asset type f at prosumer p. The balance of storage must be maintained in between operational time steps:

$$\kappa_{p,f}\eta^{\mathrm{storage}}_{p,f,1} + \varepsilon_f^{\mathrm{charge}}w^{\mathrm{charge}}_{p,f,1,\omega} - w^{\mathrm{discharge}}_{p,f,1,\omega} = w^{\mathrm{storage}}_{p,f,1,\omega}, p\in\mathscr{P}, f\in\mathscr{F}_p,$$
$$\omega\in\Omega. \quad (5)$$

$$\varepsilon_f^{\mathrm{diff}}w^{\mathrm{storage}}_{p,f,t-1,\omega} + \varepsilon_f^{\mathrm{charge}}w^{\mathrm{charge}}_{p,f,t,\omega} - w^{\mathrm{discharge}}_{p,f,t,\omega} = w^{\mathrm{storage}}_{p,f,t,\omega}, p\in\mathscr{P}, f\in\mathscr{F}_p,$$
$$t\in\{2,\ldots,|\mathscr{T}|\},$$
$$\omega\in\Omega. \quad (6)$$

Constraints (5) make sure that a flexible asset type f at prosumer p start the operational horizon ($t = 1$) in scenario ω with an initial energy level equal to a percentage of installed capacity ($\kappa_{p,f}$) plus charging (subject to losses) minus discharging. Constraints (6) make sure that flexible asset type f at prosumer p has an energy level equal to the energy level from the previous period (subject to diffusion losses) plus charging in the current period (subject to losses) minus discharging for all operational time steps and scenarios. Losses are type dependent factors for flexible asset type f and they are considered for charging ($\varepsilon_f^{\mathrm{charge}}$), discharging ($\varepsilon_f^{\mathrm{discharge}}$) and diffusion of stored energy content ($\varepsilon_f^{\mathrm{diff}}$). Note that no losses are considered for discharging in (5) or (6) since it is accounted for in (4). The maximum energy content ($\eta^{\mathrm{storage}}_{p,f}$), charging ($\eta^{\mathrm{charge}}_{p,f}$) and discharging ($\eta^{\mathrm{discharge}}_{p,f}$) of flexible asset type f at prosumer p are defined as upper bounds for all time periods and scenarios.

Constraints (7) ensure that the energy level of flexible asset type f at prosumer p is at least the required level $\gamma^{\mathrm{req}}_{p,f,t}$ in period t for all scenarios:

$$\gamma^{\mathrm{req}}_{p,f,t} \le w^{\mathrm{storage}}_{p,f,t,\omega}, p\in\mathscr{P}, f\in\mathscr{F}_p, t\in\mathscr{T}, \omega\in\Omega. \quad (7)$$

The individual objective z^{I} in (1) is combined with constraints (2)–(7) to find the subscribed capacity level that minimize the combined energy and tariff cost.

3.4. Coordinated scheduling of flexible assets

The individual prosumer model can be extended to a model where an aggregator coordinates all flexible assets by changing the objective. The combined objective function minimizes the electricity bill for all consumers with flexible assets where the billing of the grid tariff is based on the combined load profile in the following way:

$$\min z^{\mathrm{C}} = c^{\mathrm{sub}}x^{\mathrm{C}} + \sum_{\omega\in\Omega}\pi_\omega\sum_{t\in\mathscr{T}}\left(k^{\mathrm{C}}_{t,\omega} + \left(\sum_{p\in\mathscr{P}}c^{\mathrm{ret}}_{t,\omega}y^{\mathrm{load}}_{p,t,\omega}\right)\right), \quad (8)$$

where x^{C} is a decision variable for the combined subscription level for all prosumers, and $k^{\mathrm{C}}_{t,\omega}$ are variables identifying the combined tariff cost depending on the sum of imports from the grid to all prosumers.

The total electricity load of all prosumers will determine the combined tariff cost through a two-step linear function:

$$c^{\mathrm{norm}}\sum_{p\in\mathscr{P}}y^{\mathrm{load}}_{p,t,\omega} \le k^{\mathrm{C}}_{t,\omega},\ t\in\mathscr{T}, \omega\in\Omega, \quad (9)$$

$$c^{\mathrm{pen}}\left(\sum_{p\in\mathscr{P}}y^{\mathrm{load}}_{p,t,\omega} - x^{\mathrm{C}}\right) + c^{\mathrm{norm}}\sum_{p\in\mathscr{P}}y^{\mathrm{load}}_{p,t,\omega} \le k^{\mathrm{C}}_{t,\omega},\ t\in\mathscr{T}, \omega\in\Omega. \quad (10)$$

Similar to constraints (2) and (3), constraints (9) make sure that the tariff has a lower bound of *the combined* load multiplied by the cost below the subscribed capacity, whereas constraints (10) ensure that the tariff cost is increased when *combined* load exceeds the subscribed capacity to the penalty cost multiplied by the load, respectively.

The combined objective z^{C} in (8) along with constraints (4)–(7) and (9)–(10) form a problem that cannot be decomposed per

Table 2
Assumed operational characteristics of the flexible asset types available for demand-side management at each of the two prosumers (Campus 1 (C1) and Campus 2 (C2)). The parameters identify available capacity for charging, discharging and storage.

Flexible asset	η^{charge}[kWh/h]	$\eta^{\text{discharge}}$[kWh/h]	η^{storage} [kWh]
Electric battery	100	100	200
Vehicle charging	50.0	0.00	500
Curtailable loads	0.00	50.0	200

prosumer due to constraints (9)–(10) that make the tariff cost $k^{C}_{t,\omega}$ dependent on the load of all prosumers.

4. Case study for capacity-based grid tariff in Norway

In this section, the models presented in Section 3 are used to analyze the scheduling of flexible assets reacting to both an hourly retail price and a subscribed capacity-based grid tariff. We present the input data and assumptions (Section 4.1) before the results (Section 4.2). All input data, the implemented model, and output data is available in Refs. [47] for the reproduction of this case study.

4.1. Input data and problem instances

We build four classes of problem instances:

1. Individual Annual (IA): Subscribed capacity tariff based on the individual objective (1) under annual decisions on subscribed capacity level,
2. Individual Weekly (IW): Subscribed capacity tariff based on the individual objective (1) under weekly decisions on subscribed capacity level,
3. Combined Annual (CA): Subscribed capacity tariff based on the combined objective (8) under annual decisions on subscribed capacity level,
4. Combined Weekly (CW): Subscribed capacity tariff based on the combined objective (8) under weekly decisions on subscribed capacity level.

For IA and CA, we use stochastic models with sampled weeks representing the scenarios. Each week is a scenario with 168 h. For IW and CW, we optimize the subscribed capacity level weekly (only one scenario). This resembles a dynamic subscribed capacity tariff. As the model is solved under perfect foresight, it is overestimating the ability to estimate exactly the optimal subscribed capacity for the week.

The tariff rates used are as proposed by the Norwegian Regulator in Ref. [37] (see Table 1). We sample historical hourly load profiles from a rural Norwegian university campus, Campus Evenstad, from 50 weeks during 2016. We assume that two university campuses exist in the same part of the distribution grid, ‘Campus 1’ (C1) and ‘Campus 2’ (C2). Odd weeks are sampled from Campus Evenstad to create weekly load profiles with hourly resolution for C1 and even weeks for C2. Here, the samples are made so that two consecutive weeks from Campus Evenstad occur in parallel for C1 and C2 making up a total of 25 weeks for the study.

Three flexible asset types exist in the model at both prosumers: electric battery, electric vehicle charging and curtailable loads (e.g. fuel switching from electric to bio-based heating). Their assumed operational characteristics are presented in Table 2. Losses are assumed to be 1% for charging and discharging of all flexible assets. Diffusion losses are only defined for the electric battery at 0.1% per time step.

For vehicle charging, an annual demand of 14,000 km per vehicle is chosen based on the average use of battery electric vehicles in 2018 in the county of Campus Evenstad (Hedmark) [48]. Further, we assume one electric car needs 0.2 kWh per km,[1] so one car needs (on average) $\frac{14{,}000}{52}(0.2) = 54$ kWh/week. Then, a weekly demand of 500 kWh covers nine to ten vehicles (see Table 2). Some of the weekly demand must be met every 24 h, meaning daily demands sum up to the total weekly demand (see Fig. 2). The vehicle charging demand is essentially a lower bound for the energy level in the flexible asset f at prosumer p and time t implemented through the variables $\gamma^{\text{req}}_{p,f,t}$and constraints (7).

C1 and C2 face hourly retail prices that are dependent on the historical market data from price zone NO1 in Nord Pool in 2016. Retail prices follow the Nord Pool day ahead spot price plus Norwegian electricity charges and 25% VAT, and we sample hourly prices from odd weeks in 2016.

The two deterministic classes (IW and CW) for the two prosumers represent in total 50 instances for the 25 weeks, while the two stochastic classes (IA and CA) represent in total two instances for the 25 weeks. The model is implemented in the open-source optimization modeling language Pyomo [49] through Python version 2.7.8 and solved using Gurobi version 8.0.1. The optimization was run on a computer with an Intel(R) Core(TM) i7-7500U processor with CPU at 2.70 GHz and 16.0 GB installed memory (RAM). The total run time for all instances (50 deterministic + 2 stochastic) including reading, building, solving and printing results is around 60 s.

4.2. Results

This section describes the results from analyzing the four capacity subscriptions (IW, CW, IA, and CA) presented in Section 4. Recall that the modified load profile is a result of the model responding to the different schemes by (a) finding the cost minimizing subscribed capacity level and (b) operating the flexible assets to minimize the total electricity bill including variable energy costs and grid costs.

Table 3 presents the total electricity bill costs before and after the flexibility responses are optimized for the four different schemes. The cost ex-ante optimization is calculated by optimizing the subscription level without any flexibility available and includes constant charging to meet weekly vehicle charging demand of 500 kWh at each campus site. On average, the flexibility responses contribute to 5–6% savings for the weekly subscriptions (IW and CW), while 3% savings are achieved on average for the annual subscriptions (IA and CA).

The top part of Table 3 shows the results from the most expensive scenario (week 24), where costs avoided from responding to the grid tariff scheme (‘Grid’ in Table 3) are the dominant part of the savings as compared to the saved energy cost (‘Energy’ in Table 3). The results of all weeks for the weekly subscriptions (IW and CW) show that the grid savings are the dominant part of the savings for 23 weeks, i.e., there are more savings related to the grid tariff than hourly retail prices for the weekly subscriptions. For the annual subscriptions, the grid savings only dominate the savings for eight weeks for the IA scheme and six weeks for the CA scheme, indicating that responding to retail prices is more valuable than responding to the grid tariff for the annual subscriptions (the opposite to the weekly subscriptions). The bottom part of Table 3 lists the results from the scenario with the highest savings (week 2). Here, the energy costs avoided from responding to retail price variations are the dominant part of the

[1] https://pushevs.com/electric-car-range-efficiency-epa/accessed: April 15, 2020.

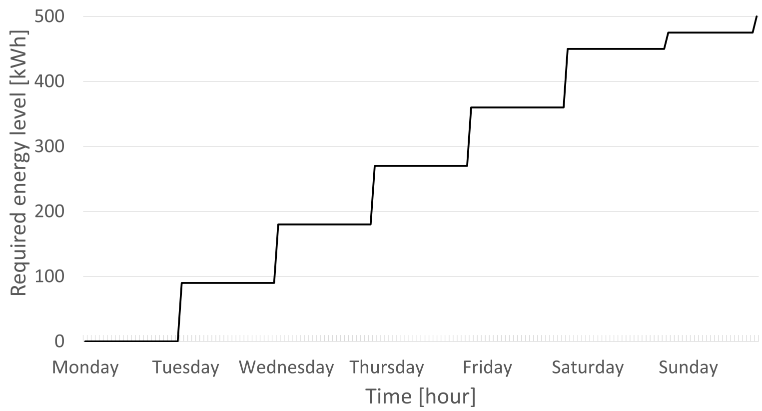


Fig. 2. The lower bound for energy that must be charged by time $t \in \mathcal{T}$ to battery electric vehicles. This offers flexible charging in every time-step with some constraints (daily demands).

Table 3
Cost results summed for both prosumers in NOK ex-ante (before flexibility responses) and ex-post (after flexibility responses) for the individual weekly (IW), combined weekly (CW), individual annual (IA), and combined annual (CA) schemes. The table displays results for the most expensive scenario (week 24, top) and the scenario with highest cost savings from flexible operation (week 2, bottom). The two last columns show cost savings from responding to a variation in day-ahead spot price ('Energy') and responding to the subscribed capacity scheme ('Grid').

Scheme	Total cost,	Total cost,	Cost decrease	
	ex-ante	ex-post	Energy	Grid
Week 24				
IW	59,300 NOK	57,600 NOK (−3%)	468 NOK	1220 NOK
CW	58,900 NOK	57,100 NOK (−3%)	494 NOK	1230 NOK
IA	69,100 NOK	67,900 NOK (−2%)	475 NOK	716 NOK
CA	68,100 NOK	66,800 NOK (−2%)	448 NOK	825 NOK
Week 2				
IW	48,200 NOK	43,300 NOK (−10%)	4170 NOK	676 NOK
CW	46,900 NOK	42,300 NOK (−10%)	3990 NOK	615 NOK
IA	48,700 NOK	44,100 NOK (−9%)	4110 NOK	401 NOK
CA	46,900 NOK	42,400 NOK (−10%)	4000 NOK	526 NOK

savings for all schemes, which is linked to the average weekly spot price being highest for week 2 (0.72 NOK/kWh). This indicates that the load reduction in response to a grid tariff could be challenged by high and variable retail prices if the two price signals are not correlated.

Table 4 presents the weekly subscription level for C1 and C2. The last two columns in Table 4 are the sum of subscription levels for C1 and C2 from the individual metering schemes. Note that for the annual subscriptions (IA and CA), the subscription level is the same for all weeks. The average of the weekly subscription levels for all 25 weeks is consistently less than the annual subscription levels (see the bottom row in Table 4), which strengthens the need for the two-stage stochastic programming approach. The highest weekly combined subscription level is chosen in week 24 (591 kWh/h, see the CW column in Table 4). The sum of the weekly individual subscription levels for week 24 exceeds the combined subscription level ($246 + 374 = 620$ kWh/h, see the last two columns in Table 4), which is also the case for 92% of the weeks (all weeks except weeks 4 and 23, see Table 4). This is an indication that rationing several prosumers combined is less conservative than rationing them individually.

Table 4
Resulting cost-optimal subscription levels in kWh/h in all 25 weeks. The columns represent the subscription levels for the individual weekly (IW), combined weekly (CW), individual annual (IA), and combined annual (CA) schemes for Campus 1 (C1), Campus 2 (C2), and combined. The last column shows the sum of individual subscription levels (C1+C2) for comparison with the combined subscription level.

	C1		C2		Combined		C1+C2	
Week	IW	IA	IW	IA	CW	CA	IW	IA
1	151	197	181	216	315	387	332	413
2	251	197	196	216	398	387	447	413
3	138	197	134	216	271	387	272	413
4	143	197	137	216	282	387	280	413
5	137	197	280	216	405	387	417	413
6	197	197	86	216	283	387	283	413
7	108	197	118	216	223	387	226	413
8	111	197	171	216	273	387	282	413
9	186	197	184	216	337	387	370	413
10	122	197	138	216	247	387	260	413
11	142	197	120	216	258	387	262	413
12	112	197	101	216	208	387	213	413
13	79	197	79	216	157	387	158	413
14	76	197	78	216	154	387	154	413
15	39	197	40	216	78	387	79	413
16	50	197	123	216	159	387	173	413
17	98	197	115	216	211	387	213	413
18	136	197	135	216	262	387	271	413
19	156	197	122	216	263	387	278	413
20	96	197	159	216	212	387	255	413
21	148	197	216	216	340	387	364	413
22	268	197	193	216	416	387	461	413
23	254	197	215	216	478	387	469	413
24	246	197	374	216	591	387	620	413
25	164	197	253	216	374	387	417	413
Average	144	197	158	216	288	387	302	413

Table 5
Annual original and resulting peak load in kWh/h for Campus 1 (C1), Campus 2 (C2) and combined for the individual weekly (IW), combined weekly (CW), individual annual (IA), and combined annual (CA) schemes. Note that the 'original' column represents the annual peak load ex-ante flexibility responses. The bold font marks the scheme triggering the lowest annual peak for C1, C2, and combined. The numbers in parentheses identify the week in which the annual peak load occurs.

Prosumer	Original	IW	CW	IA	CA
C1	413 (2)	**322** (2)	365 (2)	413 (2)	410 (2)
C2	479 (5)	**426** (24)	441 (24)	444 (24)	444 (24)
Combined	696 (24)	672 (24)	**591** (24)	696 (24)	696 (24)

Table 5 presents the results for the annual peak load at the individual prosumers (C1 and C2) and combined for both prosumers. Weekly individual (IW) subscription triggers the largest individual annual peak shaving, while weekly combined (CW) subscription best achieves combined annual peak shaving. The CW scheme reduces the original annual combined peak by 105 kWh/h (−15%), which is more than four times the annual combined peak shaving triggered by the IW scheme (24 kWh/h, −3%) (see Table 5). Annual subscriptions (IA and CA) trigger little or no annual peak load reduction of individual or combined load profiles (see Original, IA, and CA columns in Table 5).

Fig. 3 shows how the different schemes perform in reducing the weekly peak loads. For weekly subscriptions (IW and CW), some peak shaving is cost-optimal in all weeks, including weeks where the original weekly combined peak load is small (see e.g. the blue and orange bars in week 15 in Fig. 3). For annual subscriptions (IA and CA), the weekly combined peak load generally increases in low demand weeks and decreases in high demand weeks (see the yellow and gray bars in Fig. 3). However, the highest weekly combined peak load is unaffected for the annual subscriptions (see the yellow and gray bars in week 24 in Fig. 3).

Fig. 4 presents the hourly load profiles in week 24 with the highest annual combined load originally. The plot also shows the hourly retail price linked to the hourly day-ahead wholesale price. For all pricing schemes, flexible assets are operated to generally increase the load in low retail price hours, and decrease the load in high retail price hours: low loads occur in all pricing schemes when the retail price (green dotted line) is peaking in Fig. 4. For the weekly subscriptions (see Fig. 4a and b), load profile modifications are similar; however, combined peak shaving is significantly larger for the CW scheme compared to the IW scheme (see bottom row in Table 5).

Fig. 5 presents the relationship between grid costs (grid price multiplied by the load) and the combined load from C1 and C2 for the different pricing schemes. The CA scheme (yellow in Fig. 5) offers the highest cost (344 NOK/kWh) during the annual peak load in week 24 because it is the highest combined load and it exceeds the combined subscription level (387 kWh/h, see Table 4). Note that (a) paying this high penalty is cost-optimal in the CA scheme considering total cost over the whole year and (b) there is no combined peak load shaving in week 24 as a consequence of the high penalty (see the bottom row in Table 5 and the yellow bar in week 24 in Fig. 3). Fig. 5 also shows that the IA scheme has many penalty hours below the sum of the subscribed levels (413 kWh/h, see Table 4) because the individual loads exceed the individual subscription levels without causing a high combined load. This is a shortcoming of the individual subscribed capacity tariff in terms of signaling efficient grid utilization, as it often penalizes situations where the total flow into C1 and C2 is lower than the joint subscribed capacity (recall that the sum of the individual subscription levels is higher than the combined subscription level in 92% of the weeks, see Table 4). For the weekly subscriptions (IW and CW), there are significantly less penalty hours than for the annual subscriptions since the subscription can be adjusted for each week (see yellow and gray dots compared to orange and blue dots in Fig. 5). The CW scheme has the least amount of penalty hours after flexibility responses (see orange dots in Fig. 5), and it is the scheme that most successfully reduces the annual combined peak load (see Table 5).

5. Discussion

Our case study has been performed assuming perfect foresight on hourly load and retail prices for 25 weeks and no disutility (costs) of operating flexible assets except energy losses (see constraints (4)–(3.3) in Section 3.3). This means our results represent an upper bound to how much cost reduction prosumers can obtain for the different pricing schemes. Note that the stochastic structure of the problem in our case study is related to price and load variation between weeks, i.e., there is no uncertainty within a week. Note also that because we consider energy losses from flexibility responses, total energy consumption increases slightly after demand response even though total costs decrease.

The CW scheme is better at decreasing the weekly combined peak load than the IW scheme. This is a central feature as it is the combined load that dimension the grid connecting C1 and C2 to the rest of the system. However, three weeks show a higher combined peak load for the CW scheme compared to the IW scheme (see

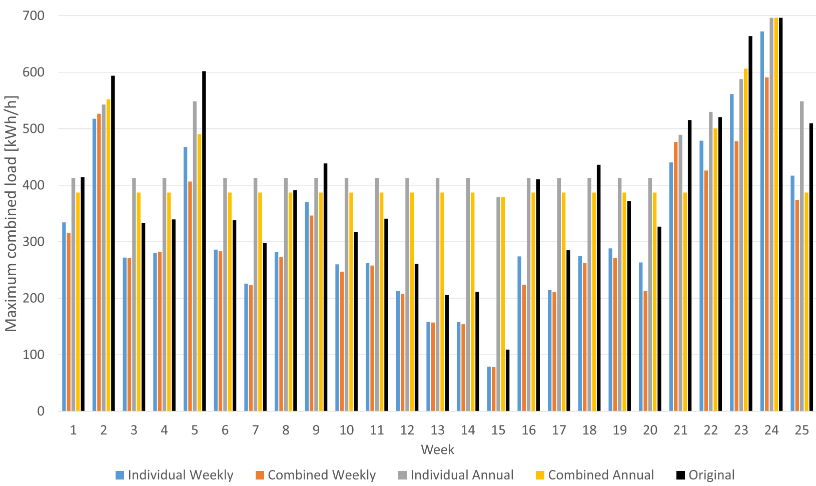
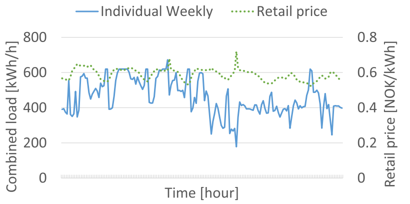
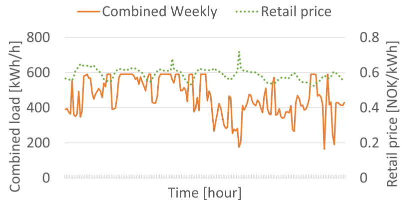


Fig. 3. Weekly combined maximum load after cost-optimal response to the individual weekly (IW) scheme (blue), combined weekly (CW) scheme (orange), individual annual (IA) scheme (gray), and combined annual (CA) scheme (yellow). The original maximum loads in the different weeks are displayed in black. The highest combined load occurs in week 24 where the combined weekly (CW) scheme triggers most peak load shaving. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

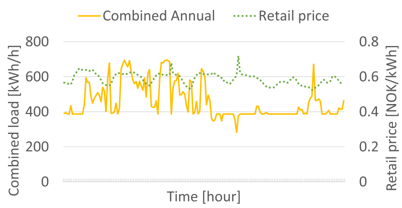


(a) Resulting cost-optimal load (blue) with the individual weekly (IW) scheme.



(b) Resulting cost-optimal load (orange) with the combined weekly (CW) scheme.

(c) Resulting cost-optimal load (gray) with the individual annual (IA) scheme.



(d) Resulting cost-optimal load (yellow) with the combined annual (CA) scheme.

Fig. 4. Resulting combined hourly load profile for 168 h for the individual weekly (IW) scheme (Fig. 4a), combined weekly (CW) scheme (Fig. 4b), individual annual (IA) scheme (Fig. 4c), and combined annual (CA) scheme (Figure d) in week 24 when the original maximum combined load is occurring. The left axis shows hourly load in kWh/h (solid lines) and the right axis shows hourly retail price in NOK/kWh (green dotted lines). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

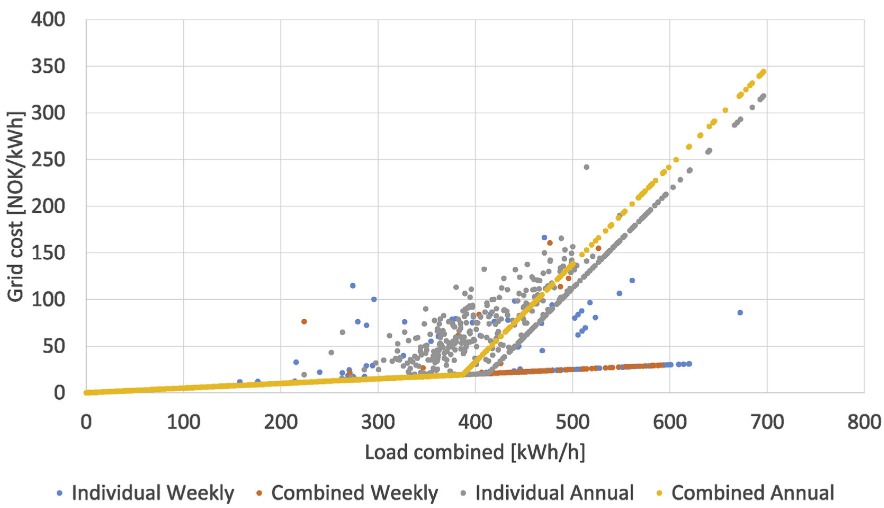


Fig. 5. Resulting hourly load dependent grid tariff costs, i.e., load dependent price multiplied by the load, in NOK/kWh plotted against the combined load of Campus 1 (C1) and Campus 2 (C2) for the individual weekly (IW) scheme (blue), combined weekly (CW) scheme (orange), individual annual (IA) scheme (gray), and combined annual (CA) scheme (yellow). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

weeks 2, 4, and 21 in Fig. 3). This occurs due to three different (but related) reasons that are worth noticing:

- For week 2, the opportunity to respond to retail prices is more valuable than responding to the grid tariff scheme (see Table 3). The two opportunities for cost saving could be conflicting.
- For week 4, the sum of the individual subscription levels is slightly lower than the combined subscription level (see Table 4), so the individual subscriptions are more 'conservative' than the combined subscription.
- For week 21, low subscription cost and high penalty loads in the CW scheme are compensated by high subscription cost and low penalty loads in the IW scheme, so peak shaving is not always the cost-optimal response with the subscribed capacity scheme.

Two main factors should be considered depending on the goal of introducing a capacity-based grid tariff scheme: (1) The dynamics of the grid tariff, i.e., the adjustment frequency of tariff rates and subscription levels, and (2) the load signal that the grid tariff will depend on.

The first factor, the grid tariff dynamics, will impact the achievement of peak shaving through flexibility (see Fig. 3). For an annual decision on the grid subscription level, the cost-optimal strategy is to consider a full year of costs when finding the best subscription level. This consideration means the subscription level is too low for critical hours because costs are minimized for the whole year. Annual subscriptions also lead to more penalty hours than weekly subscriptions, i.e., annual subscriptions make it cost-optimal for prosumers to exceed their subscription level. However, weekly subscriptions trigger load reduction in weeks when grid capacity is not scarce, which results in a potential loss of consumer welfare by penalizing utilization of idle grid capacity. A lower bound on the subscription level combined with dynamic subscription rates can be introduced to avoid rationing of capacity during non-critical hours.

The second factor, the load signal, will impact at which connection point peak shaving is triggered (see Table 5). Under the condition that prosumers have significantly different hourly load profiles,[2] shaving peaks based on individual metering does not maximize the annual peak shaving of the combined load profile. There is more variety in load profiles of buildings for various purposes (e.g. households, shops, offices, etc.) [50], and the flexibility potential will likely vary for the different buildings [51]. The objective of reducing individual loads could be in competition with reducing the combined load, i.e., the individual load could increase and the combined load decrease within a measuring period (and vice versa). If the goal of a capacity-based grid tariff scheme is to trigger combined peak load shaving for a collection of prosumers, price signals based on individual metering are likely to be suboptimal (see Table 5) and could compromise consumer welfare when considering the disutility of offering flexibility. If the price signal is based on the combined load at a bottleneck connection of the grid, it is more likely to trigger combined peak load shaving.

In Norway, all grid-connected consumers are obliged to have individual metering, and this requirement is not challenged by introducing combined price signals. One could identify combined loads through: (a) summing individually metered data, or (b) combined metering at a potential bottleneck. This also points to other alternatives for local coordination in the grid, for example through flexibility markets. The efficiency of flexibility markets for resource allocation, either as an alternative or supplement to dynamic capacity-based grid tariffs, is an interesting area of future research.

[2] A quality check has been performed with our model confirming there is no difference between individual (IW and IA) and combined (CW and CA) metering schemes when two prosumers have identical load profiles.

6. Conclusion

This paper analyzes four different capacity-based grid tariff subscriptions by using a two-stage stochastic programming model in a case study of a Norwegian campus site with flexible assets. The novelty of our analysis includes: (1) comparing long-term annual tariff adjustment with short-term weekly tariff adjustment and (2) comparing the combined and coordinated demand response of several prosumers with the individual responses of single prosumers. The results show that cost-optimal operation of the flexible assets varies depending on the design of the grid tariff scheme. We find that a weekly adjustment of the subscribed grid tariff triggers a reduction in the maximum weekly load more efficiently than an annual subscription in 92% of the simulated weeks, while the combined subscription triggers combined load reduction more efficiently than individual subscriptions in 88% of the simulated weeks. According to our results, the capacity-based grid tariff subscription scheme is likely to be successful in promoting efficient grid development if: (1) the tariff parameters (subscription level) can be adjusted more frequently than annually and (2) the price signals for scarcity in the grid depend on the combined load of several consumers rather than the individual loads. The analysis also indicates that the tariff rates should be adjusted within a year to account for annual load variability and avoid rationing when grid capacity is not scarce. Depending on where a bottleneck in the grid is located, the price signal from a capacity-based tariff should be based on the combined load of several consumers behind this bottleneck (rather than individual load profiles) given different individual load profiles.

Further research should expand the stylized case study to see the impact in a larger collection of different prosumers and consumers. Also, the case study does not address remuneration to flexibility providers, for example in a flexibility market as a supplement or alternative to capacity-based grid tariffs. Combined metering schemes call for some remuneration from all who benefit from flexibility to those who provide flexibility. Further research should compare the difference and substitution between flexibility market designs and capacity-based grid tariff schemes.

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.

CRediT authorship contribution statement

Stian Backe: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Visualization, Data curation, Writing - original draft. **Güray Kara:** Conceptualization, Writing - original draft. **Asgeir Tomasgard:** Conceptualization, Supervision, Writing - review & editing.

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Appendix A. Nomenclature

List of model components	
Sets	
$\mathcal{F}$	Set of flexible asset types
$\mathcal{F}_p$	Set of flexible asset types at $p \in \mathcal{P}$
$\mathcal{P}$	Set of prosumers
$\mathcal{T}$	Set of market clearing time steps
Ω	Set of stochastic scenarios
Input Data	
$\varepsilon_f^{\text{charge}}$	Charging losses of $f \in \mathcal{F}$
$\varepsilon_f^{\text{diff}}$	Diffusion losses (self-discharge) of $f \in \mathcal{F}$
$\varepsilon_f^{\text{discharge}}$	Discharging losses of $f \in \mathcal{F}$
$\eta_{p,f}^{\text{charge}}$	Charging capacity of $f \in \mathcal{F}_p$ at $p \in \mathcal{P}$
$\eta_{p,f}^{\text{discharge}}$	Discharging capacity of $f \in \mathcal{F}_p$ at $p \in \mathcal{P}$
$\eta_{p,f}^{\text{storage}}$	Energy storage capacity of $f \in \mathcal{F}_p$ at $p \in \mathcal{P}$
$\gamma_{p,f,t}^{\text{req}}$	Minimum required energy content of $f \in \mathcal{F}_p$ at $p \in \mathcal{P}$ at time $t \in \mathcal{T}$
$\kappa_{p,f}$	Share of energy storage capacity initially available in $f \in \mathcal{F}_p$ at $p \in \mathcal{P}$
π_ω	Probability of scenario $\omega \in \Omega$
$\xi_{p,t,\omega}^{\text{load}}$	Net demand for electricity at $p \in \mathcal{P}$ in time $t \in \mathcal{T}$ and scenario $\omega \in \Omega$
c^{norm}	Energy dependent grid cost below subscription level (per kWh)
c^{pen}	Energy dependent penalty cost for exceeding grid subscription level (per kWh)
$c_{t,\omega}^{\text{ret}}$	Retail cost of electricity import (incl. taxes) at time $t \in \mathcal{T}$ and scenario $\omega \in \Omega$ (per kWh)
c^{sub}	Grid subscription cost per power level (per kWh/h)
Variables	
$k_{t,\omega}^{\text{C}}$	The (combined) tariff cost on import from the grid in time $t \in \mathcal{T}$ and scenario $\omega \in \Omega$
$k_{p,t,\omega}^{\text{I}}$	The (individual) tariff cost on import from the grid to $p \in \mathcal{P}$ in time $t \in \mathcal{T}$ and scenario $\omega \in \Omega$
$w_{p,f,t,\omega}^{\text{charge}}$	Charging of $f \in \mathcal{F}_p$ at $p \in \mathcal{P}$at time $t \in \mathcal{T}$and scenario $\omega \in \Omega$
$w_{p,f,t,\omega}^{\text{discharge}}$	Discharging of $f \in \mathcal{F}_p$ at $p \in \mathcal{P}$at time $t \in \mathcal{T}$and scenario $\omega \in \Omega$
$w_{p,f,t,\omega}^{\text{storage}}$	Available energy in flexible asset type $f \in \mathcal{F}_p$ at prosumer $p \in \mathcal{P}$ at time $t \in \mathcal{T}$ and scenario $\omega \in \Omega$
x^{C}	The (combined) subscribed capacity level
x_p^{I}	The (individual) subscribed capacity level at prosumer $p \in \mathcal{P}$
$y_{p,t,\omega}^{\text{load}}$	Resulting grid import at $p \in \mathcal{P}$ in time $t \in \mathcal{T}$ and scenario $\omega \in \Omega$

References

[1] Lund H, Østergaard PA, Connolly D, Mathiesen BV. Smart energy and smart energy systems. Energy 2017;137:556–65. https://doi.org/10.1016/j.energy.2017.05.123.

[2] Faruqui A, George S. Quantifying customer response to dynamic pricing. Electr J 2005;18(4):53–63. https://doi.org/10.1016/j.tej.2005.04.005.

[3] EURELECTRIC. Flexibility and aggregation: requirements for their interaction in the market. April 15, 2020, https://cdn.eurelectric.org/media/1845/tf_bal-agr_report_final_je_as-2014-030-0026-01-e-h-5B011D5A.pdf; 2014. URL.

[4] D'hulst R, Labeeuw W, Beusen B, Claessens S, Deconinck G, Vanthournout K. Demand response flexibility and flexibility potential of residential smart appliances: experiences from large pilot test in Belgium. Appl Energy 2015;155: 79–90. https://doi.org/10.1016/j.apenergy.2015.05.101.

[5] Yin R, Kara EC, Li Y, DeForest N, Wang K, Yong T, Stadler M. Quantifying flexibility of commercial and residential loads for demand response using setpoint changes. Appl Energy 2016;177:149–64. https://doi.org/10.1016/j.apenergy.2016.05.090.

[6] Ottesen SØ, Tomasgard A, Fleten S-E. Multi market bidding strategies for demand side flexibility aggregators in electricity markets. Energy 2018;149: 120–34. https://doi.org/10.1016/j.energy.2018.01.187.

[7] Chen Z, Zhang Y, Tang W, Lin X, Li Q. Generic modelling and optimal day-ahead dispatch of micro-energy system considering the price-based integrated demand response. Energy 2019;176:171–83. https://doi.org/10.1016/j.energy.2019.04.004.

[8] Finck C, Li R, Zeiler W. Economic model predictive control for demand flexibility of a residential building. Energy 2019;176:365–79. https://doi.org/10.1016/j.energy.2019.03.171.

[9] de Sá Ferreira R, Barroso LA, Lino PR, Carvalho MM, Valenzuela P. Time-of-use tariff design under uncertainty in price-elasticities of electricity demand: a stochastic optimization approach. IEEE Transactions on Smart Grid 2013;4(4): 2285–95. https://doi.org/10.1109/TSG.2013.2241087.

[10] Deng R, Yang Z, Chow M-Y, Chen J. A survey on demand response in smart grids: mathematical models and approaches. IEEE Transactions on Industrial Informatics 2015;11(3):570–82. https://doi.org/10.1109/TII.2015.2414719.

[11] Pallonetto F, Oxizidis S, Milano F, Finn D. The effect of time-of-use tariffs on the demand response flexibility of an all-electric smart-grid-ready dwelling. Energy Build 2016;128:56–67. https://doi.org/10.1016/j.enbuild.2016.06.041.

[12] Bjarghov S, Korpås M, Zaferanlouei S. Value comparison of EV and house batteries at end-user level under different grid tariffs. IEEE: IEEE International Energy Conference (ENERGYCON); 2018. p. 1–6. https://doi.org/10.1109/ENERGYCON.2018.8398742. 2018.

[13] Bjarghov S, Doorman G. Utilizing end-user flexibility for demand management under capacity subscription tariffs. In: 2018 15th international conference on the European energy market (EEM). IEEE; 2018. p. 1–5. https://doi.org/10.1109/EEM.2018.8469832.

[14] Almenning OM, Bjarghov S, Farahmand H. Reducing neighborhood peak loads with implicit peer-to-peer energy trading under subscribed capacity tariffs. In: International conference on smart energy systems and technologies. SEST), IEEE; 2019. p. 1–6. https://doi.org/10.1109/SEST.2019.8849067. 2019.

[15] Pinel D, Bjarghov S, Korpås M. Impact of grid tariffs design on the Zero emission neighborhoods energy system investments. IEEE: IEEE Milan PowerTech; 2019. p. 1–6. https://doi.org/10.1109/PTC.2019.8810942. 2019.

[16] MIT, Utility of the Future. The Re-evolution of short- and long-term electricity market design. April 15, 2020, https://energy.mit.edu/wp-content/uploads/2016/12/Utility-of-the-Future-Full-Report.pdf; 2016. URL.
[17] Statnett Svenska Kraftnät. The nordic balancing Concept (version 1). April 15, 2020, https://www.statnett.no/globalassets/om-statnett/nyheter-og-pressemeldinger/nyhetsarkiv-2018/the-nordic-balancing-concept.pdf; 2017. URL.
[18] Ottesen SØ, Tomasgard A, Fleten S-E. Prosumer bidding and scheduling in electricity markets. Energy 2016;94:828–43. https://doi.org/10.1016/j.energy.2015.11.047.
[19] Agrell PJ, Bogetoft P, Mikkers M. Smart-grid investments, regulation and organization. Energy Pol 2013;52:656–66. https://doi.org/10.1016/j.enpol.2012.10.026.
[20] Corneli S, Kihm S. Will distributed energy end the utility natural monopoly. April 15, 2020, https://emp.lbl.gov/sites/default/files/corneli_29june2016.pdf; 2016. URL.
[21] EURELECTRIC. Network tariff structure for a small energy system: a EURELECTRIC paper. April 15, 2020, http://www.elecpor.pt/pdf/20130409_network-tariffs-paper_final_to_publish.pdf. URL.
[22] Strbac G, Mutale J. Framework and methodology for pricing of distribution networks with distributed generation. April 15, 2020, https://pdfs.semanticscholar.org/44cb/118bca415699dc09de52d2d0b9785a3cbeeb.pdf; 2005. URL.
[23] EURELECTRIC. Network Tariffs: A EURELECTRIC position paper. 2016. https://www.energinorge.no/contentassets/1d7d414f48df48ddac0fc485fdece8ea/eurelectric-network_tariffs__position_paper_final_2016.pdf. [Accessed 15 April 2020].
[24] Kirkerud JG, Trømborg E, Bolkesjø TF. Impacts of electricity grid tariffs on flexible use of electricity to heat generation. Energy 2016;115:1679–87. https://doi.org/10.1016/j.energy.2016.06.147.
[25] Costello KW, Hemphill RC. Electric utilities "death spiral": hyperbole or reality? Electr J 2014;27(10):7–26. https://doi.org/10.1016/j.tej.2014.09.011.
[26] Sæle H. Consequences for residential customers when changing from energy based to capacity based tariff structure in the distribution grid. In: PowerTech, 2017. IEEE Manchester, IEEE; 2017. p. 1–6. https://doi.org/10.1109/PTC.2017.7981177.
[27] Simshauser P. Distribution network prices and solar PV: resolving rate instability and wealth transfers through demand tariffs. Energy Econ 2016;54:108–22. https://doi.org/10.1016/j.eneco.2015.11.011.
[28] ENTSO-E Overview of Transmission Tariffs in Europe: Synthesis 2019. 2019. https://eepublicdownloads.blob.core.windows.net/public-cdn-container/clean-documents/mc-documents/190626_MC_TOP_7.2_TTO_Synthesis2019.pdf. [Accessed 23 April 2020].
[29] Albadi MH, El-Saadany EF. A summary of demand response in electricity markets. Elec Power Syst Res 2008;78(11):1989–96. https://doi.org/10.1016/j.epsr.2008.04.002.
[30] Lummi K, Rautiainen A, Järventausta P, Heine P, Lehtinen J, Apponen R, Hyvärinen M. Variations of power charge basis of power-based distribution tariff of small customers. In: IEEE innovative smart grid technologies-Asia (ISGT-Asia). IEEE; 2016. p. 478–84. https://doi.org/10.1109/ISGT-Asia.2016.7796432. 2016.
[31] Kornrumpf T, Meese J, Zdrallek M, Neusel-Lange N, Roch M. Economic dispatch of flexibility options for grid services on distribution level. In: Power systems computation conference (PSCC). IEEE; 2016. p. 1–7. https://doi.org/10.1109/PSCC.2016.7540836. 2016.
[32] Papadaskalopoulos D, Strbac G. Decentralized participation of flexible demand in electricity markets—part i: market mechanism. IEEE Trans Power Syst 2013;28(4):3658–66. https://doi.org/10.1109/TPWRS.2013.2245686.
[33] Papadaskalopoulos D, Strbac G, Mancarella P, Aunedi M, Stanojevic V. Decentralized participation of flexible demand in electricity markets—part ii: application with electric vehicles and heat pump systems. IEEE Trans Power Syst 2013;28(4):3667–74. https://doi.org/10.1109/TPWRS.2013.2245687.
[34] Li R, Wu Q, Oren SS. Distribution locational marginal pricing for optimal electric vehicle charging management. IEEE Trans Power Syst 2013;29(1):203–11. https://doi.org/10.1109/TPWRS.2013.2278952.
[35] Bjørndal E, Buvik M, Gramme E, Bjørndal M, Børke Nærup C. End-user flexibility in the local electricity grid - blurring the vertical separation of market and monopoly?. In: 52nd Hawaii international conference on system sciences. HICSS; 2019. p. 3560–70. https://doi.org/10.24251/HICSS.2019.431.
[36] Sæle H, Høivik Ø, Nordgard D. Evaluation of alternative network tariffs-for residential customers with hourly metering of electricity consumption. Helsinki: CIRED Workshop; 2016. https://doi.org/10.1049/cp.2016.0825.
[37] Hansen H, Jonassen T, Løchen K, Mook V. Høringsdokument nr 5-2017: forslag til endring i forskrift om kontroll av nettvirksomhet, Norges vassdrags- og energidirektorat. April 15, 2020, http://publikasjoner.nve.no/hoeringsdokument/2017/hoeringsdokument2017_05.pdf; 2017. URL.
[38] Kall P, Wallace SW, Kall P. Stochastic programming. Springer; 1994.
[39] Daneshvar M, Pesaran M, Mohammadi-ivatloo B. Transactive energy integration in future smart rural network electrification. J Clean Prod 2018;190:645–54. https://doi.org/10.1016/j.jclepro.2018.04.043.
[40] Wang Q, Wang J, Guan Y. Stochastic unit commitment with uncertain demand response. IEEE Trans Power Syst 2012;28(1):562–3. https://doi.org/10.1109/TPWRS.2012.2202201.
[41] Zhou Z, Zhang J, Liu P, Li Z, Georgiadis MC, Pistikopoulos EN. A two-stage stochastic programming model for the optimal design of distributed energy systems. Appl Energy 2013;103:135–44. https://doi.org/10.1016/j.apenergy.2012.09.019.
[42] Moradzadeh B, Tomsovic K. Two-stage residential energy management considering network operational constraints. IEEE Transactions on Smart Grid 2013;4(4):2339–46. https://doi.org/10.1109/TSG.2013.2265313.
[43] Birge JR, Louveaux F. Introduction to stochastic programming. Springer Science & Business Media; 2011. https://doi.org/10.1007/978-1-4614-0237-4.
[44] Sundstrom O, Binding C. Flexible charging optimization for electric vehicles considering distribution grid constraints. IEEE Transactions on Smart Grid 2012;3(1):26–37. https://doi.org/10.1109/TSG.2011.2168431.
[45] Aalami H, Moghaddam MP, Yousefi G. Demand response modeling considering interruptible/curtailable loads and capacity market programs. Appl Energy 2010;87(1):243–50. https://doi.org/10.1016/j.apenergy.2009.05.041.
[46] Fares RL, Webber ME. A flexible model for economic operational management of grid battery energy storage. Energy 2014;78:768–76. https://doi.org/10.1016/j.energy.2014.10.072.
[47] Backe S. Reproducible model to compare individual and coordinated demand response with dynamic and static power grid tariffs. Mendeley Data; 2020. p. v1. https://doi.org/10.17632/s7x9gxtwmj.1.
[48] SSB, 12576. Road traffic volumes, by region, vehicle type, type of fuel, contents and year. 2018. https://www.ssb.no/en/statbank/table/12576/.
[49] Hart WE, Laird CD, Watson J-P, Woodruff DL, Hackebeil GA, Nicholson BL, Siirola JD. Pyomo-optimization modeling in python, vol. 67. Springer; 2017. https://doi.org/10.1007/978-1-4614-3226-5.
[50] Lindberg K, Bakker S, Sartori I. Modelling electric and heat load profiles of non-residential buildings for use in long-term aggregate load forecasts. Util Pol 2019;58:63–88. https://doi.org/10.1016/j.jup.2019.03.004.
[51] Le Dréau J, Heiselberg P. Energy flexibility of residential buildings using short term heat storage in the thermal mass. Energy 2016;111:991–1002. https://doi.org/10.1016/j.energy.2016.05.076.

Paper II

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Helping end-users help each other: Coordinating development and operation of distributed resources through local power markets and grid tariffs

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ABSTRACT

There is an ongoing transition in the power system towards an increasing amount of flexible resources and generation technologies at the distribution system level. An appealing alternative to facilitate efficient utilization of such decentralized energy resources is to coordinate the power at the neighbourhood level. This paper proposes a game-theoretic framework to analyze a local trading mechanism and its feedback effect on grid tariffs under cost recovery conditions for the distribution system operator. The novelty of the proposed framework is to consider both long-term and short-term aspects to evaluate the socio-economic value of establishing a local trading mechanism. Under our assumptions, the main finding is that the establishment of local electricity markets can decrease the total costs by facilitating coordination of resources and thus create higher socio-economic value than the uncoordinated solution. Furthermore, a sensitivity analysis on the tariff levels reveals that there are two equilibrium solutions, one where the grid costs are exactly balanced by tariff income and one where the neighbourhood decides to disconnect from the larger power system. These results indicate that although a local trading mechanism can reduce the need for grid capacity, it may not be cost optimal for neighbourhoods to become completely self-sufficient.

1. Introduction

One of the fundamental issues in power system economics is the potential of market failure due to a lack of demand-side elasticity (Stoft, 2002). At the distribution grid level, inelastic demand means that real-time control problems have traditionally been resolved at the grid infrastructure planning stage so that capacity is robustly adequate to cover the peak load (Strbac, 2008). However, there is an ongoing transition within power system development due to an increasing amount of flexible resources at the distribution grid level (Eid et al., 2016).

The price-responsiveness from end-users increase because of two fundamental drivers: (1) the information available to the end-users is increasing due to deployment of smart metering technologies, and (2) increased deployment of electricity as an energy carrier for potentially flexible demand types. Smart meters are currently being deployed throughout Europe, enabling hourly or sub-hourly billing of electricity consumption (Zhou and Brown, 2017). Such price variations can induce a change in consumption patterns if flexible energy resources such as smart management of heating systems and electric vehicle (EV) charging are available (Faruqui et al., 2010; Salpakari et al., 2017; Knezović et al., 2017).

An appealing alternative to facilitate efficient utilization of decentralized energy resources (DERs) is to balance the power at the neighbourhood level (Heinisch et al., 2019). However, as described in Askeland et al. (2019), the current regulatory framework in Norway and several other countries may not facilitate efficient decentralized decision-making when multiple stakeholders are involved.

This paper uses a game-theoretic framework to investigate a local trading mechanism, and its feedback effect on grid tariffs under cost recovering conditions for the distribution system operator (DSO) in a neighbourhood context. An equilibrium model comprising two levels is developed to study the efficiency of current and prospective pricing mechanisms. Also, a system optimization model serves as a benchmarking tool.

Abbreviations: **DER**, Distributed Energy Resources; **DSO**, Distribution System Operator; **ER**, 'Energy resources' agent group; **EV**, Electric Vehicle / 'Electric vehicle charging facility' agent group; **KKT**, Karush-Kuhn-Tucker; **LM**, 'Local market' case study; **MCP**, Mixed Complementarity Problem; **MPEC**, Mathematical Program with Equilibrium Constraints; **NOLM**, 'No local market' case study; **P2P**, Peer-to-peer; **RB**, 'Residential buildings' agent group; **SK**, 'Combined school and kindergarten' agent group; **SO**, 'System optimization' case study; **ZEN**, Zero Emission Neighbourhood.

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The remainder of this paper is organized as follows. In section 2 we provide a survey of related literature. The modeling framework is presented in section 3. The data used for a case study is presented in section 4. Section 5 presents results from the case study before conclusions are drawn in section 6.

2. Literature review

An adaptation of electricity grid pricing mechanisms is increasingly being addressed in the scientific literature. This paper is at the intersection between two related research topics, namely electricity grid tariff design and local electricity markets.

Electricity grids are natural monopolies due to economies of scale. Traditionally, the DSO is the sole owner of the electricity grid in a given area and passes the costs on to the end-user as fixed and volumetric grid tariffs (Eid et al., 2014). However, the current tariff structures can create distorted incentives for end-users to invest excessively in DERs (Eid et al., 2014; Pollitt, 2018). Capacity-based tariffs are being proposed as a prospective solution since it will be a better representation of the upstream grid costs and create an incentive to reduce the peak load (Simshauser, 2016). However, a reduction of individual peaks may not always be effective at reducing aggregate peak load (Backe et al., 2020), and several scholars suggest that the potential welfare gains from capacity-based tariffs can be limited (Passey et al., 2017; Brown and Sappington, 2018). In this context, we contribute to the literature by investigating how a combination of grid tariffs and local markets can provide incentives for efficient development and operation of the distribution grid.

There exists a rather large body of literature related to investigating the impact of various tariff schemes on specific end-user groups, see e.g. Kirkerud et al. (2016); Parra and Patel (2016); Bergaentzlé et al. (2019); Sandberg et al. (2019); Pinel et al. (2019); Backe et al. (2020). These studies investigate how the business case and decisions of different types of agents are affected by changes in the tariff structure. Our paper differs from this line of research because we consider the electricity grid tariffs as a modeling result in a bilevel approach rather than an input to a single level optimization problem.

Our work considers the interaction between the distribution network level and the end-users under cost recovery conditions for the DSO. In this regard, the approach of this paper is related to the research summarized in Table 1. However, some distinct differences can be pointed out since our research also include the interaction between agents at the local level through a local market mechanism. Besides, we consider grid investments and operation as a function of the aggregate neighbourhood load.

Interaction between agents at the local level can be achieved through ‘peer-to-peer’ (P2P) trading or other forms of local market mechanisms (Sousa et al., 2019). In Zhang et al. (2018) the authors analyze P2P trading for matching inflexible local generation with flexible demand in a microgrid, and they find that the trading triggers peak load reduction. Almenning et al. (2019) also analyzes P2P trading in a neighbourhood focusing on trading in response to a subscribed grid tariff, and they also find that P2P trading triggers a reduction of high loads. Lüth et al. (2018) focuses on the role of batteries in P2P trading, and their results highlight economic viability from an end-user perspective. None of these studies (Zhang et al., 2018; Almenning et al., 2019; Lüth et al., 2018) consider a reaction by the DSO (i.e., adjustment of the grid capacity) as a consequence of trading in a neighbourhood.

The properties of the problem addressed in this paper are consistent with non-cooperative Stackelberg-type games (Von Stackelberg, 2010), which are characterized by a leader who moves first and one or more followers acting optimally in response to the leader's decisions. Games with a Stackelberg structure can be formulated as mathematical programs with equilibrium constraints (MPECs) (Luo et al., 1996). This is the case for Zugno et al. (2013), Momber et al. (2016), Schittekatte and Meeus (2020), and Askeland et al. (2020) who formulate MPECs to investigate the effect of indirect load control. In this paper, we use an iterative procedure to solve the set of non-linear equations similar to Schittekatte et al. (2018), Hoarau and Perez (2019), Askeland and Korpås (2019), and Abada et al. (2020). The reason for choosing this procedure instead of an MPEC approach is that an iterative procedure has computational advantages over an MPEC formulation, which would severely impact our tractable problem size. Furthermore, there is no need for an MPEC formulation since the grid tariff structure we consider can effectively be handled by an iterative procedure based on cost recovery rules for the DSO. We formulate the neighbourhood equilibrium as a complementarity problem (Gabriel et al., 2012). A complementarity problem is the combination of the Karush-Kuhn-Tucker (KKT) conditions (Kuhn and Tucker, 1951) of all agents, which are being solved simultaneously to derive the equilibrium. Complementarity modeling is particularly useful for power market modeling since the introduction of dual variables in the model formulation allows for market interactions between agents to be formulated directly. More details on complementarity modeling for energy modeling purposes can be found in Gabriel et al. (2012). The complementarity formulation for the neighbourhood level allows for interaction between agents within the neighbourhood level and enables an investigation of local electricity markets without introducing the computational difficulties of an MPEC formulation.

To summarize, this paper brings together two related bodies of literature by considering both grid tariff design and a local market mechanism in a consistent modeling approach. Furthermore, the proposed approach allows for local markets to be coupled to existing market structures and allow consumers to choose which market to trade in. No prior works that consider local markets and its feedback effect on grid development and grid tariffs have been identified, and we aim to contribute to closing this gap in the literature.

3. Method

This section presents the game-theoretic setup that has been developed. First, the optimization problems of the agents in the neighbourhood and the DSO are presented. Thereafter, the solution procedure for coupling the two levels are described before the input data

Table 1
Related research on indirect load control.

Reference	Tariff calculation	Grid costs considered	Interaction between agents
Zugno et al. (2013)	MPEC	No	Retailer - consumer
Momber et al. (2016)	MPEC	No	Aggregator - EV consumer
Schittekatte et al. (2018)	Iterative procedure	Sunk	DSO - consumer
Hoarau and Perez (2019)	Iterative procedure	Sunk	DSO - consumer
Askeland and Korpås (2019)	Iterative procedure	Prospective	DSO - consumer
Abada et al. (2020)	Iterative procedure	Sunk	DSO - community
Schittekatte and Meeus (2020)	MPEC	Prospective	DSO - consumer
Askeland et al. (2020)	MPEC	Sunk	DSO - consumer
This paper	Iterative procedure	Prospective	DSO - consumer and between consumers

for the case study is presented. In the presented model, the following core assumptions are made:

- Grid charges only apply to electricity purchased from the wholesale power market and not on locally traded electricity. Since locally traded electricity is balanced locally at each time step, the local trade does not contribute to the capacity-based charge.
- We assume that there is sufficient grid capacity within the local system. Therefore, only the connection between the neighbourhood and the larger power system is constrained.
- We assume that the DSO can not choose to curtail load or generation. Hence, it is necessary to build sufficient capacity to cover the peak network usage. Although the economics concerning load or generation curtailment is outside the scope of this paper, this is an aspect that could be considered in further work.

3.1. Model overview

An outline of the model is presented in Fig. 1. The structure is a bilevel model where some decisions are made on the DSO level while others occur on the neighbourhood level. We consider the DSO as the leader in the Stackelberg game since it sets the grid tariff rates while the end-user agents responds to the tariff determined by the DSO. Decision variables at one level are perceived as parameters for the other level. One example is the level of grid tariffs, which is determined based on cost recovery criteria on the DSO level but perceived as parameters by the agents at the neighbourhood level. The benefit of this bilevel structure in our modeling framework is the ability to analyze the feedback effect between neighbourhood response, coordination, DSO strategy, and regulatory framework. Appendix A provides an overview of mathematical symbols and describes how the parameters and variables relates to each level in the overall model.

3.2. Neighbourhood level

In this section, the problem of the individual agent in the neighbourhood is described as an optimization problem. The agents can be of different types: customer with inflexible load, prosumer, EV charging facility, owner of a power plant and grid storage, or a combination of these. The model formulation presented in this section allows for all of these types of agents to be represented through different parameter settings.

Since the optimization problems for the agents in the neighbourhood are linear, their KKT conditions are both necessary and sufficient for global optimality (Kuhn and Tucker, 1951). Hence, to allow for the modeling of a local market mechanism, the optimization problems for the agents in the neighbourhood are represented through their KKT conditions, which are formulated as a mixed complementarity problem (MCP) in Appendix B. We indicate dual variables associated with each of the constraints. These dual variables are used in the MCP formulation of the problem.

3.2.1. Objective function of neighbourhood agents

The objective of the neighbourhood agents is to minimize their individual costs according to (1a). Details of the cost components are described in (1b) - (1f). These costs consist of investments in storage and energy resources ($Cost_c^N$), energy from the power market ($Cost_c^P$), energy from the local market ($Cost_c^L$), electricity taxes ($Cost_c^T$), and grid charges ($Cost_c^G$). The grid charges apply to energy purchased from the

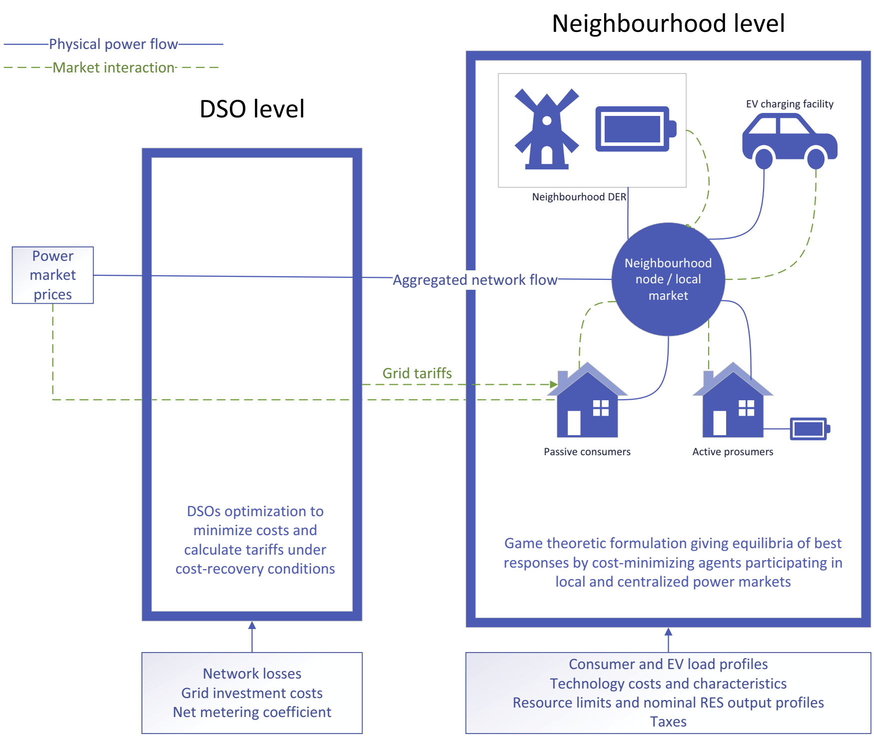

Fig. 1. Outline of the model structure.

power market, but not to locally traded energy. The actual grid costs are not considered directly at the building level since these costs are imposed indirectly through the grid tariffs (*vnt* and *cnt*).

$$Min : Cost_c = Cost_c^N + Cost_c^P + Cost_c^L + Cost_c^T + Cost_c^G \tag{1a}$$

$$Cost_c^N = I_c^S * c_c^S + I_c^E * c_c^E \tag{1b}$$

$$Cost_c^P = \sum_{h=1}^{H} W_h * \left(imp_{c,h}^P - exp_{c,h}^P \right) * \lambda_h^P \tag{1c}$$

$$Cost_c^L = \sum_{h=1}^{H} W_h * \left(imp_{c,h}^L - exp_{c,h}^L \right) * \lambda_h^L \tag{1d}$$

$$Cost_c^T = \sum_{h=1}^{H} W_h * \left(imp_{c,h}^P + imp_{c,h}^L \right) * T \tag{1e}$$

$$Cost_c^G = \sum_{h=1}^{H} W_h * \left(imp_{c,h}^P - NM * exp_{c,h}^P \right) * vnt + c_c^G * cnt \tag{1f}$$

In these equations, W_h denotes the scaling factor to provide operational costs on an annual basis. To represent annual costs the scaling factor takes the value $W_h = \frac{8760}{H}$ for hourly time-steps.

3.2.2. Energy balance

The energy balance of the agents is described by (2) and states that energy imports subtracted exports must be equal to fixed and flexible demand subtracted generation from PV at each agent.

$$\begin{aligned} & D_{c,h} + d_{c,h}^{\Delta+} - d_{c,h}^{\Delta-} - g_{c,h}^E \\ & = imp_{c,h}^P - exp_{c,h}^P + imp_{c,h}^L - exp_{c,h}^L \ \forall c,h \quad \left(\lambda_{c,h}^{EB}\right) \end{aligned} \tag{2}$$

The agents can trade both with the local and centralized electricity markets to satisfy their energy balance.

3.2.3. Battery charge level

A battery makes it possible to shift energy load temporally. This temporal load shifting is represented in (3), which describes how the charge level depends on the charge level in the previous time step and on the battery operation. Converter losses are imposed through the parameter L_c, while self-discharge of the battery from one time-step to the next is imposed through the parameter R_c.

$$\begin{aligned} & s_{c,h} = s_{c,h-1} * (1 - R_c) \\ & + d_{c,h}^{\Delta+} * (1 - L_c^S) - d_{c,h}^{\Delta-} * (1 + L_c^S) - D_{c,h}^{\Delta-} \ \forall c, h{>}1 \ (\lambda_{c,h}^{S1}) \end{aligned} \tag{3}$$

The battery formulation allows for the representation of both a bidirectional battery which can store electricity for later use and unidirectional EV charging. In the case of EV charging, the parameter $D_{c,\,h}^{\Delta-}$ represents the energy used for EV driving needs.

We specify boundary conditions for the battery charge level as described in (4). This means that the charge level in the last time-step is linked to the first time step. Thereby, we do not need to specify the initial charge level since the optimization model calculates it.

$$\begin{aligned} & s_{c,1} = s_{c,H} * (1 - R_c) \\ & + d_{c,1}^{\Delta+} * \left(1 - L_c^S\right) - d_{c,1}^{\Delta-} * \left(1 + L_c^S\right) - D_{c,1}^{\Delta-} \ \forall c \quad \left(\lambda_{c,1}^{S1}\right) \end{aligned} \tag{4}$$

Potentially, this formulation can result in simultaneous charge and discharge during the same time step. However, positive converter losses and energy costs will prevent this from occurring due to the associated costs.

3.2.4. Storage capacity

The agent decides the storage capacity to be installed, so the case that the economic benefit of having an additional unit of storage exceeds the investment costs will trigger additional investments. However, a maximum limit on battery storage capacity can be imposed according to (5). In order to represent agents without investment options, the maximum capacity limit can be set to zero.

$$c_c^S \le U_c^S \ \forall c \quad \left(\mu_c^{S2}\right) \tag{5}$$

Furthermore, the amount of energy that can be stored and the installed storage capacity limits the converter capacities according to (6)–(8). In the case of unidirectional EV charging, the discharging power factor (P_c^{dis}) can be set to zero. Note that the model is also capable of handling vehicle-to-grid directly, but this is out of the scope of this paper.

$$s_{c,h} \le c_c^S \ \forall \ c, h \quad \left(\mu_{c,h}^{S3}\right) \tag{6}$$

$$d_{c,h}^{\Delta+} \le c_c^S * P_c^{ch} \ \forall \ c, h \quad \left(\mu_{c,h}^{S4}\right) \tag{7}$$

$$d_{c,h}^{\Delta-} \le c_c^S * P_c^{dis} \ \forall \ c, h \quad \left(\mu_{c,h}^{S5}\right) \tag{8}$$

3.2.5. Measured peak power

Measured peak power at each end-user is equal to the maximum power injected to or withdrawn from the wholesale power market according to (9). Although the maximum load usually occurs as a result of an import situation, we also account for situations where the peak power is defined by exports to the grid. This means that we assume a grid tariff scheme where the agents have to pay a capacity-based grid tariff for their measured peak power for the whole period considered.

$$imp_{c,h}^P + exp_{c,h}^P \le c_c^G \ \forall \ c, h \quad \left(\mu_{c,h}^G\right) \tag{9}$$

Note that electricity traded in the local market do not influence the agent's peak power since any electricity sold locally also has to be consumed by the other agents at the local level.

3.2.6. Energy resource capacity and generation

Similar to energy storage, the agent can invest in energy resources such as rooftop PV. A limit, for example due to limited rooftop area, can be imposed according to (10). This value can also be set to zero if the agent cannot invest in energy resources due to factors outside the modeling framework.

$$c_c^E \le U_c^E \ \forall \ c \quad \left(\mu_c^{E1}\right) \tag{10}$$

Electricity generation, $g_{c,\,h}^E$, is described by (11) and has the option of generation curtailment, by generating below the limit given by the resource availability. The maximum output is the nominal generation each time-step multiplied with the installed capacity. Hence, the nominal generation is specified according to e.g., wind or solar conditions.

$$g_{c,h}^E \le c_c^E * G_{c,h}^E \ \forall \ c, h \quad \left(\mu_{c,h}^{E2}\right) \tag{11}$$

3.2.7. Local energy market

The local exports must equal the local imports according to (12). We assume that there are no grid constraints at the local level, making trading with the neighbours an alternative to purchasing energy from the grid.

$$\sum_{c=1}^{C}\left(imp^{L}_{c,h} - exp^{L}_{c,h}\right) = 0 \ \forall \ h \quad \left(\lambda^{L}_{h}\right) \tag{12}$$

Note that this is the equilibrium condition in the neighbourhood. The dual value of this constraint becomes the market price in the local energy market. The local market price is the value of energy at the local level, considering both short-term operation and long-term investments.

3.3. DSO level

The DSO level describes the optimization problem of the DSO in a regulatory context. In this problem, the decisions at the neighbourhood level regarding investments, operation, and trading in the local and wholesale markets are perceived as parameters outside the DSOs control. Based on the aggregate neighbourhood-level decisions, grid capacity investments and tariff levels are optimized.

3.3.1. Objective function of the DSO

The objective of the DSO is to minimize the grid costs, as formulated in (13a). With the DSO as a perfectly regulated leader, the DSOs goal would be welfare maximization by reducing the combined costs of the DSO and all the end-user agents. However, in our modeling framework the DSO considers the end-user agent decisions as parameters and therefore only the DSOs costs are considered by the DSO. This has a close resemblence to how DSOs are currently regulated in Norway[1] since the regulator defines a maximum income and the self-interest pursuing DSO is incentivized to reduce costs in order to increase profits. The costs faced by the DSO consist of investment costs and variable costs. Potential sunk costs are assumed to be collected through a fixed annual fee independent of this optimization problem. Since the DSO has no decisions related to the sunk costs, these are not included in the objective function.

$$Min: \ Cost_{DSO} = Cost^{N}_{DSO} + Cost^{V}_{DSO} \tag{13a}$$

$Cost^{N}_{DSO}$ is the investment cost for additional grid capacity and consists of the amount of capacity multiplied with annualized investment costs as described in (13b). The DSOs variable costs, $Cost^{V}_{DSO}$, consist of linear network losses, according to (13c).

$$Cost^{N}_{DSO} = I^{G}_{DSO} * c^{G}_{DSO} \tag{13b}$$

$$Cost^{V}_{DSO} = \sum_{h=1}^{H} W_{h} * e^{G}_{h} * L^{G} * \lambda^{P}_{h} \tag{13c}$$

3.3.2. Neighbourhood load

Given that some neighbourhood agents might export to the power market while others import from it, these individual flows are aggregated for each time step to calculate the total net electricity flow in to or out from the neighbourhood. Therefore, the electricity flow to/from the neighbourhood is the absolute value of the aggregate trading with the power market. To maintain the linear properties of the problem, the network imports are represented by (14) while exports are represented by (15). Only one of these terms will have a nonzero value at each time step and the total electricity transmission is calculated in (16). This formulation is valid as long as power market prices are non-negative since the transmission of electricity is penalized in the objective function due to the associated losses.

[1] https://www.nve.no/norwegian-energy-regulatory-authority/economic-regulation/

$$e^{GI}_{h} \geq \sum_{c=1}^{C}\left(imp^{P}_{c,h} - exp^{P}_{c,h}\right) \ \forall h \tag{14}$$

$$e^{GE}_{h} \geq \sum_{c=1}^{C}\left(exp^{P}_{c,h} - imp^{P}_{c,h}\right) \ \forall h \tag{15}$$

$$e^{G}_{h} = e^{GI}_{h} + e^{GE}_{h} \ \forall h \tag{16}$$

Note that the electricity trade within the local market is not a part of the DSOs consideration since the supply and demand remain within the neighbourhood level.

3.3.3. Grid capacity

The DSO needs to ensure enough capacity for the transmission of electricity, as described in (17). The network capacity consists of already built infrastructure given exogenously, and investments in infrastructure. We assume that the DSO do not have the option of curtailment as an alternative to building grid capacity.

$$C^{G}_{DSO} + c^{N}_{DSO} \geq e^{G}_{h} \ \forall h \tag{17}$$

3.3.4. Grid tariff calculation

Based on the optimization, the DSO also calculates the resulting grid tariffs according to (18) for the volumetric tariff $\left(\frac{EUR}{kWh}\right)$and (19) for the capacity-based tariff $\left(\frac{EUR}{kW}\right)$. Here, it is assumed that the DSO will recover the variable costs through the volumetric tariff and investment costs through the capacity-based tariff. For simplicity, and since the aim is to investigate the economic feasibility of substituting grid capacity with local flexibility, we do not include sunk cost recovery. Sunk cost recovery is a topic that has been extensively considered in Schittekatte et al. (2018) and Hoarau and Perez (2019).

$$vnt = \frac{Cost^{V}_{DSO}}{\sum_{c=1}^{C}\sum_{h=1}^{H} W_{h} * \left(imp^{P}_{c,h} - NM * exp^{P}_{c,h}\right)} \tag{18}$$

$$cnt = \frac{Cost^{N}_{DSO}}{\sum_{c=1}^{C} c^{G}_{c}} \tag{19}$$

Note that with this formulation, all the DSOs costs are recovered through the tariff income from the neighbourhood agents. Cost recovery at the DSO level means that cost differences in the resulting cases are due to the effect of regulations on system costs and not because of grid tariff avoidance. Therefore, this setup, with all the DSOs costs recovered by the tariff income, enables a holistic investigation of tariff design in combination with local energy markets.

3.4. Solution approaches

Even though the physical properties of the system are the same, the different decision-making assumptions require different solution approaches. Both a centralized optimization and a game-theoretic equilibrium is computed to assess the efficiency of various pricing mechanisms. The main difference between these approaches lies in the decision-making assumptions. For the system optimization, it is assumed that all investment and operational decisions on both the DSO and the neighbourhood agent level are made by one entity. Such a system optimal solution provide the theoretically best outcome in terms of total costs, but the assumption that agent decisions (such as DER investments and operation) can be controlled centrally is not valid in a market context since such choices are up to the individual agents. Contrary to system optimization, the game-theoretic equilibrium approach allows for decentralized decision-making by the individual agents and the DSO. Decentralized decision-making requires modeling of the pricing mechanism between the agents such as grid tariffs and local market prices.

3.4.1. Centralized optimization

For the centralized optimization, all the direct costs on both the DSO and neighbourhood agent levels are combined in one objective function, as described in (20).

$$Min: \ Cost_{DSO} + \sum_{c=1}^{C}\left(Cost_c^N + Cost_c^P + Cost_c^T\right) \tag{20}$$

Furthermore, we include the technical constraints for the neighbourhood agents in (2)–(12) and for the DSO in (14)–(17). Note that we include the local market balance since it taxes energy transfer from one agent to another in the same way as the equilibrium. Furthermore, the grid tariff cost component is not included since the DSOs costs are considered directly instead.

The centralized optimization forms a single linear programming problem which is solved directly in GAMS with the CPLEX solver.

3.4.2. Decentralized decision-making

In the case of decentralized decision-making, we assume non-cooperative behaviour for all the agents in the model. Therefore, each agent optimizes their individual objective function and interact with the other agents through pricing mechanisms. Decentralized decisions require a game-theoretic equilibrium approach with two levels: (1) The DSO level, and (2) The neighbourhood agent level. The DSO level is solved by treating the variables of the neighbourhood agents as parameters and solving the optimization problem in section 3.3. The neighbourhood agent equilibrium requires a complementarity formulation due to the interaction between the agents in the local market. Therefore, the neighbourhood agent problem described in section 3.2 is represented by its KKT conditions formulated as MCP conditions in Appendix B.

Modeling of two levels requires a solution algorithm to iterate until convergence is reached. The convergence criterion is that the cost

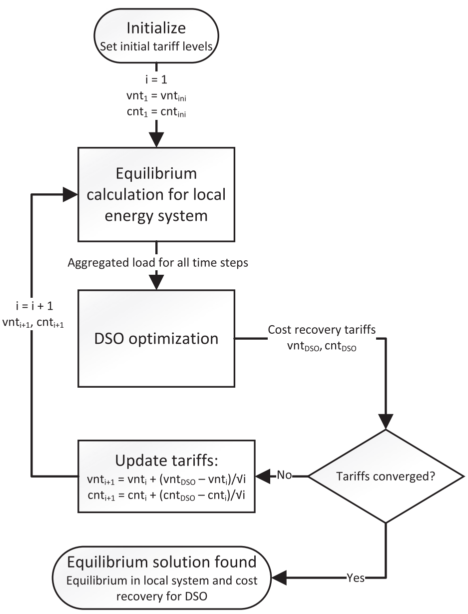

Fig. 2. Outline of equilibrium solution algorithm.

recovering grid tariffs do not change from one iteration to the next. The iterative solution algorithm presented in Fig. 2 is inspired by the procedure employed in Schittekatte et al. (2018) and can be described as follows:

1. Initialize the algorithm with starting tariff values (e.g., zero).
2. For the given tariffs, calculate the equilibrium of the neighbourhood level by solving the complementarity problem presented in Appendix B.
3. For the resulting grid transmission, solve the DSOs optimization problem presented in section 3.3.
4. For the given set of cost recovery tariffs, compare to previous tariffs and determine if change is lower than convergence tolerance.
5. If tariff convergence not reached: Update tariffs with decreasing step size and go to step 2.
6. If tariff convergence is reached: Equilibrium solution with DSO cost recovery found.

A decreasing step size is employed to ensure stable progress towards the equilibrium point. As we change the tariffs, the neighbourhood has a unique equilibrium for each set of grid tariffs since the KKT conditions are necessary and sufficient for optimality. An increase in grid tariffs gives the following effects:

- **DSO income effect 1:** A change in tariff levels will give a positive change on the tariff income per unit of capacity and electricity consumption.
- **DSO income effect 2:** A change in tariff levels will have a zero or negative effect on the contracted capacity and electricity consumption since grid usage might be substituted by something else.
- **DSO cost effect:** A change in tariff levels will give a zero or negative change in DSO costs since the grid usage will stay constant or be decreased when the cost of using grid capacity is increased.

Hence, because a change in tariff levels work in different directions, a change in tariff levels can give both a positive and negative change in DSO profits. Therefore, the model can potentially have several equilibrium solutions that satisfy the DSO cost recovery constraint. We do a tariff sensitivity analysis in section 5.4 that demonstrates the existence of two equilibrium points for the case considered in this paper. However, it should be noted that the existence of two equilibrium point in our analysis is not a general result since the DSO profit is a nonmonotone function of the grid tariffs. More details regarding the equilibrium tariffs and convergence of the model can be found in section 5.4.

The decentralized model is also implemented in GAMS and solved as a linear program with the CPLEX solver for the DSO level. The neighbourhood equilibrium is calculated by solving the complementarity formulation in Appendix B using the PATH solver. These models are solved iteratively until convergence is reached (see Fig. 2).

4. Case study

This section describes the input data used for the case study. The system we model is inspired by the Zero Emission Neighbourhood (ZEN[2]) pilot project called Ydalir.[3] Investment costs are represented through their annual payment costs with an interest rate of 5% and technology-specific lifetimes.

4.1. Agents and load profiles

Since the focus of this paper is on the interaction between agents with different characteristics under various regulatory frameworks, agents are categorized by five agent groups: Combined school and kindergarten (SK), residential buildings (RB), large scale energy resources

[2] https://fmezen.no/
[3] https://www.ydalirbydel.no/ydalir/

Table 2
Agents represented in the model.

Agent group	Load profile	Investment options	Flexible resources
Combined school and kindergarten (SK)	3000 m^2 kindergarten +7000 m^2 school	N/A	N/A
Residential buildings (RB)	20,000 m^2	Batteries and PV available	Battery operation and PV curtailment
Large scale energy resources (ER)	N/A	Batteries and PV available at lower cost	Battery operation and PV curtailment
EV charging facility (EV)	Charging of 200 EVs per day	N/A	Charging of EVs
Distribution system owner (DSO)	Aggregate load of neighbourhood agents	Grid capacity	N/A

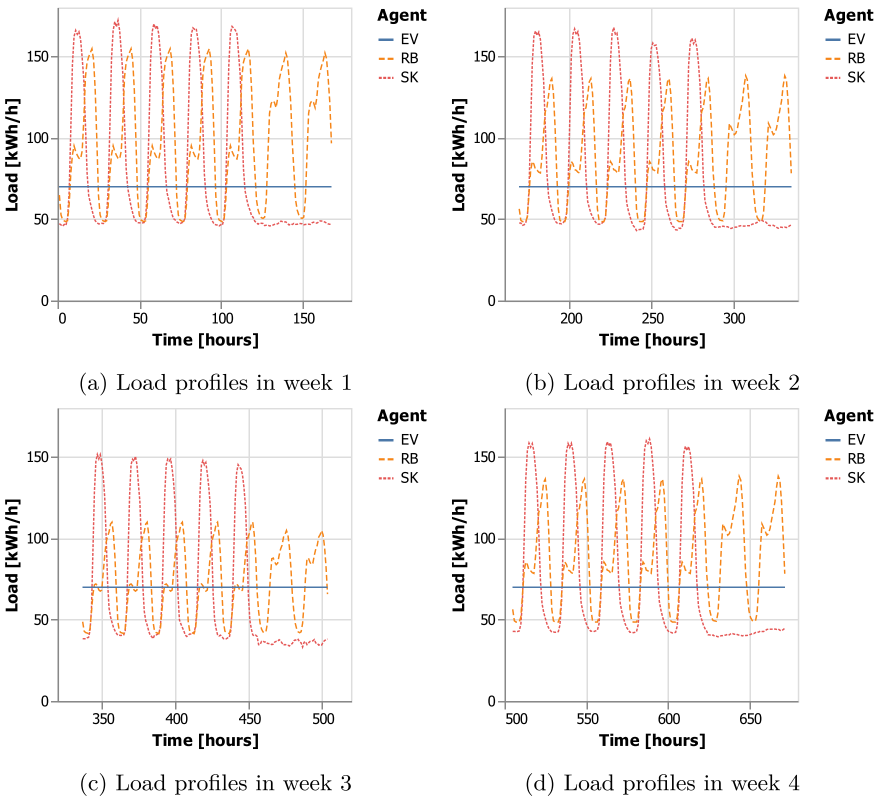

Fig. 3. Load profiles for the neighbourhood agents.

(ER), EV charging facility (EV), and distribution system operator (DSO). An overview of the characteristics of each group can be found in Table 2.

Electricity load profiles for agents SK and RB have been generated based on the floor area according to the methodology presented in Lindberg et al. (2019). We generate four representative weeks for a year, one for each season. Regarding the demand for EV charging, a yearly driving distance of 14,000 km per vehicle is assumed.[4] Further, one electric car needs 0.2 kWh per km (Sørensen et al., 2018), so one car needs about $\frac{14,000}{365} * 0.2 = 8$ kWh/day. For 200 EVs, we get a daily charging need of about 1,600 kWh/day. Based on these assumptions, a charging need of 70 kWh for each hour is specified for the EV agent. The load profiles for the neighbourhood agents are presented in Fig. 3.

The energy resource agent (ER) does not have any load profile specified but can invest in batteries and PV capacity to trade electricity with other neighbourhood agents or the power market. Lastly, the DSOs load profile is the aggregate load of all the other neighbourhood agent groups.

4.2. Technology costs and characteristics

In the modeled system, some of the agents can invest in technologies such as grid capacity, PV systems, and batteries. Also, the EV agent has inherent flexibility regarding when to charge the EVs.

The DSO is responsible for the grid capacity connecting the neighbourhood to the transmission network. For the regional grid in Norway, the transmission fee is approximately 50 €/kW of peak power measured at the point of the TSOs grid.[5] Furthermore, it is assumed that the DSOs costs are approximately equal to the transmission

[4] SSB, Road traffic volumes 2005–2018, https://www.ssb.no/en/statbank/table/12576/

[5] https://www.statnett.no/en/for-stakeholders-in-the-power-industry/tariffs/this-years-tariff. Accessed: 2020-10-07]

system cost per unit of capacity. This gives an assumed total cost of 100 €/kW of grid capacity, which is used for the case study. In general, grid costs are lumpy and vary depending on site-specific properties. However, since our interest is mainly regarding game-theoretic aspects of pricing mechanisms, this simplification is appropriate for investigating such fundamental pricing aspects. In our case study, all network capacity needs to be built. In addition to the investments, network losses are specified to 6%.

The Danish energy agency publish characteristics for a range of technologies including PV and batteries.[6] The technology costs for the ER agent is based on the general technology cost in 2020 where the utility-scale PV systems cost is 0.42 M€/MWp. Note that this cost level is very low in the context of neighbourhood-scale systems, but we use it to illustrate a situation where it is cost optimal for end-users to invest in PV systems. It can also be argued that this cost is realistic as a consequence of investment subsidies.[7] Using an interest rate of 5% and a lifetime of 20 years, this translates to an annual cost of 34 €/kWp for the ER agent. Large scale lithium-ion battery costs are currently around 150 €/kWh. Assuming a lifetime of 10 years for batteries and an interest rate of 5% gives an annual cost of 19 €/kWh for battery capacity.

It is assumed that because of economies of scale, small scale systems cost more than large scale ones per unit of capacity. A premium of 20% is therefore assumed for smaller systems, which in this example applies to the RB agent. Therefore, the annual PV cost is 40.8€/kWp, while annual battery costs are 22.8 €/kWh for the RB agent.

Converter losses are assumed to be 5% for batteries in both directions. Furthermore, the power/energy for batteries is assumed to be fixed at 0.5 kW/kWh. The self-discharge of batteries is assumed to be 0.1% per hour.

For the EV agent, we assume the flexibility associated with the charging of EVs is 8 hours by specifying an EV storage capacity of $70 * 8 = 560$ kWh. In addition, the charging capacity factor is set to 0.5 to allow for a charging capacity of up to 280 kW. No discharge to the grid is allowed by setting the discharging capacity factor to zero. EV charging losses are equal to the bi-directional batteries at 5%.

The nominal PV generation data is obtained from PVGIS[8] for the location of the Ydalir project. After PV-system losses, the annual PV generation is 779 kWh/kWp of installed capacity. Nominal PV generation for the four representative weeks is presented in Fig. 4.

4.3. Market price and regulatory assumptions

End-users can have different contracts ranging from spot price based contracts varying each time step to fixed price contracts. For simplicity, and in order to focus on the variability of load profiles and decentralized generation, the wholesale energy price is set to 0.05€/kWh for all time steps. For systems with large shares of energy communities, there might be an effect on the wholesale price, but this aspect is out of the scope of this work. This means that the time-varying input data is limited to the load profiles and PV generation.

Electricity consumption is usually subjected to taxes. In this paper, it is assumed that such a tax applies to power imports from both the wholesale power market and the local market and is specified to 1.6¢/kWh according to the current taxes on electric power in Norway.[9]

The grid tariffs are endogenous to the model, but it is necessary to specify the net metering coefficient exogenously. In this case study, the net metering coefficient has been set to zero, which means that only electricity imports are subject to the volumetric grid tariffs. This is in line with current practice in several countries, including Norway.

4.4. Regulatory frameworks

The analyses are based on three different cases:

1. **Case LM:** Assumes decentralized decision-making where the agents in the neighbourhood optimize their individual objective, but can trade with each other. The neighbourhood agents can also trade with the wholesale power market, and the DSO agent sets the grid tariffs for such trades based on cost-recovery conditions.
2. **Case NOLM:** Similiar to case LM, but local trades are not allowed. This situation is similar to current regulations in many countries.
3. **Case SO:** System optimization model used for benchmarking. All decisions are assumed to be made centrally to minimize the total system cost for the neighbourhood and the DSO as a whole. The system cost incorporates the grid costs directly in addition to costs for all neighbourhood agents. Grid costs are distributed evenly by dividing the total grid costs by the number of agents in the neighbourhood.

5. Results and discussion

5.1. Total system costs and resource allocation

First, we focus on the system as a whole under different regulatory frameworks. Fig. 5 provide information on total system costs and how these costs are distributed among the neighbourhood agents. The DSO is not represented explicitly as an agent in these figures since the grid costs are imposed on the neighbourhood agents through the grid fees. Since the grid costs are forwarded to the neighbourhood agents through the grid tariffs, the net costs for the DSO are zero. Furthermore, Table 3 provides more detailed information regarding costs, tariffs, and investments.

The total costs are lowest in the SO case, which provides a benchmark for the cases with decentralized decision-making. We use the SO case as a benchmark since it provides the optimal solution for the system as a whole when the aim is to minimize total costs. Hence, from an efficiency point of view, policies should aim to achieve a solution close to the SO solution under decentralized decision-making. Compared to the SO solution, we observe a cost increase of 1.2% for the LM case where local trading is allowed and 4.1% for the NOLM case where no trading occurs within the neighbourhood. In addition to the total cost decrease, the LM solution pareto-dominates the NOLM solution since no agent is worse off and some are better off when the local market is included. The grid capacity is the same for the LM and the SO cases, while it is significantly higher in the NOLM case. The fact that the LM case provides a system with the same grid capacity as in the SO case indicates that the combination of decentralized trading and a rather simple grid tariff scheme can impose the grid costs on end-users in a cost-reflective way.

In general, the LM solution can not achieve lower total costs than the SO solution since it is not technically possible to achieve lower costs than the centralized optimization. Also, if we keep the tariff rates fixed, the LM solution will never have higher total costs than the NOLM solution since the neighbourhood agents can always choose to not trade and achieve the NOLM outcome. Hence, if tariff rates does not change, the LM solution will always be equal to or between the system optimal solution and the NOLM solution. However, since the tariff rates are designed as a response to the neighbourhood equilibrium, some agents might be negatively affected by the introduction of such a market. The composition of the neighbourhood agents will be important for the benefits provided by the local market. The market has the highest value when there are some inflexible and some flexible agents since such a situation means that we need a mechanism to incentivize the flexible agents to flatten the coincident peak for the neighbourhood rather than their individual peak.

[6] https://ens.dk/en/our-services/projections-and-models/technology-data [Accessed: 2020-02-04]
[7] https://www.enova.no/privat/alle-energitiltak/solenergi/el-produksjon-/
[8] https://ec.europa.eu/jrc/en/pvgis
[9] https://www.skatteetaten.no/en/business-and-organisation/vat-and-duties/excise-duties/about-the-excise-duties/electrical-power-tax/ [Accessed: 2020-10-07.]

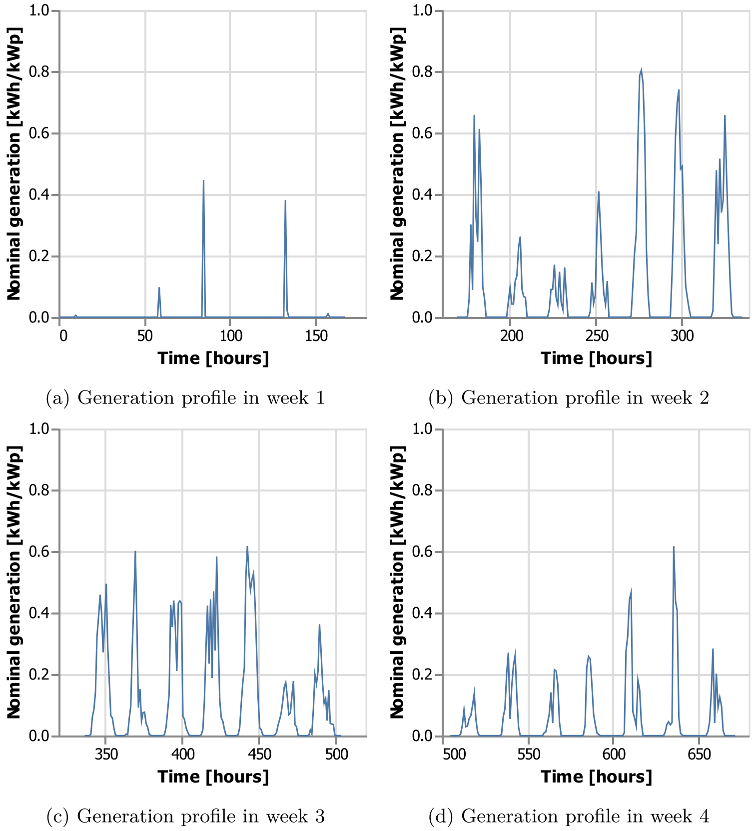

Fig. 4. Nominal PV generation in the neighbourhood.

Comparing the LM and the NOLM cases, it can be observed that a local market can efficiently allocate the resources in the neighbourhood since the solution is close to the SO case. In the following, we will dig deeper into these findings to explain how local market mechanisms can benefit both the DSO and other neighbourhood agents.

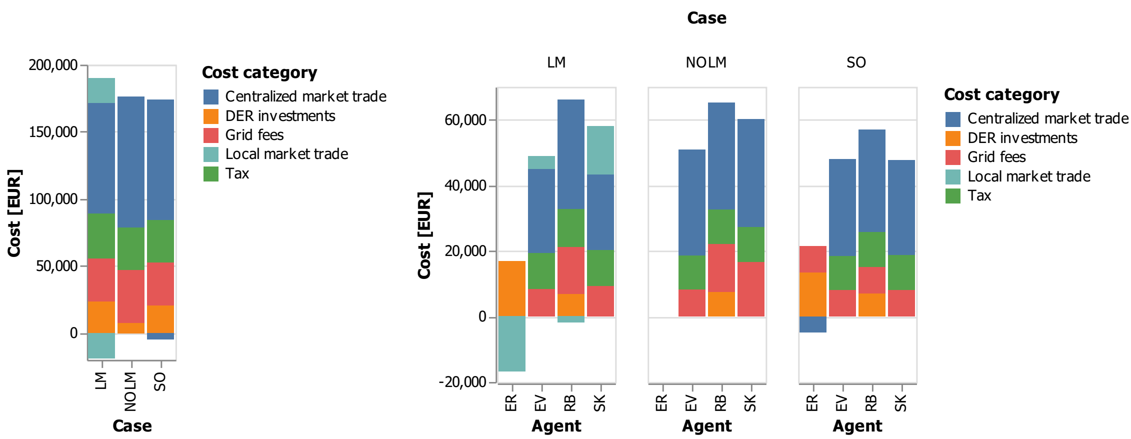

Fig. 5. Total system costs (left) and cost allocation per agent (right) for three cases: Decentralized decision-making with local market (LM), decentralized decision-making without local market (NOLM) and centralized decision-making (SO).

Table 3
Overview of key results for three cases: Decentralized decision-making with local market (LM), decentralized decision-making without local market (NOLM) and centralized decision-making (SO). Cost data are for one year based on the four weeks condidered in the analyses.

	LM	NOLM	SO
Total costs [€]	171,148	176,089	169,174
Net costs ER agent [€]	0	0	16,637
Net costs EV agent [€]	48,853	50,834	47,967
Net costs RB agent [€]	64,256	65,119	56,936
Net costs SK agent [€]	58,039	60,136	47,634
Volumetric tariff [¢/kWh]	0.301	0.299	N/A
Capacity-based tariff [€/kW]	100	85.5	N/A
Grid capacity [kW]	271	337	271
Total PV [kW]	663	175	568
ER agent PV [kW]	495	0	395
RB agent PV [kW]	168	175	173
Total battery [kWh]	0	14	0
ER agent battery [kWh]	0	0	0
RB agent battery [kWh]	0	14	0

5.2. Business case for stakeholders and assets

Now, we focus on the difference between the LM and the NOLM cases. The NOLM case is most representative of current regulatory frameworks in Europe.

The ER agent has no load profile but can invest in energy resources if this turns out to be profitable. Therefore, the ER agent can obtain zero costs if no investments are made. This happens in the NOLM case, where all electricity needs to be traded with the wholesale electricity market. Since the available neighbourhood-scale plants cannot recover the investment costs by participating in the wholesale market, no investments are made by the ER agent when there is no local market. Instead, despite higher unit costs, neighbourhood investments are exclusively made by the RB agent, which invests in a PV system with batteries to decrease the agents' individual costs through behind the meter optimization.

Fig. 5 also reveal that the investments in a PV system become profitable for the ER agent when the local market is introduced. Furthermore, Table 3 shows that the ER agent has zero costs also in the LM case since it invests until the point that the income from the local market exactly balances the investment costs.[10]

Investments made by the ER agent are exclusively in a PV system in the LM case, and there are no investments in batteries for the neighbourhood for neither the LM case nor the SO case (see Table 3). Consequently, batteries are not able to reduce the total system costs since no battery investments occur in the SO case. Despite the lack of bi-directional batteries in the LM and the SO cases, the neighbourhood has a significant flexibility resource through the EV agent since neighbourhood load balancing can efficiently be performed by appropriate charging of the EVs within certain limits. Additional investments in batteries are only profitable in the NOLM case for the RB agent (see Table 3). The battery investments occur in the NOLM case because each agent optimizes behind their own meter and, therefore, can benefit from investing in resources that limit their interaction with the grid. However, such individualistic behaviour produces higher total system costs because the regulatory framework triggers sub-optimal investments. Sub-optimal investments also induce sub-optimal operations, which we elaborate on next.

5.3. Pricing mechanisms and operational decisions

One key finding from the previous sections is that the local market can reduce the required grid capacity to the neighbourhood (see Table 3). This is feasible because the aggregate neighbourhood peak load is reduced in the LM and the SO cases compared to the NOLM case. Fig. 6 shows the aggregate load for the week with the highest load (week 1) along with the local market price. Note that the price can be very high and such price spikes might be hard to monitor in practice. Price spikes can also give the impression of market power, although such effects are outside the scope of this paper since we model the neighbourhood agents as price-takers. The introduction of a local market leads to better coordination of the flexible resources in the neighbourhood, and the aggregate peak load is 20% lower in the LM and SO cases compared to the NOLM case. When the market is not available, we see load spikes even though the agents are faced with a grid tariff penalizing high loads. The lacking aggregate neighbourhood peak load reduction in the NOLM case happens because the agents with flexible resources are incentivized to reduce their individual peak load rather than contributing to reducing the aggregate neighbourhood peak load.

Fig. 7 highlights the importance of coordination within the neighbourhood. The plot represents 24 h during the winter season when the original aggregate neighbourhood peak load is the highest (time steps 25–48), and we will refer to this time period as 'the critical winter day'. It is evident that during 'the critical winter day', the neighbourhood agents all employ a flat trading profile seen from the wholesale power market in the LM case compared to the NOLM case. Constant power purchase from the centralized power market would not be possible for the SK agent in particular without the local market since the SK agent has no flexible resources, and its demand varies over the day.

Since trading with the centralized power market is rather constant during this day, we can extract some information from how the agents interact with the local market, as depicted in Fig. 8. For example, the EV agent buys more than 100 kWh/h during the first 5 h through the SK and RB agents in the local power market, and the EVs are charged while the SK and RB agents have unused capacity. Note that the local trading happens even though the SK and RB agents do not produce energy, but are forwarding power bought from the centralized power market. The roles are switched during daytime when the EV and RB agents sell power to the SK agent during the second half of the day.

Note that the EV sales are not due to discharging (vehicle-to-grid) from the EVs; it is electricity purchased from the centralized power market by the EV agent that is sold in the local market instead of being used for EV charging. The forwarding of power from the centralized market via neighbourhood agents occurs because of the tariff scheme in place, where the agents pay for their individual peak load. When agents have unused capacity (low load), they choose to use this capacity to buy more power than needed for their own consumption and sell it to other neighbourhood agents that need it. Forwarding power to a neighbouring agent is an illustration of how local markets can facilitate coordination among different stakeholders by creating appropriate incentives for coordination. The incentives are created because the grid capacity is free of charge for end-users that are not close to their peak power while it is expensive for end-users that are close to their peak power. Hence, since different agents value the same resource differently, the business case for a local market is created. Consequently, situations where the aggregate neighbourhood load is high will be signalled to the end-users through high prices in the local market when all the end-users are close to their peak load.

These findings highlight that with the local market framework, agent EV charges the EVs during the first part of the day in order to balance the electricity consumption for the neighbourhood as a whole. Without the local market, the rational choice for the EV agent is to spread the EV charging evenly throughout the day to minimize the agents individual peak load, regardless of the overall load situation (see Fig. 9). Such individualistic incentives are consistent with the situation without a local market (NOLM) and result in a higher aggregate neighbourhood peak load, as depicted in Fig. 6.

[10] The ER agent does not turn a profit due to the price-taker assumption inherent in the equilibrium conditions in the model.

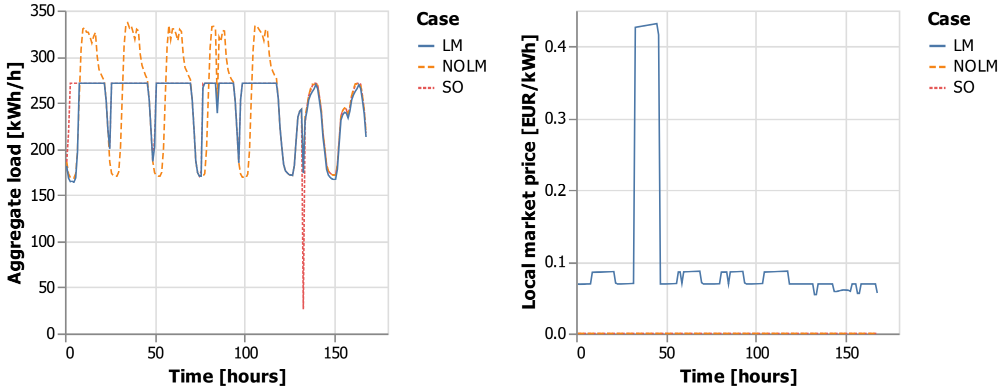

Fig. 6. Aggregate load for three different regulatory frameworks (left) and corresponding local market price for the LM case (right) during the winter week.

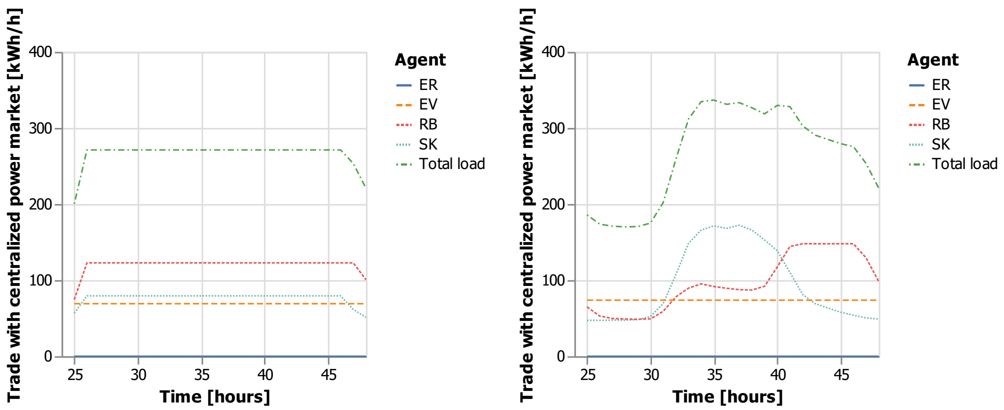

Fig. 7. Trading with the centralized power market during 'the critical winter day' when the local market is available (left) and without the local market (right).

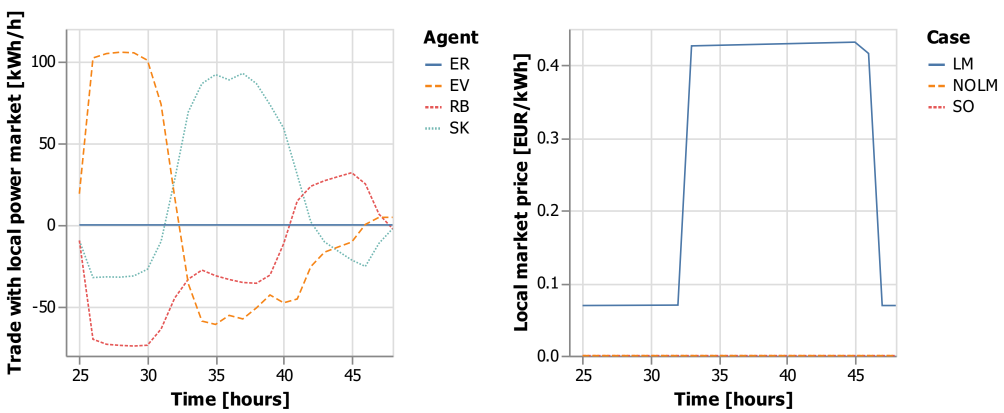

Fig. 8. Trading in local market (left) and corresponding local market price (right) during the critical winter day (hours 25–48).

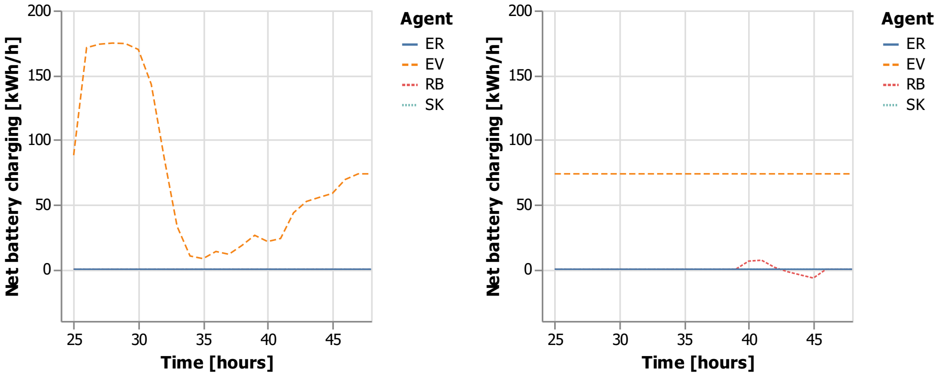

Fig. 9. EV charging and battery operation during 'the critical winter day' when the local market is available (left) and without the local market (right).

5.4. Equilibrium tariffs and DSO cost recovery

For completeness, we explore what happens when the tariffs deviate from the equilibrium state for the LM case. Fig. 10 presents how the DSOs profit, and the grid capacity changes when we vary the tariffs from zero and upwards. The base tariffs, representing a 0% deviation, are equivalent to case LM. We run analyses using the MCP model starting from a tariff deviation of −100% and increase the tariffs in 10% intervals. Agent ER and RB invest in increasing amounts of PV and batteries as the tariffs increase since interaction with the wholesale market becomes increasingly expensive.

Fig. 10 shows that we have two equilibria that satisfy the DSO cost recovery criterion of zero profits. The first equilibrium occurs at a tariff deviation of 0%, which is the LM solution where the DSOs expenses are exactly balanced by tariff income. The second equilibrium occurs when the tariffs are increased by more than 42 times (+4,210%) from the first equilibrium level. The second equilibrium occurs when the tariffs becomes so high that the neighbourhood agents decide to be completely self-sufficient, and the DSO has no investments and no income. These results indicate that it can be costly to replace the grid entirely with decentralized resources.

5.5. Impact of tax rate on the results

So far, we have included an electricity tax on imports from both the wholesale power market and the local market. However, such a tax inherently promotes behind the meter optimization in the local market and therefore we expect the tax rate to limit the trading in the local market. To investigate the effect of the electricity tax rate on the results, we compare the results for different tax rates in the LM case.

Table 4 reports the results for three different electricity tax rates: 1) zero taxes, 2) tax as before, 3) double tax rate. The total costs are almost equal to the SO case when we remove the electricity tax and the LM solution becomes more expensive than the SO solution as the electricity tax is incresed. The reason for the deviation from the system optimal solution is mainly that the tax limits the trading in the local market since the agents need to pay a premium on electricity imports from the other agents in the local market.

The tax rate makes imports from both the wholesale and local markets more expensive. An increase in the tax rate mainly affects the PV capacity in the local system. When there is no tax on electricity, all the PV capacity is installed at the ER agent since it has the lowest investment costs. As the tax increases, the PV capacity shifts to the RB agent

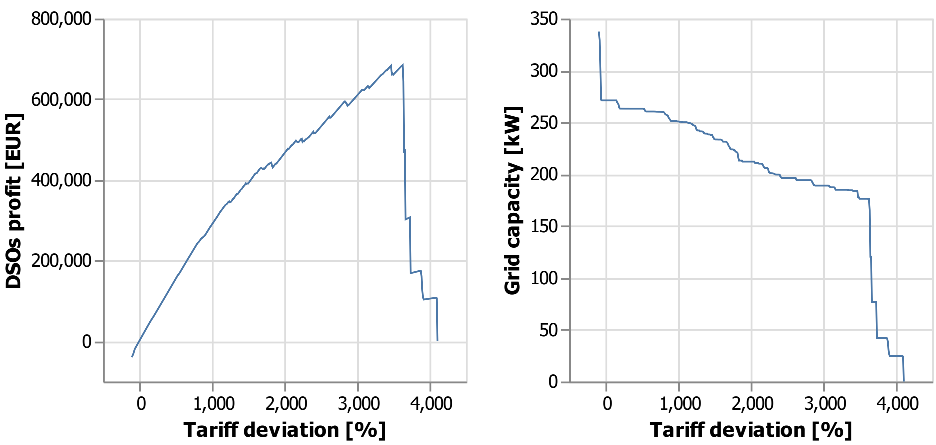

Fig. 10. Response by neighbourhood to increasing grid tariffs. Figure shows DSOs profit (left) and the grid capacity (right). The figures start at a − 100% deviation from the tariffs in the LM case.

Table 4
Sensitivity to tax change for the LM case.

	Tax = 0	Tax = 1.6	Tax = 3.2
Cost change from SO [%]	+0.01	+1.17	+1.97
Volumetric tariff [¢/kWh]	0.300	0.301	0.301
Capacity-based tariff [€/kW]	100	100	100
Grid capacity [kW]	271	271	271
Total PV [kW]	610	663	769
ER agent PV [kW]	610	495	460
RB agent PV [kW]	0	168	309
Total Battery [kWh]	0	0	0

as the cost reduction from self-consumption of energy dominates the investment cost increase at the RB agent. The ER agent, however, decreases investments because it becomes less competitive in the local market when its product is taxed. In total, the PV capacity increases with a higher tax rate since the increase at the RB agent is higher than the decrease at the ER agent.

6. Conclusion and policy implications

In this paper, we propose a game-theoretic framework to analyze a local trading mechanism and its feedback effect on grid tariffs under cost recovering conditions for the DSO. In this game-theoretic model, we construct a case study which is inspired by regulatory issues that have been identified in an ongoing pilot project in Norway. Our results are based on calculations using representative data from four weeks, where each week represents one season of the year.

Within our assumptions, our main finding is that the establishment of a local electricity market in a neighbourhood pareto-dominates the situation without a local market and could decrease the total costs by facilitating local coordination of resources and thus create socio-economic value. The novelty of our analysis is to show how local market activity does not just save costs for neighbourhood stakeholders, but in fact, impacts the regulated tariff rates as the local market activity defer some of the DSO costs. When we compare the establishment of a local market with a regulatory framework without any local market, we observe a reduction in total costs including the need for grid capacity for the system as a whole.

The local market creates value because it is able to coordinate the flexible assets on the neighbourhood level rather than at the individual end-user level. The presence of a capacity-based tariff in combination with a local market mechanism is crucial for these findings since it creates the appropriate price signal to lower the aggregate peak load for the neighbourhood. The peak load is reduced because the local market price reflects the scarcity of capacity in the overall neighbourhood.

Two equilibrium solutions satisfy the DSO cost-recovery criterion: (1) The DSOs costs are exactly balanced by tariff income and a significant interaction between the neighbourhood and the larger power system and (2) at very high tariffs the neighbourhood decides to completely disconnect from the larger power system. In the second equilibrium, the DSO has zero costs and income. These results indicate that although a local trading mechanism can reduce the need for grid capacity, it can be costly to disconnect from the system completely.

Local electricity markets are currently prohibited in most parts of the world. Although the establishment of a local electricity market shows promising potential according to our results, there are several considerations to be made upon evaluating the allowance of local electricity trading. Firstly, the cost of establishing and administrating a local electricity market cannot exceed its net saving potential. With automation and smart metering infrastructure, this countervailing cost is hopefully small enough. Secondly, the saving potential identified in our analysis is dependent on rational and reliable reactions by distributed market participants to reduce peak neighbourhood load rather than increasing the grid capacity. Thirdly, the highest value of establishing a local market is likely to be related to deferring grid development, i.e., defer upgrading grid capacity in an area where power outtake is increasing.

Whether a DSO is willing to depend on the rational reactions by market participants rather than relying on robust development and dimensioning of grid infrastructure is worth considering. An underlying assumption in this paper is that the agents are risk-neutral and, therefore, purely motivated by reducing their expected costs. However, since different regulatory frameworks might fundamentally affect the cost distribution for the involved stakeholders, further research could go in the direction of including risk preferences in the modeling framework.

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Appendix A Mathematical symbols

Nomenclature

Sets	
$c \in [1,\dots,C]$	Neighbourhood agents
$h \in [1,\dots,H]$	Hours
Parameters	
λ_h^P	Power market price in hour h (€/kWh)
C^G	Existing transmission capacity (kW)
$D_{c,h}$	Electricity demand in hour h (kWh/h)
$D_{c,h}^{\Delta-}$	EV demand in hour h (kWh/h)
$G_{c,h}^E$	Energy resource availability at agent c in hour h (kW/kWp)
I_c^E, I_c^S	Annualized investment costs at agent c (€/kW/year)
I^G	Annualized investment cost for grid capacity (€/kW/year)
L^G	Transmission losses (%)
L_c^S	Energy storage converter losses at agent c (%)
NM	Net-metering coefficient
P_c^{ch}	Energy storage capacity ratio for charging at agent c (kW/kWh)
P_c^{dis}	Energy storage capacity ratio for discharging at agent c (kW/kWh)
R_c	Energy storage self-discharge at agent c (%/h)
T	Excise tax (€/kWh)
U_c^E, U_c^S	Resource limits at agent c (kW)
W_h	Weight of hour h (h/h)
Upper-level variables	
c_{DSO}^G	Investment in interconnection capacity (kW)
cnt	Capacity-based network tariff (€/kW)
e_h^{GE}	Neighbourhood exports in hour h (kWh/h)
e_h^G	Neighbourhood load in hour h (kWh/h)
e_h^{GI}	Neighbourhood imports in hour h (kWh/h)
vnt	Volumetric network tariff (€/kWh)
Lower-level variables	
$exp_{c,h}^P$	Energy exported to grid at agent c in hour h (kWh/h)
λ_h^L	Market price in the local market in hour h (€/kWh)
c_c^E	Energy resource capacity at agent c (kW)
c_c^G	Measured peak load at agent c (kW)
c_c^S	Storage capacity at agent c (kWh)
$d_{c,h}^{\Delta+}, d_{c,h}^{\Delta-}$	Battery charge/discharge at agent c in hour h (kWh/h)
$exp_{c,h}^L$	Energy exported to local market at agent c in hour h (kWh/h)
$g_{c,h}^E$	Energy generation at agent c in hour h (kWh/h)
$imp_{c,h}^P$	Energy imported from grid at agent c in hour h (kWh/h)
$imp_{c,h}^L$	Energy imported from local market at agent c in hour h (kWh/h)
$s_{c,h}$	Battery state of charge at agent c in hour h (kWh)

Appendix B MCP formulation of local energy system

We derive the KKT conditions of the neighbourhood level based on the optimization problem described in section 3.2. Since our original problem is linear and has a convex feasible area, the KKT conditions are necessary and sufficient.

$$I_c^S + \mu_c^{S2} - \sum_{h=1}^{H}\left(\mu_{c,h}^{S3} + P_c^{ch} * \mu_{c,h}^{S4} + P_c^{dis} * \mu_{c,h}^{S5}\right) \geq 0 \perp c_c^S \geq 0 \ \forall c \tag{B.1}$$

$$I_c^E + \mu_c^{E1} - \sum_{h=1}^{H} \mu_{c,h}^{E2} * G_{c,h}^E \geq 0 \perp c_c^E \geq 0 \ \forall c \tag{B.2}$$

$$\begin{aligned} &W_h * \left(\lambda_h^P + T + vnt\right) \\ &-\lambda_{c,h}^{EB} + \mu_{c,h}^G \geq 0 \perp imp_{c,h}^P \geq 0 \ \forall c,h \end{aligned} \tag{B.3}$$

$$\begin{aligned} &-W_h * \left(\lambda_h^P + NM*vnt\right) \\ &+\lambda_{c,h}^{EB} + \mu_{c,h}^G \geq 0 \perp \ exp_{c,h}^P \geq 0 \ \forall c,h \end{aligned} \tag{B.4}$$

$$W_h * \left(\lambda_h^L + T\right) - \lambda_{c,h}^{EB} \geq 0 \perp imp_{c,h}^L \geq 0 \ \forall c,h \tag{B.5}$$

$$-W_h * \lambda_h^L + \lambda_{c,h}^{EB} \geq 0 \perp \ exp_{c,h}^L \geq 0 \ \forall c,h \tag{B.6}$$

$$cnt - \sum_{h=1}^{H} \mu_{c,h}^G \geq 0 \perp c_c^G \geq 0 \ \forall c \tag{B.7}$$

$$\lambda_{c,h}^{EB} - \left(1 - L_c^S\right) * \lambda_{c,h}^{S1} + \mu_{c,h}^{S4} \geq 0 \perp d_{c,h}^{\Delta +} \geq 0 \ \forall c,h \tag{B.8}$$

$$\left(1 + L_c^S\right) * \lambda_{c,h}^{S1} - \lambda_{c,h}^{EB} + \mu_{c,h}^{S5} \geq 0 \perp d_{c,h}^{\Delta -} \geq 0 \ \forall c,h \tag{B.9}$$

$$-\lambda_{c,h}^{EB} + \mu_{c,h}^{E2} \geq 0 \perp g_{c,h}^E \geq 0 \ \forall c,h \tag{B.10}$$

$$\begin{aligned} &\lambda_{c,h}^{S1} - (1 - R_c) * \lambda_{c,h+1}^{S1} \\ &+\mu_{c,h}^{S3} \geq 0 \perp s_{c,h} \geq 0 \ \forall c,h<H \end{aligned} \tag{B.11}$$

$$\lambda_{c,H}^{S1} - (1 - R_c) * \lambda_{c,1}^{S1} + \mu_{c,H}^{S3} \geq 0 \perp s_{c,H} \geq 0 \ \forall c \tag{B.12}$$

$$\begin{aligned} &imp_{c,h}^P - exp_{c,h}^P + imp_{c,h}^L - exp_{c,h}^L \\ &-D_{c,h} - d_{c,h}^{\Delta +} + d_{c,h}^{\Delta -} + g_{c,h}^E = 0 \perp \lambda_{c,h}^{EB} \ \forall c,h \end{aligned} \tag{B.13}$$

$$\begin{aligned} &(1 - R_c) * s_{c,h-1} + (1 - L_c) * d_{c,h}^{\Delta +} \\ &-(1 + L_c) * d_{c,h}^{\Delta -} - D_{c,h}^{\Delta -} - s_{c,h} = 0 \perp \lambda_{c,h}^{S1} \ \forall c,h>1 \end{aligned} \tag{B.14}$$

$$\begin{aligned} &(1 - R_c) * s_{c,H} + (1 - L_c) * d_{c,1}^{\Delta +} \\ &-(1 + L_c) * d_{c,1}^{\Delta -} - D_{c,h}^{\Delta -} - s_{c,1} = 0 \perp \lambda_{c,1}^{S1} \ \forall c \end{aligned} \tag{B.15}$$

$$U_c^S - c_c^S \geq 0 \perp \mu_c^{S2} \geq 0 \ \forall c \tag{B.16}$$

$$c_c^S - s_{c,h} \geq 0 \perp \mu_{c,h}^{S3} \geq 0 \ \forall c,h \tag{B.17}$$

$$c_c^S * P_c^S - d_{c,h}^{\Delta +} \geq 0 \perp \mu_{c,h}^{S4} \geq 0 \ \forall c,h \tag{B.18}$$

$$c_c^S * P_c^S - d_{c,h}^{\Delta -} \geq 0 \perp \mu_{c,h}^{S5} \geq 0 \ \forall c,h \tag{B.19}$$

$$c_c^G - imp_{c,h}^P - exp_{c,h}^P \geq 0 \perp \mu_{c,h}^G \geq 0 \ \forall c,h \tag{B.20}$$

$$U_c^E - c_c^E \geq 0 \perp \mu_c^{E1} \geq 0 \ \forall c \tag{B.21}$$

$$c_c^E * G_{c,h}^E - g_{c,h}^E \geq 0 \perp \mu_{c,h}^{E2} \geq 0 \ \forall c,h \tag{B.22}$$

$$\sum_{c=1}^{C}\left(exp_{c,h}^L - imp_{c,h}^L\right) = 0 \perp \lambda_h^L \ \forall h \tag{B.23}$$

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Magnus Askeland: Conceptualization, Methodology, Software, Validation, Investigation, Writing - Original Draft, Writing - Review & Editing, Visualization.

Stian Backe: Conceptualization, Methodology, Writing - Review & Editing.

Sigurd Bjarghov: Conceptualization, Writing - Review & Editing.

Magnus Korpås: Conceptualization, Methodology, Writing - Review & Editing, Funding acquisition, Supervision.

References

Abada, Ibrahim, Ehrenmann, Andreas, Lambin, Xavier, 2020. Unintended consequences: the snowball effect of energy communities. Energy Policy 143, 111597. https://doi.org/10.1016/j.enpol.2020.111597.

Almenning, O.M., Bjarghov, S., Farahmand, H., 2019. Reducing neighborhood peak loads with implicit peer-to-peer energy trading under subscribed capacity tariffs. *International Conference on Smart Energy Systems and Technologies (SEST)*, pages 1–6. https://doi.org/10.1109/SEST.2019.8849067 Sep. 2019

Askeland, Magnus, Korpås, Magnus, 2019. Interaction of DSO and local energy systems through network tariffs. *International Conference on the European Energy Market, EEM* ISBN 9781728112572.

Askeland, Magnus, Backe, Stian, Lindberg, Karen Byskov, 2019. Zero energy at the neighbourhood scale: Regulatory challenges regarding billing practices in Norway. IOP Conference Series: Earth and Environmental Science 352 (1). https://doi.org/10.1088/1755-1315/352/1/012006 ISSN 17551315.

Askeland, Magnus, Burandt, Thorsten, Gabriel, Steven A., 2020. A stochastic MPEC approach for grid tariff design with demand side flexibility. Energy Systems https://doi.org/10.1007/s12667-020-00407-7 ISSN 1868-3975.

Backe, Stian, Kara, Güray, Tomasgard, Asgeir, 2020. Comparing individual and coordinated demand response with dynamic and static power grid tariffs. Energy 201, 117619. https://doi.org/10.1016/j.energy.2020.117619 ISSN 0360-5442. http://www.sciencedirect.com/science/article/pii/S036054422030726X.

Bergaentzlé, Claire, Jensen, Ida Græsted, Skytte, Klaus, Olsen, Ole Jess, 2019. Electricity grid tariffs as a tool for flexible energy systems: A Danish case study. Energy Policy 126 (November 2018), 12–21. https://doi.org/10.1016/j.enpol.2018.11.021 ISSN 03014215.

Brown, David P., Sappington, David E.M., 2018. On the role of maximum demand charges in the presence of distributed generation resources. Energy Econ. 69, 237–249. https://doi.org/10.1016/j.eneco.2017.11.023 ISSN 0140-9883.

Eid, Cherrelle, Guillén, Javier Reneses, Marín, Pablo Frías, Hakvoort, Rudi, 2014. The economic effect of electricity net-metering with solar PV: consequences for network cost recovery, cross subsidies and policy objectives. Energy Policy 75, 244–254. https://doi.org/10.1016/j.enpol.2014.09.011 ISSN 03014215.

Eid, Cherrelle, Codani, Paul, Perez, Yannick, Reneses, Javier, Hakvoort, Rudi, 2016. Managing electric flexibility from distributed energy resources: a review of incentives for market design. Renewable and Sustainable Energy Reviews 64, 237–247. https://doi.org/10.1016/j.rser.2016.06.008 ISSN 18790690.

?A3B2 tlsb -0.01w?>Faruqui, Ahmad, Harris, Dan, Hledik, Ryan, 2010. Unlocking the €53 billion savings from smart meters in the EU: How increasing the adoption of dynamic tariffs could make or break the EU's smart grid investment. Energy Policy 38 (10), 6222–6231. https://doi.org/10.1016/j.enpol.2010.06.010 ISSN 0301–4215. http://www.sciencedirect.com/science/article/pii/S0301421510004738 The socio-economic transition towards a hydrogen economy - findings from European research, with regular papers.

Gabriel, Steven A., Conejo, Antonio J., Fuller, J. David, Hobbs, Benjamin F., Ruiz, Carlos, 2012. Complementarity Modeling in Energy Markets. volume 180. Springer Science & Business Media. https://doi.org/10.1007/978-1-4419-6123-5 ISBN 978–1–4419-6123-5 (eBook).

Heinisch, Verena, Odenberger, Mikael, Göransson, Lisa, Johnsson, Filip, 2019. Organizing prosumers into electricity trading communities: costs to attain electricity transfer limitations and self-sufficiency goals. Int. J. Energy Res., 1–19 https://doi.org/10.1002/er.4720 ISSN 0363-907X.

Hoarau, Quentin, Perez, Yannick, 2019. Network tariff design with prosumers and electromobility: who wins, who loses? Energy Econ. 83, 26–39. https://doi.org/10.1016/j.eneco.2019.05.009 ISSN 01409883.

Kirkerud, Jon Gustav, Trømborg, Erik, Bolkesjø, Torjus Folsland, 2016. Impacts of electricity grid tariffs on flexible use of electricity to heat generation. Energy 115, 1679–1687. https://doi.org/10.1016/j.energy.2016.06.147 ISSN 0360–5442.

Knezović, Katarina, Marinelli, Mattia, Zecchino, Antonio, 2017. Peter Bach Andersen, and Chresten Traeholt. Supporting involvement of electric vehicles in distribution grids: lowering the barriers for a proactive integration. Energy 134, 458–468. https://doi.org/10.1016/j.energy.2017.06.075 ISSN 03605442.

Kuhn, H.W., Tucker, A.W., 1951. Nonlinear programming. Proceedings of the Second Berkeley Symposium on Mathematical Statistics and Probability , pp. 481–492 Berkeley, Calif.. University of California Press. URL. https://projecteuclid.org/euclid.bsmsp/1200500249.
Lindberg, K.B., Bakker, S.J., Sartori, I., 2019. Modelling electric and heat load profiles of non-residential buildings for use in long-term aggregate load forecasts. Util. Policy 58 (January), 63–88. https://doi.org/10.1016/j.jup.2019.03.004 ISSN 09571787.
Luo, Zhi-Quan, Pang, Jong-Shi, Ralph, Daniel, 1996. Mathematical programs with equilibrium constraints. Cambridge University Press.
Lüth, Alexandra, Zepter, Jan Martin, del Granado, Pedro Crespo, Egging, Ruud, 2018. Local electricity market designs for peer-to-peer trading: The role of battery flexibility. Appl. Energy 229, 1233–1243 ISSN 0306-2619. 11. https://doi.org/10.1016/j.apenergy.2018.08.004.
Momber, Ilan, Wogrin, Sonja, Roman, Tomas Gomez San, 2016. Retail pricing: a bilevel program for PEV aggregator decisions using indirect load control. IEEE Trans. Power Syst. 31 (1), 464–473. https://doi.org/10.1109/TPWRS.2014.2379637 ISSN 08858950.
Parra, David, Patel, Martin K., 2016. Effect of tariffs on the performance and economic benefits of PV-coupled battery systems. Appl. Energy 164, 175–187 2016. ISSN 03062619. https://doi.org/10.1016/j.apenergy.2015.11.037.
Passey, Robert, Haghdadi, Navid, Bruce, Anna, MacGill, Iain, 2017. Designing more cost reflective electricity network tariffs with demand charges. Energy Policy 109 (April), 642–649. https://doi.org/10.1016/j.enpol.2017.07.045 ISSN 03014215.
Pinel, Dimitri, Bjarghov, Sigurd, Korp, Magnus, 2019. Impact of Grid Tariffs Design on the Zero Emission Neighborhoods Energy System Investments. *IEEE Milan PowerTech*, pages 1–6, 2019.
Pollitt, Michael G., 2018. Electricity network charging in the presence of distributed energy resources: principles, problems and solutions. Econ. Energy Environ. Policy 7 (1), 89–103. https://doi.org/10.5547/2160-5890.7.1.mpol ISSN 21605890.
Salpakari, Jyri, Rasku, Topi, Lindgren, Juuso, Lund, Peter D., 2017. Flexibility of electric vehicles and space heating in net zero energy houses: an optimal control model with thermal dynamics and battery degradation. Appl. Energy 190, 800–812. https://doi.org/10.1016/j.apenergy.2017.01.005 ISSN 03062619.
Sandberg, Eli, Kirkerud, Jon Gustav, Trømborg, Erik, Bolkesjø, Torjus Folsland, 2019. Energy system impacts of grid tariff structures for flexible power-to-district heat. Energy 168, 772–781. https://doi.org/10.1016/j.energy.2018.11.035 ISSN 0360-5442.
Schittekatte, Tim, Meeus, Leonardo, 2020. Least-cost distribution network tariff design in theory and practice. Energy J. 41 (01), 119–156. https://doi.org/10.5547/01956574.41.5.tsch ISSN 01956574.
Schittekatte, Tim, Momber, Ilan, Meeus, Leonardo, 2018. Future-proof tariff design: recovering sunk grid costs in a world where consumers are pushing back. Energy Econ. 70, 484–498. https://doi.org/10.1016/j.eneco.2018.01.028 ISSN 01409883.
Simshauser, Paul, 2016. Distribution network prices and solar PV: resolving rate instability and wealth transfers through demand tariffs. Energy Econ. 54, 108–122. https://doi.org/10.1016/j.eneco.2015.11.011 ISSN 01409883.
Sørensen, Åse Lekang, Jiang, Shanshan, Torsæter, Bendik Nybakk, Völler, Steve, 2018. Smart EV charging systems for zero emission neighbourhoods. Technical Report 5, SINTEF/NTNU. https://fmezen.no/wp-content/uploads/2018/06/ZEN-Report-no-5.pdf.
Sousa, Tiago, Soares, Tiago, Pinson, Pierre, Moret, Fabio, Baroche, Thomas, Sorin, Etienne, 2019. Peer-to-peer and community-based markets: a comprehensive review. Renew. Sust. Energ. Rev. 104 (June 2018), 367–378. https://doi.org/10.1016/j.rser.2019.01.036 ISSN 18790690.
Stoft, Steven, 2002. Power system economics. J. Energy Literature 8. https://doi.org/10.1002/9781119434573.ch1.
Strbac, Goran, 2008. Demand side management: benefits and challenges. Energy Policy 36 (12), 4419–4426. https://doi.org/10.1016/j.enpol.2008.09.030 ISSN 03014215.
Von Stackelberg, Heinrich, 2010. Market Structure and Equilibrium. Springer Science & Business Media. .
Zhang, Chenghua, Wu, Jianzhong, Zhou, Yue, Cheng, Meng, Long, Chao, 2018. Peer-to-peer energy trading in a microgrid. Appl. Energy 220, 1–12. https://doi.org/10.1016/j.apenergy.2018.03.010 ISSN 0306-2619. http://www.sciencedirect.com/science/article/pii/S0306261918303398.
Zhou, Shan, Brown, Marilyn A., 2017. Smart meter deployment in Europe: a comparative case study on the impacts of national policy schemes. J. Clean. Prod. 144, 22–32 2017. ISSN 09596526. https://doi.org/10.1016/j.jclepro.2016.12.031.
Zugno, Marco, Morales, Juan Miguel, Pinson, Pierre, Madsen, Henrik, 2013. A bilevel model for electricity retailers' participation in a demand response market environment. Energy Econ. 36, 182–197. https://doi.org/10.1016/j.eneco.2012.12.010 ISSN 01409883.

Paper III

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Paper III

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Heat and electric vehicle flexibility in the European power system: A case study of Norwegian energy communities

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Sector coupling

ABSTRACT

This paper investigates sector coupling between the central power system and local energy communities, including heat supply for buildings and charging of electric vehicles. We propose a stochastic linear programming framework to study long-term investments under uncertain short-term operations of nationally aggregated assets. We apply the model to a case study assuming European power sector decarbonization towards 2060 according to a 1.5 degree scenario, and we investigate the impact of coupling building heat systems and electric vehicle charging in Norway with the European power market. The case study focuses on the role of Norway in a European perspective because: (1) Norwegian electricity production is mainly based on flexible and renewable hydropower, (2) Norwegian building heating systems are currently mainly electric, and (3) Norway is already introducing electric vehicles at large. We focus on the European power market to test our hypothesis that it is more cost-efficient to decarbonize when the central power system is coordinated with building heat systems and electric vehicle charging. For Europe as a whole, results show that the average European electricity cost reduces by 3% and transmission expansion decreases by 0.4% when Norwegian heat systems are developed in coordination with the European power system. The average Norwegian electricity cost decreases by 19%. The strategy includes supplying up to 20% of Norwegian buildings with district heating fueled by waste and biomass, and the remaining electric heating supply is dominated by heat pumps.

1. Introduction

European energy policy pursue the growth of variable renewable energy sources (VRES), however, targets for the needed degree of restructuring of the power system are not clearly stated [1]. Integration of VRES will require grid infrastructure, energy storage, flexibility, sector coupling, and short-term fuel switching [2,3], with corresponding changes in market structure and business models [4]. The interest in Zero Energy Buildings [5] is strengthened as buildings in Zero Emission Neighbourhoods [6] are developing towards networks of energy responsive building envelopes [7]. The European Commission highlights the need to facilitate active demand-side participation in future European power markets [8]. This paper studies how the short-term interaction between buildings, electric vehicles (EV), and the central power system affects the long-term energy decarbonization pathway. Research has demonstrated that the residential sector has an important impact on the aggregated peak load in the European power system [9], and buildings [10] and EVs [11] can facilitate more efficient operation of the power system. However, it is still unclear how the link between the building-, transport-, and power sector can impact European decarbonization.

Several power system models study decarbonization [12] and sector coupling [13]; however, to the authors' knowledge, existing models do not reconcile the following four aspects: (1) multiple long-term investment periods, (2) chronological operational periods, (3) uncertain short-term operations, and (4) short-term sector coupling between the power system, building heat systems, and charging of electric vehicles (EVs). In this context, we propose an extension of The European Model for Power System Investment with (high shares of) Renewable Energy (EMPIRE) [14–16].

Abbreviations: NTC, Net transfer capacity; EU, European Union; EMPIRE, The European Model for Power System Investment with (high shares of) Renewable Energy; CHP, Combined heat and power; VRES, Renewable energy sources; PV, Photovoltaic; EV, Electric vehicle; V2G, Vehicle-to-grid; WtE, Waste-to-Energy; O&M, Operation and maintenance; HWST, Hot water storage tank; COP, Coefficient of performance

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We apply the extended EMPIRE model on a European case study focusing on how heat systems in buildings and charging of EVs are developed and operated when integrated with the European power system. In [17], an assessment of space heating flexibility has been performed, and they call for further work on how identified flexibility can be utilized in a larger context. In [18], they find that EV charging load could exceed available electricity capacity in some European countries and that flexible EV charging could limit some capacity inadequacy. In this paper, we focus on how sector coupling affects the development of conventional flexibility assets, e.g. hydropower, and flexibility from heat systems in buildings and smart charging of EVs. Norway is in focus because its electricity supply is dominated by flexible hydropower, building heat systems are mainly electric, and EVs are phased in by favorable policies. Our hypothesis is that increasing the flexibility of building heat systems and EV charging in Norway will benefit the European power system as a whole because flexible Norwegian hydropower can be utilized as a 'green battery' in Europe [19,20]. Essentially, we test whether adding more flexibility to an already flexible region of the power system can benefit the whole system. The case study analyzes how sector coupling affects the development of: generation assets for building heat and electricity, power transmission assets, and storage and flexibility assets, including hydropower, building heat, and EVs.

The structure of the paper is as follows: Section 2 presents related research to identify the novelty of our modelling framework and our case study. Section 3 presents the modelling framework including the new sector coupling features of EMPIRE, and Section 4 presents the European case study. Finally, Section 5 presents and discusses the case study results, before the paper is concluded in Section 6.

2. Background

This section discusses several techno-economic energy system models that have been used for analyses of European decarbonization towards 2050.

A comprehensive multi-scale analysis is presented in [21] investigating transition pathways towards the EU low carbon economy [22] without considering endogenous uncertainty within the modeling frameworks. In [23], short-term uncertainty in long-term energy system models is shown to be important when considering VRES like wind. The E2M2 model considers short-term uncertainty of VRES in [24], but storage and demand response technologies are not considered. Flexibility in a VRES dominated power system, including transmission, has been studied in The North Sea region using the PowerGIM model in [25] without considering sector coupling. The Balmorel model has been used to analyze sector coupling between the heat and electricity sectors [26–28], but does not consider short-term uncertainty of VRES.

The German heat and electricity sector has been studied with the REMod-D model [29] and results show that 100% renewable supply is feasible [30]. The Nordic and Baltic region is analyzed with Balmorel in [27] where they find that electricity-to-heat converters and hot water storage tanks (HWST) are important assets. Increased flexibility in electricity systems dominated by combined heat- and power (CHP) plants through HWST and electric boilers are shown to decrease wind curtailment in [31]. Integrated operation of electricity and district heating systems has been analyzed in [32] demonstrating reduced operational costs, and the theoretical maximum of flexibility from CHP systems coupled with HWST have been analyzed in [33]. Price effects on electricity based heating in Norway are analyzed with Balmorel in [28] where they find that fuel switching in heat systems have growing importance with more VRES in the power system. Both heat and electricity is considered in a stochastic version of TIMES in [34] studying the impact of net Zero Energy Buildings in the Scandinavian energy system. In [34], they find that such buildings will (1) partly replace investments in non-flexible hydropower, wind power and (CHP) and (2) trigger investments in more electricity based heating systems. Europe as a whole has been studied in [35] focusing on the utilization of excess production by VRES for building heating, and they find that heat pumps are a preferred technology to perform the sector coupling. In [36], the PyPSA [37] framework has been used to study sector coupling between the European power system, the heat sector, and the transport sector in 2050, and they find that transmission exchange combined with energy flexibility through sector coupling can reduce total system costs of decarbonization by 37%.

The EMPIRE model has been used to analyze decarbonization of the European power system considering uncertainty [14]. An updated version of EMPIRE is presented in [15] explaining the multi-horizon stochastic programming structure [38], and a case study of the European power system decarbonization shows large wind power expansion and major net transfer capacity (NTC) expansion between European countries [15]. Demand response features have also been developed in EMPIRE [16] and tested in a European case study. EMPIRE has been linked with the model ZENIT in [39] to analyze how energy resources in neighbourhoods integrate into the Nordic power system, but only considers contributions of electricity production from neighbourhoods.

In summary, we identify two research gaps: (1) The lack of a modeling framework consolidating long-term energy system planning, short-term uncertainty, and sector coupling, and (2) the lack of a previous study focusing on the Norwegian sector coupling with a European perspective. To cover these gaps, the continuation of this paper proposes a modeling framework (Section 3) and a case study (Section 4).

3. Method

This section presents the stochastic programming model EMPIRE [14–16] which has been re-implemented in the open-source Python-based optimization suite Pyomo [40].

3.1. Model structure

EMPIRE [14–16] is a techno-economic capacity expansion model [41] applied to the European energy system represented by a network. An open version of EMPIRE can be downloaded from [42]. The nodes in the network represent auction zones for clearing energy supply and demand, and the arcs represent exchange of electricity between these zones. The model supports investment decisions in generation, storage, and transmission assets on a country/zonal level made subject to the need to meet energy demand on an hourly basis without exceeding a European-wide emission cap. Energy demand, as well as asset options, their related costs and operational characteristics, are input to the model. The output supports decisions regarding technology choices, investment volume and timing, as well as hourly operations assuming perfect competition. Investments and operations related to generation and storage capacity happen in the nodes, cross-border exports and imports are described by arcs, whereas investments in transmission are described by a pair of unidirectional arcs between the same two nodes.

EMPIRE forms a linear two-stage stochastic program [43] where the first-stage decisions represent investments in period i, and the second-stage decisions represent operations in period i and scenario ω. The stochastic scenarios consider uncertainty in the availability of wind-, solar-, hydropower generation; electric specific and building heat load; coefficient of performance (COP) for heat pumps; and required energy for flexible demand, e.g. EV charging. EMPIRE uses a multi-horizon structure [38] illustrated in Fig. 1. Each scenario $\omega_{x,y,z}$ represents time series, and scenario z represents one realization of season y in investment period x.

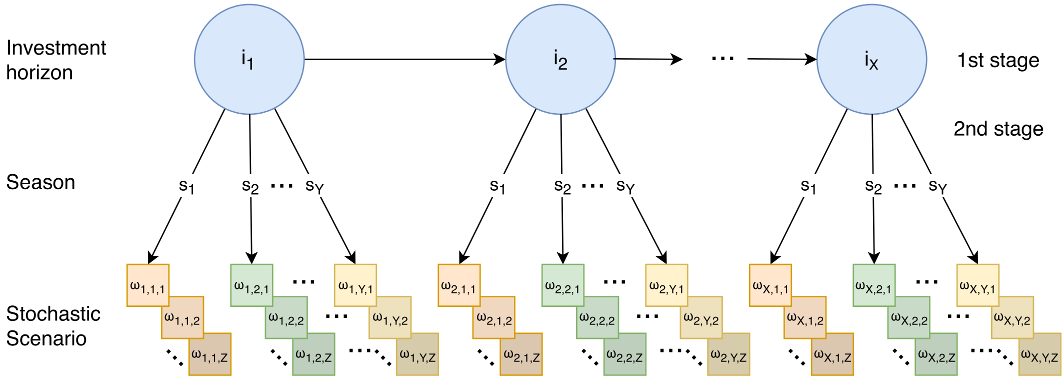


Fig. 1. Illustration of the stochastic structure of the EMPIRE model. The blue circles represent investment periods with first-stage decisions, and each period contains seasons and stochastic scenarios with second-stage decisions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2. Sector coupling features

3.2.1. Building heat

One of the contributions of this paper is the development of EMPIRE to include sector coupling of building heat systems with the central power system. This feature is developed by categorizing energy demand into electric specific demand and building heat demand as described in [44]. Electric specific demand includes all electricity demand that *must* be met with electricity, while building heat demand includes space and hot water demand in buildings that *can* be met with either electricity or other heat producing technologies, e.g. district heating. The model supports investments in technologies that can generate and store heat and electricity, including CHP plants. In addition, the model supports investment in technologies converting electricity to heat, e.g. heat pumps. Through the electricity-to-heat converters, it is feasible to satisfying building heat demand with 100% electricity.

Fig. 2 represents the link between operations in a specific node, operational period, investment period, and stochastic scenario. Supply by generators is either electricity, heat, or both (CHP). Converters transform electricity to heat but not heat to electricity. Generators and converters must satisfy electric specific and building heat demand. More electricity and heat in one operational time step can be supplied or converted to be stored for later within the same season and stochastic scenario. If there is less supply than demand for electricity or heat, storage must be discharged or load must be shed. Heat, naturally, cannot be exchanged between countries.

Fig. 2 also illustrates how the model considers flexibility from supply-, converter-, and storage assets. For every hour, the model has flexibility to cover electricity demand by producing electricity in that hour or discharging stored electricity. Similarly for heat, there is flexibility to produce or discharge stored heat to cover heat demand, and additionally an option of converting electricity to heat with either produced or stored electricity. Note that demand is not considered flexible. However, the model can consider demand flexibility if parts of the demand is considered as a storage. Charging the storage is equivalent to the net addition of demand in an hour, while discharging the storage is equivalent to net removal of demand in an hour.

3.2.2. Electric vehicle charging

To consider flexible EV charging, the demand response features of EMPIRE presented in [16] are used. More specifically, EV demand is considered to be a *shiftable volume load* [16], i.e. energy demand that must be met by a certain time period with any charging pattern given it meets the energy demand and satisfies some charging constraints. The input of EV demand affects the total EV charging flexibility, and it is the minimum cumulative charging to be made within a node and period, e.g. every 24 h. We consider uncertainty of EV flexibility by allowing EV demand to vary across different stochastic scenarios. The charging constraints also affect the EV charging flexibility for every node and investment period, and they include a maximum charging limit

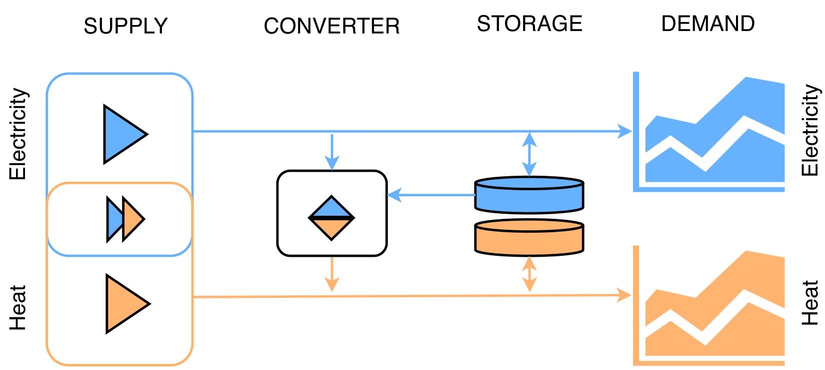


Fig. 2. Illustration of the sector coupling between the electricity and the building heat sector in the EMPIRE model. The sector coupling is on an hourly time resolution in the model.

dependent on the endogenous EV charging capacity expansion. We also consider vehicle-to-grid (V2G) through the possibility of discharging EVs.

3.3. Mathematical formulation

The following section presents in detail the mathematical formulation of EMPIRE used in this paper including the developments presented in Section 3.2. It is best read assisted by the full nomenclature of EMPIRE found in Appendix A.

3.3.1. Objective function

The objective function in EMPIRE quantifies costs of investing and operating the respective energy system, and it is formulated in the following way:

$$\min z = \sum_{i\in\mathcal{I}} (1+r)^{-5(i-1)} \times \Big[\sum_{n\in\mathcal{N}} \sum_{a\in\mathcal{G}_n\cup\mathcal{B}_n\cup\mathcal{R}_n} c^{\text{node}}_{a,i} x^{\text{node}}_{a,n,i} + \sum_{n\in\mathcal{N}} \sum_{b\in\mathcal{B}_n} c^{\text{storCH}}_{b,i} x^{\text{storCH}}_{b,n,i} + \sum_{(n_1,n_2)\in\mathcal{L}} c^{\text{tran}}_{n_1,n_2,i} x^{\text{tran}}_{n_1,n_2,i} + \vartheta \sum_{\omega\in\Omega} \pi_\omega \sum_{s\in\mathcal{S}} \alpha_s \sum_{h\in\mathcal{H}_s} \sum_{n\in\mathcal{N}} \sum_{g\in\mathcal{G}_n} q^{\text{gen}}_{g,i} y^{\text{gen}}_{g,n,h,i,\omega} + \vartheta \sum_{\omega\in\Omega} \pi_\omega \sum_{s\in\mathcal{S}} \alpha_s \sum_{h\in\mathcal{H}_s} \sum_{n\in\mathcal{N}} \left(q^{ll,EL}_{n,i} y^{ll,EL}_{n,h,i,\omega} + q^{ll,HT}_{n,i} y^{ll,HT}_{n,h,i,\omega}\right)\Big]. \tag{1}$$

The objective function (1) discounts all costs at an annual rate of r, and the investment periods are given as five-year blocks. The first three terms of (1) relates to investment costs in additional capacity of generation, storage, and transmission. The last three terms relate to operational- and load shedding costs. The terms for operational costs are scaled with the scenario probability π_ω, the seasonal scaling factor α_s annualizing the seasonal costs, and the five-year scale factor $\vartheta = \sum_{j=0}^{4} (1+r)^{-j}$ scaling and discounting the annual operational costs to the five-year investment periods.

3.3.2. Investment constraints

Installed capacity of assets in each period is defined in the following way:

$$v^{\text{node}}_{a,n,i} = \bar{x}^{\text{node}}_{a,n,i} + \sum_{j=i'}^{i} x^{\text{node}}_{a,n,j}, \quad a \in \mathcal{G}_n \cup \mathcal{B}_n \cup \mathcal{R}_n,\ n \in \mathcal{N},\ i \in \mathcal{I},\ i' = \max\{1, i - i^{\text{life}}_a\}. \tag{2}$$

Constraints (2) make sure installed capacity is defined as initial capacity plus capacity expansion up until the period of consideration for every generator, storage, and electricity-to-heat converter. Note that constraints (2) consider the asset lifetime. Equivalent constraints also apply for transmission lines and charging/discharging capacity of storage.

Capacity expansion of storage is separate for charging/discharging capacity and energy storage capacity. However, some storage technology types $b \in \mathcal{B}^\dagger \subseteq \mathcal{B}$ cannot expand charging/discharging capacity without also expanding energy storage capacity. A fixed capacity expansion ratio, β^{stor}_b, is defined for $b \in \mathcal{B}^\dagger$, and constraints (3) apply:

$$v^{\text{storCH}}_{b,n,i} = \beta^{\text{stor}}_b v^{\text{node}}_{b,n,i}, \quad b \in \mathcal{B}^\dagger \cap \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I}. \tag{3}$$

3.3.3. Operational constraints

There are two main groups of equations in EMPIRE that ensure the operational balance between supply and demand of electric specific and building heat load:

$$\sum_{g\in\mathcal{G}_{\text{EL}}\cap\mathcal{G}_n} \beta^{\text{CHP}}_g y^{\text{gen}}_{g,n,h,i,\omega} + \sum_{b\in\mathcal{B}_{\text{EL}}\cap\mathcal{B}_n} \eta^{\text{dischrg}}_b y^{\text{dischrg}}_{b,n,h,i,\omega} + \sum_{(n_1,n_2)\in\mathcal{A}^{\text{in}}_n} \eta^{\text{tran}}_{n_1,n_2} y^{\text{tran}}_{n_1,n_2,h,i,\omega} + y^{\text{ll,EL}}_{n,h,i,\omega} = \xi^{\text{load,EL}}_{n,h,i,\omega} + \sum_{b\in\mathcal{B}_{\text{EL}}\cap\mathcal{B}_n} y^{\text{chrg}}_{b,n,h,i,\omega} + \sum_{(n_1,n_2)\in\mathcal{A}^{\text{out}}_n} y^{\text{tran}}_{n_1,n_2,h,i,\omega} + \sum_{r\in\mathcal{R}_n} y^{\text{E2H}}_{r,n,h,i,\omega}, \quad n\in\mathcal{N},\ h\in\mathcal{H},\ i\in\mathcal{I},\ \omega\in\Omega, \tag{4}$$

$$\sum_{g\in\mathcal{G}_{\text{HT}}\cap\mathcal{G}_n} y^{\text{gen}}_{g,n,h,i,\omega} + \sum_{b\in\mathcal{B}_{\text{HT}}\cap\mathcal{B}_n} \eta^{\text{dischrg}}_b y^{\text{dischrg}}_{b,n,h,i,\omega} + \sum_{r\in\mathcal{R}_n} \eta^{\text{E2H}}_{n,r,h,i,\omega} y^{\text{E2H}}_{r,n,h,i,\omega} + y^{\text{ll,HT}}_{n,h,i,\omega} = \xi^{\text{load,HT}}_{n,h,i,\omega} + \sum_{b\in\mathcal{B}_{\text{HT}}\cap\mathcal{B}_n} y^{\text{chrg}}_{b,n,h,i,\omega}, \quad n\in\mathcal{N},\ h\in\mathcal{H},\ i\in\mathcal{I},\ \omega\in\Omega. \tag{5}$$

Constraints (4) ensure the balance of electric specific load, which means that total supply from electric generators and storage units, as well as imports and electric load shedding, must be balanced with electric load, exports, and charging. Note that $\beta^{\text{CHP}}_g = 1$ for all $g \notin \mathcal{G}_{\text{EL}} \cap \mathcal{G}_{\text{HT}}$, that is all non-CHP electric generators. For CHP generators ($g \in \mathcal{G}_{\text{EL}} \cap \mathcal{G}_{\text{HT}}$), β^{CHP}_g represents how much electricity is being produced per unit of heat output.

Similarly, constraints (5) make sure the building heat load is balanced such that total supply from building heat generators and storage units, as well as conversions of electricity to heat and heat load shedding, must be balanced with heat load and charging. Note that conversion of electricity to heat links constraints (4) and (5) together, and that hourly scenario dependent converter efficiency is ensured in constraints (5).

Annual CO2eq. emissions from energy production for every investment period are restricted with an emission cap:

$$\sum_{s\in\mathcal{S}} \alpha_s \sum_{h\in\mathcal{H}_s} \sum_{n\in\mathcal{N}} \sum_{g\in\mathcal{G}_n} q^{\text{CO2}}_{g,i} y^{\text{gen}}_{n,g,h,i,\omega} \leqslant Q^{\text{CO2}}_i, \quad i\in\mathcal{I},\ \omega\in\Omega. \tag{6}$$

Constraints (6) ensure that no operational scenario can produce more annual CO2eq. emissions than the cap allows. These constraints ensure that the optimal solution of EMPIRE represents an energy system with the needed emission reductions, while the objective (1) is focusing on minimizing total system costs. The alternative to including the carbon cap constraints (6) is to include carbon pricing as part of the operational costs of carbon emitting generators. However, future carbon prices are harder to forecast than future carbon caps, so we include constraints (6). Note that the dual variables of constraints (6) represent the shadow prices of meeting the carbon cap which makes carbon prices an output of EMPIRE.

Generators are subject to the following operational constraints:

$$y^{\text{gen}}_{g,n,h,i,\omega} \leqslant \xi^{\text{gen}}_{g,n,h,i,\omega} v^{\text{node}}_{g,n,i}, \quad g\in\mathcal{G}_n,\ n\in\mathcal{N},\ h\in\mathcal{H},\ i\in\mathcal{I},\ \omega\in\Omega, \tag{7}$$

$$y^{\text{gen}}_{g,n,h,i,\omega} - y^{\text{gen}}_{g,n,h-1,i,\omega} \leqslant \gamma^{\text{gen}}_g v^{\text{node}}_{g,n,i}, \quad g\in\mathcal{G}_{\text{Ramp}}\cap\mathcal{G}_n,\ n\in\mathcal{N},\ s\in\mathcal{S},\ h\in\{h^2_s,\dots,|\mathcal{H}_s|\},\ i\in\mathcal{I},\ \omega\in\Omega. \tag{8}$$

Constraints (7) ensure that generator type g cannot produce more than what is installed in node n and period i and what is available in hour h and scenario ω. Thus, constraints (7) allow for the consideration of uncertain availability of e.g. VRES. Constraints (8) ensure that some generators are subject to up-ramping restrictions, i.e. increasing generator output between two consecutive hours is limited by a share of installed capacity.

Hydroelectric generators are subject to additional constraints:

$$\sum_{h\in\mathcal{H}_s} y^{\text{gen}}_{\text{RegHyd}',n,h,i,\omega} \leqslant \xi^{\text{RegHydLim}}_{n,i,s,\omega},$$
$$n \in \mathcal{N},\, s \in \mathcal{S},\, i \in \mathcal{I},\, \omega \in \Omega, \tag{9}$$

$$\sum_{\omega\in\Omega} \pi_\omega \sum_{s\in\mathcal{S}} \alpha_s \sum_{h\in\mathcal{H}_s} \sum_{g\in\mathcal{G}^{\text{Hyd}}\cap\mathcal{G}_n} y^{\text{gen}}_{n,g,h,i,\omega} \leqslant \xi^{\text{HydLim}}_n,$$
$$n \in \mathcal{N},\, i \in \mathcal{I}. \tag{10}$$

Generation by regulated hydro plants is restricted by season and node through constraints (9), while expected annual production for all hydro plants in a node are constrained by (10)

Storage assets are subject to the following operational constraints:

$$\kappa_b v^{\text{node}}_{n,b,i} + \eta^{\text{chrg}}_b y^{\text{chrg}}_{n,b,h^1_s,i,\omega} - y^{\text{discrg}}_{n,b,h^1_s,i,\omega} = w^{\text{stor}}_{n,b,h^1_s,i,\omega},$$
$$b \in \mathcal{B}_n,\, n \in \mathcal{N},\, s \in \mathcal{S},\, i \in \mathcal{I},\, \omega \in \Omega, \tag{11}$$

$$w^{\text{stor}}_{b,n,h-1,i,\omega} + \eta^{\text{chrg}}_b y^{\text{chrg}}_{b,n,h,i,\omega} - y^{\text{discrg}}_{b,n,h,i,\omega} = \eta^{\text{bleed}}_b w^{\text{stor}}_{b,n,h,i,\omega},$$
$$b \in \mathcal{B}_n,\, n \in \mathcal{N},\, s \in \mathcal{S},\, h \in \{h^2_s, ..., |\mathcal{H}_s|\},$$
$$i \in \mathcal{I},\, \omega \in \Omega. \tag{12}$$

$$w^{\text{stor}}_{n,b,h^1_s,i,\omega} = w^{\text{stor}}_{n,b,|\mathcal{H}_s|,i,\omega},$$
$$b \in \mathcal{B}_n \backslash \mathcal{B}_{\text{FX}},\, n \in \mathcal{N},\, s \in \mathcal{S},\, i \in \mathcal{I},\, \omega \in \Omega, \tag{13}$$

$$\xi^{\text{FX}}_{n,h,i,\omega} \leqslant w^{\text{stor}}_{n,b,h,i,\omega},$$
$$b \in \mathcal{B}_{\text{FX}},\, n \in \mathcal{N},\, h \in \mathcal{H},\, i \in \mathcal{I},\, \omega \in \Omega. \tag{14}$$

Storage assets start with an initial energy level available as a percentage of installed capacity ensured by constraints (11), and their state of charge considering losses is ensured by constraints (12). Normal storage assets run a full cycle over each representative time period in each season through (13), while flexible demand, $b \in \mathcal{B}_{\text{FX}}$, is represented as storage that needs to be filled by specified hours within representative periods through constraints (14).

Flexibility in EMPIRE is related to an asset's ability to adapt its operation to different operational scenarios, and it can be provided by all assets in EMPIRE, including generators, storage, transmission, and electricity-to-heat converters. The generators with more operational constraints, like generators subject to ramping constraints (8), have less flexibility than generators without ramping constraints, e.g. regulated hydropower.

3.3.4. Other constraints

In addition to the constraints presented in the previous section, all variables in EMPIRE are subject to non-negativity constraints. Capacity expansion is subject to upper bounds, and all asset operations are bounded by installed capacity.

4. Case study

This section describes our European case study and the input to the EMPIRE model. The main purpose of the case study is to study the impact of the sector coupling features presented in Section 3.2 with a European perspective.

We consider eight five-year investment periods from 2020 to 2060, and we assume an annual discount rate of 5% following [14]. The instances contain 35 nodes[1] and 85 bidirectional arcs representing existing and potential European power exchanges. Norway is divided into five nodes representing the Norwegian Nord Pool price zones. No transmission expansion between the Norwegian zones is allowed. The CO2eq. cap is assumed to follow [45] from 1, 110 to 22 Mton CO2eq. per year from 2020 to 2060. Emission factors for stationary combustion are estimated according to [46], and we assume only operational emissions and no emissions related to VRES including biomass. Cost of load shedding is assumed to be €22, 000/MWh following [47].

[1] The model includes nodes for all countries in the EU-27 minus Cyprus and Montenegro plus Bosnia Hercegovina, Great Britain, North Macedonia, Serbia, Switzerland, and five Norwegian nodes representing Nord Pool bidding zones.

Table 1
Heat technology capital costs gathered from [48]. All generators are assumed to supply a district heating grid. CHP = Combined Heat and Power, HOP = Heat Only Plant (no electricity generation).

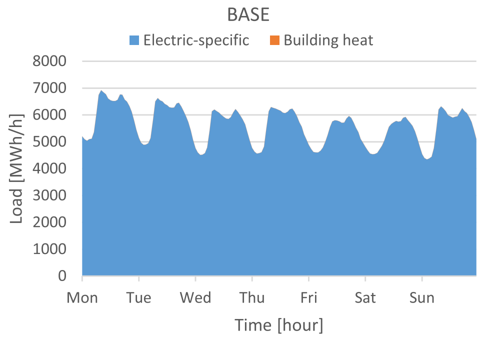
Technology	Capital cost [€/kW-heat] '20-'30	'30-'45	'45-'60
Converter			
Convector	966.7	933.3	833.3
Heat Pump (air-to-air)	440.0	514.3	485.7
Generator			
Waste-to-Energy (CHP)	1870.0	1780.0	1610.0
Waste-to-Energy (HOP)	1840.0	1750.0	1640.0
Bio Wood Chip (CHP)	1000.0	950.0	880.0
Bio Wood Chip (HOP)	790.0	750.0	680.0
Storage			
Hot Water Storage Tank (small)	410.0	410.0	410.0
Hot Water Storage Tank (large)	150.0	150.0	150.0

We include 16 electricity generator types and two electricity storage types (see Appendix B), and we do not consider carbon capture and storage technologies. Additionally, we consider two electricity-to-heat converter types, two non-electric building heat generator types, two CHP generator types, and two heat storage types (see Table 1). Technology costs for electricity generators come from [49], and fuel costs come from [50]. For building heat technologies, costs come from [48]. Costs for transmission expansion is according to [15].

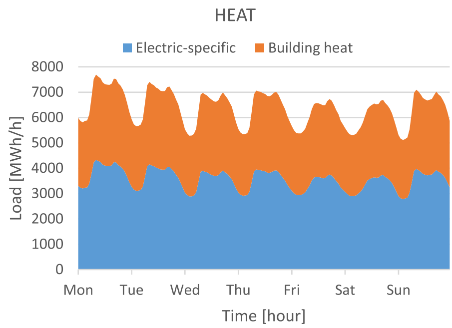
Operational scenarios have an hourly resolution and consist of six seasons per investment period: four regular seasons and two peak seasons. The regular seasons have 168-h duration and the peak seasons have 24-h duration. We consider three stochastic scenarios for all seasons. The uncertain data input are: VRES availability, load, COP for heat pumps, and EV demand.

Based on historical data, uncertainty related to VRES availability and load are produced by the scenario sampling routine described in [15]. The sampling routine is initiated by defining four partitions of a year containing hourly data that represents four regular seasons. The data set we sample from consist of several years of data for VRES availability from renewables.ninja [51,52] and load from ENTSO-E Transparency Platform. The sampling routine consist of the following steps: (1) selecting a random year, (2) selecting randomly the same 168 consecutive hours for each stochastic process within a season, and (3) repeating the former step for all seasons. The sampling routine is performed for all scenarios, and it is repeated for any sampled scenario that deviates too much from the mean, variance, skewness, and kurtosis of the respective underlying full data set. To represent extreme situations, we also construct two peak seasons containing 24 consecutive hours of extreme load situations. The first peak day contains the highest load summed over all countries, and the second peak day contains the highest hourly load of a single country. For heat pumps, we sample temperatures in Norway for the same hours for the year 2016, and we perform a linear regression based on data for BOSCH BMS500-AAM018-1CSXXA [53] to estimate a temperature dependent time series for the COP assuming an indoor temperature of 22 degrees.

As we consider the stochastic processes of load and VRES availability across Europe to be complex and mutually dependent, we sample from historical observations chronologically to preserve autocorrelation. Additionally, the same historic hours are sampled for the different European countries to preserve spatial cross-correlation. We also sample the same hours of a year for the different stochastic input to further preserve cross-correlation between the stochastic processes.



(a)



(b)

Fig. 3. A winter week for NO1 in BASE (a) and HEAT (b). All load is defined as electric specific load based on historic load profiles in BASE, whereas 40% and 20% of this load is defined as building heat load in HEAT for Norwegian winter and summer seasons, respectively.

Regarding uncertainty related to EV demand, we consider annual EV demand in Norway as projected in [54], from 2 TWh/year in 2020 to 15 TWh/year by 2060. Note that EV demand includes not only cars, but also buses and ferries [55]. The annual EV demand is made into a constant 24-h demand with a $\pm$ 5% random variability across the three stochastic scenarios.

We define two European instances in EMPIRE for comparison:

- BASE: All load in Europe is electric specific (see Fig. 3a) without defining building heat load. All load can only be met with electricity generation.
- HEAT: Part of Norwegian total load is defined as building heat load (see Fig. 3b). Heat load can be met with electricity-to-heat converters, including heat pumps and convectors, or non-electric heat generation and heat storage (see Table 1).

We only consider building heat load in Norway because we hypothesize that flexible Norwegian hydropower is more valuable for other purposes in the coming decades than meeting building heat load. Norwegian building heat supply is currently largely electric, while Norwegian electricity generation is dominated by flexible hydropower. Statistics from [56,54] show that 60% of electricity demand in buildings is for heating purposes and buildings make up about half of the total Norwegian electricity demand. Thus, the heat load in HEAT is estimated as 40% and 20% of the hourly electricity load from BASE for the Norwegian nodes for winter and summer seasons, respectively (see Fig. 3b). To make a fair comparison, the sum of heat and electricity demand is equal for BASE and HEAT if building heat load is met with existing building heat systems. Note in Fig. 3 that the total hourly load is higher in HEAT compared to BASE as the building heat load is adjusted by the COP of heat pumps. Defining building heat load as a share of historic electricity load can be used for Norway as heat supply to buildings is mainly electric [56], however, other approaches for projecting building heat load should be used for countries where building heat is not mainly covered with electricity, see e.g. [29,44].

To project future load profiles, we shift historic load profiles according to energy demand forecasts. This is done by calculating two averages: (1) the average load in node n in the first investment period ($i = 1$) based on the historic load profile for one stochastic scenario ω ($\xi^{\text{load,avg}}_{n,1,\omega}$) and (2) the average demand in one hour based on the annual demand estimate from the EU reference scenario [50] for investment period i ($\xi^{\text{dem,avg}}_{n,i}$). The load $\xi^{\text{load}}_{n,h,i,\omega}$ in hour h in node n, investment period i, and scenario ω is then calculated $\forall\ h \in \mathcal{H}$:

$$\xi^{\text{load}}_{n,h,i,\omega} = \xi^{\text{load}}_{n,h,1,\omega} - \xi^{\text{load,avg}}_{n,1,\omega} + \xi^{\text{dem,avg}}_{n,i}.$$

Electricity load data are based on historic load from ENTSO-E and shifted according to the annual demand growth anticipated in the EU decarbonization scenario 2016 presented in [50] towards 2050 and a linear interpolation towards 2060. For Norway, we estimate the annual electricity demand towards 2040 according to [54] and a linear interpolation for following investment periods in BASE. In HEAT, we categorize the annual electricity demand into electric specific demand for all sectors and building heat demand according to [54,56] adjusted by the COP of heat pumps (see Fig. 4). We allocate the annual demand within Norway according to the historical share of the total annual electricity use of the five Nord Pool zones, and this allocation method is used for any data related to Norway unless otherwise stated.

In both BASE and HEAT, investment costs for EV charging infrastructure are estimated according to Table 5.5 in [57]. We estimate initial charging capacity in Norway to be 300 MW assuming 15, 000 charging stations with an average capacity of 20 kW based on [58]. We assume existing charging capacity is retired by 2030 and allocate the initial capacity according to the share of publicly available car charging stations in each Norwegian zone in 2018 presented in [59]. We assume no losses related to EV charging. We also allow 20% of EV charging capacity to be used for V2G without costs or losses.

Initial electricity generation capacity per country is estimated according to [60]. We also assume only initial electricity-to-heat converters in buildings in Norway estimated as a share of peak heat load in each node as presented in [61]: 28% for heat pumps adjusted by the COP and 72% for convectors. We assume no fuel costs for Waste-to-Energy (WtE) generators. Because of waste treatment constraints, we also assume output from WtE generators must remain constant in each season with no intra-weekly up-ramping. The maximum installed capacity of WtE in Norway is estimated to be 1, 140 MW[2]. Emissions from burning waste are assumed to be 37.0 kgCOeq/GJ according to [48]. For the bio-based heat generation, fuel costs are chosen according to [50]. For initial capacity of HWSTs in Norway, we assume a Norwegian population of 5.3 million according to [63] and 1 kWh energy and charging capacity of small HWST capacity per person[3], and we assume no retirement of initial HWST capacity.

The energy community flexibility in our case study is related to HWST and charging/discharging of EVs, and we do not consider

[2] According to [62], Norway produces 3.6 million tons of burnable waste annually, and an energy value of 2.78 MWh/ton [48] can at maximum produce 10, 000 GWh/year, or 1, 140 MWh/h.

[3] One tank has 3 kWh energy capacity on average [48], and we assume two persons per tank and that two thirds of the tank is available for flexibility

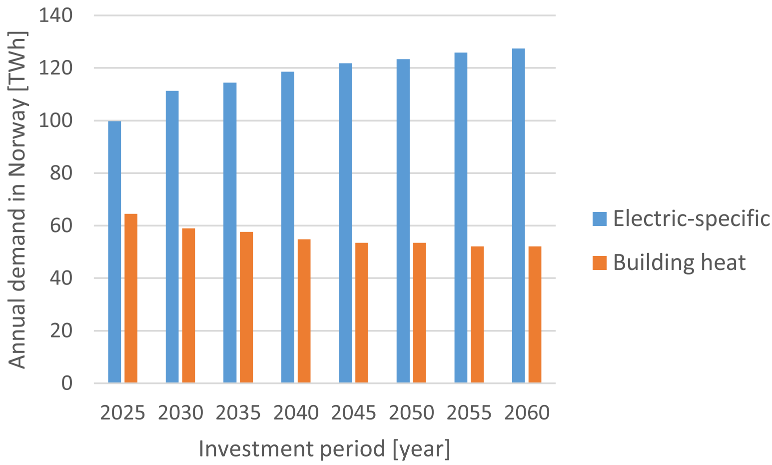


Fig. 4. Assumed development of annual electric specific and heat demand in Norway in HEAT.

flexibility in the thermal mass of buildings or other controllable loads in the communities.

5. Results and discussion

This section presents the results from our case study described in Section 4. BASE is solved in 9, 000 seconds, while HEAT is solved in 11, 000 seconds using interior point method (barrier algorithm) [64] without crossover with the FICO® Xpress Solver v8.8.1 [65] running on a computer cluster with CPU 2x 4 GHz Intel E5-2643v3 (6 core) and 512 Gb RAM.

5.1. Total system costs and emissions

The total discounted system costs for Europe from 2020 to 2060 for BASE is €2.47 trillion or an average undiscounted cost of European electricity of €100/MWh. In HEAT, 1% of total European electricity demand is identified as building heat demand in Norway. In BASE, all demand is assumed to be electric specific, so the main difference between BASE and HEAT is that building heat demand can be met by non-electric heat supply or more efficient electricity-to-heat converters in HEAT. This opportunity reduces the total system cost for Europe by €7.14 billion (− 0.29%) in HEAT, which means discounted savings of €3.2/MWh of building heat demand. The average undiscounted cost of European electricity reduces to €96/MWh (− 4%) in HEAT. The total number of hours with electricity prices > €1, 000/MWh reduces by 19% and the number of hours with prices < €1/MWh reduces by 5% in HEAT compared to BASE. The undiscounted average cost of electricity in Norway is €86/MWh in BASE and reduces to €70/MWh (− 19%) in HEAT.

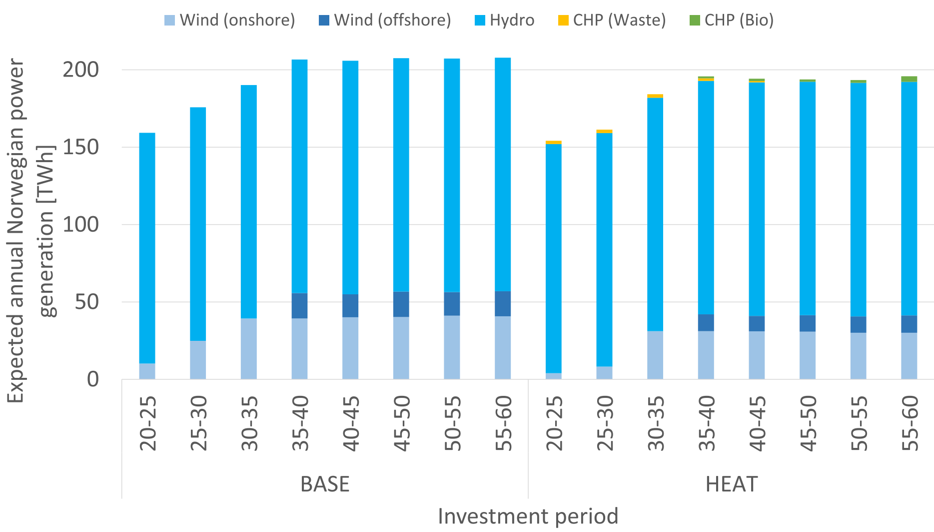


Fig. 5. Expected annual electricity generation from all Norwegian zones (NO1-NO5) from 2020 to 2060.

Table 2
Total expected demand and generation in Norway for BASE and HEAT from year 2020 to 2060.

Instance	BASE	HEAT
Electric specific demand, Norway [TWh]	6,200	4,700
Building heat demand, Norway [TWh]	–	2,200
Expected electricity generation, Norway [TWh]	7,800	7,400
– of which hydro [TWh]	6,000	6,000
– of which wind [TWh]	1,800	1,200
– of which CHP [TWh]	–	100
Expected non-electric heat generation, Norway [TWh]	–	400
Expected electric heat generation, Norway [TWh]	–	1,900
– of which convector [TWh]	–	300
– of which heat pump [TWh]	–	1,600

Total expected European emissions are capped for all generators, including heat generators, according to [45] and binding for all investment periods in BASE and HEAT. This is because of the emission cap constraints (6) in Section 3.3 which ensure that the scenarios with the highest emissions in all investment periods have the same emissions in BASE and HEAT. Note that both instances satisfy the emission targets in [45] for all investment periods. The undiscounted CO2eq. price ranges between €40/ton and €60/ton until 2040, and increases beyond €100/ton after 2040. The highest indicated CO2eq. price is €974/ton from 2055 to 2060 in BASE.

5.2. Expected annual heat and electricity generation

Hydropower dominates Norwegian electricity generation for both instances (see Fig. 5), while onshore- and offshore wind grows towards 2060 in both instances (see Fig. 5). Total electricity production in Norway, mainly from wind, is decreased in HEAT compared to BASE (see Table 2), while total expected hydropower output is the same.

Decreased electricity production in HEAT compared to BASE is because of two reasons: (1) building heat supply is met by CHP plants incinerating waste and biomass and (2) energy efficiency is increased through increased use of heat pumps. Up to 20% of building heat supply comes from CHP plants in HEAT, while the remaining building heat demand is met with electricity mainly used in heat pumps (see Fig. 6). The CHP plants are fueled solely by municipal waste until 2035, while emission constraints ensure an increasing amount of biomass is burned towards 2060. For the European power system as a whole, onshore- and offshore wind is decreased in HEAT compared to BASE compensated by energy from CHP plants and efficiency gains through heat pump use in Norway (see Fig. 7).

5.3. Transmission

Norwegian expected annual electricity imports decrease by 4% and exports increase by 8% in HEAT compared to BASE (see Fig. 8). The increased Norwegian electricity exports in HEAT compared to BASE does not lead to increased NTC expansion. On the contrary, there is 500 MW less NTC expansion between NO1 and Sweden in HEAT compared to BASE. This is because Sweden develops 8 GW less wind power, or an average decrease of 8 TWh/year, towards 2060 in HEAT compared to BASE, while wind power capacity in NO1 is the same. Consequently, electricity exports from Sweden are reduced in HEAT compared to BASE, and the required transmission capacity between Sweden and NO1 is reduced. Note that Norway as a whole develops 11 GW less wind in HEAT, or an average decrease of 13 TWh/year.

5.4. Flexibility in local energy communities

5.4.1. Heat converter and storage flexibility

There is significant capacity expansion of HWST in Norway in HEAT, where most expansion happen between 2030 and 2050. The heat storage is mostly utilized to balance the electricity use of electricity-to-heat converters. HWST are generally charged when Norwegian exports are decreased because that means electricity is available for heat conversion. The vice versa is also the case: HWST are generally discharged when exports are high because less electricity is available for heat conversion. In such a way, the central power system and the building heat systems are operated more cost efficiently through the flexibility provided by regulated hydropower, electricity-to-heat converters, and HWST. There is only capacity expansion of the 'large' HWST as it is a cheaper investment alternative (see Table 1). The new HWST storage capacity reaches 106 GWh for Norway in total by 2060, which would

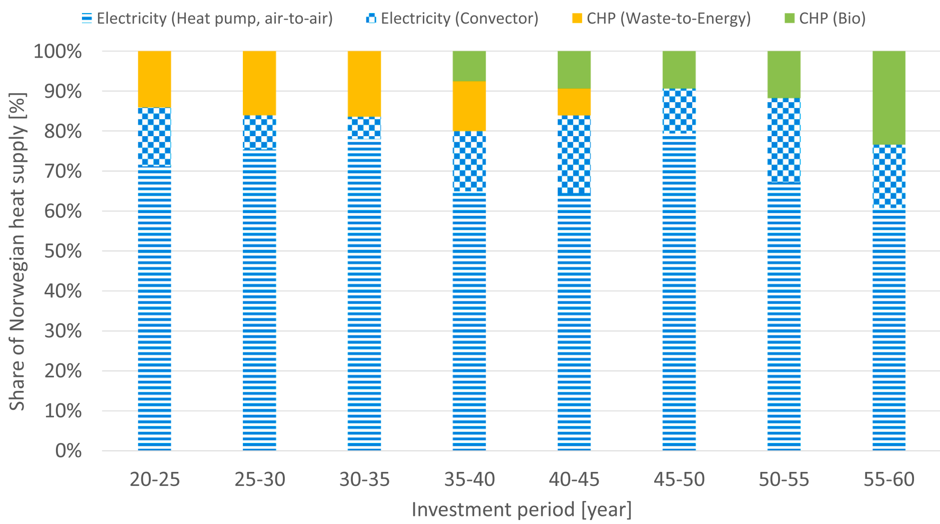


Fig. 6. Share of annual heat supply by technology in all Norwegian zones (NO1-NO5) from 2020 to 2060.

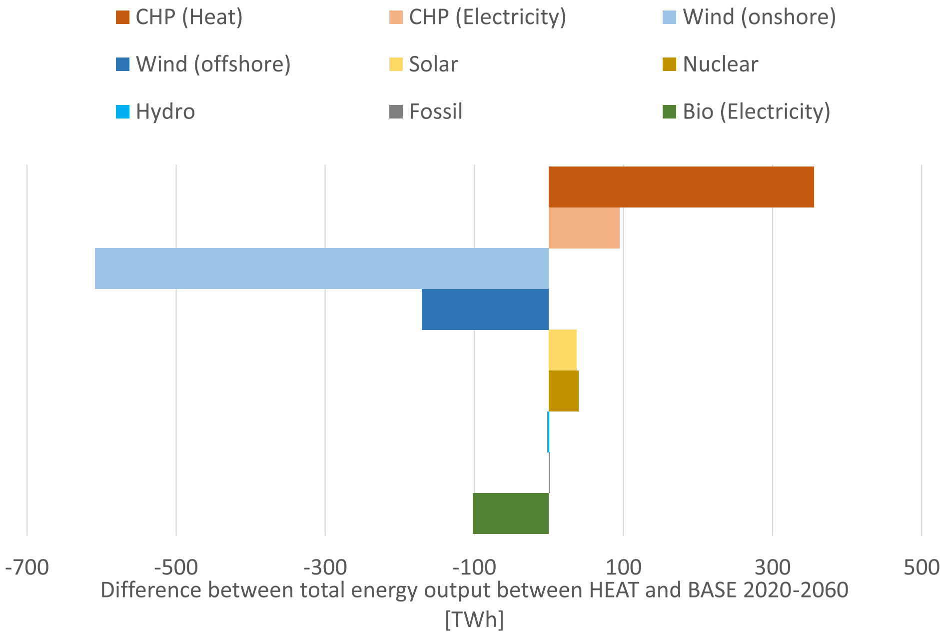


Fig. 7. Difference in total energy output from 2020 to 2060 by technology for all European countries in HEAT compared to BASE.

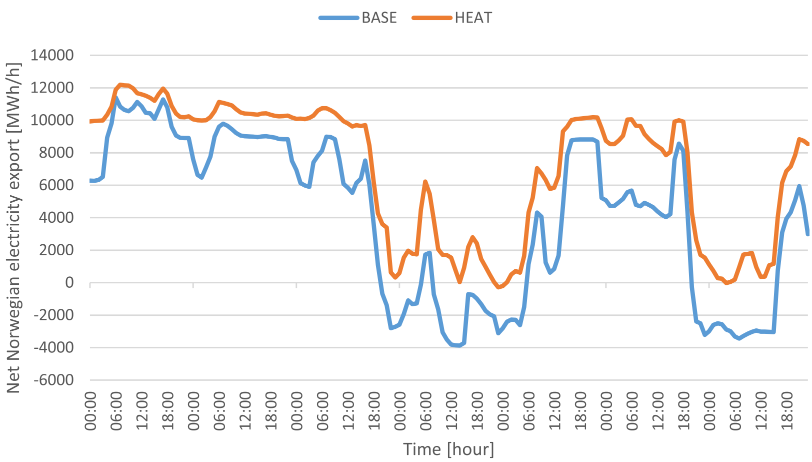


Fig. 8. Net hourly electricity export from Norway in the same fall week scenario for BASE and HEAT between 2030 and 2035. Negative values means net import to Norway.

require a total area[4] of 32, 000-133, 000 m^2 [48].

5.4.2. Electric vehicle charging

The total capacity expansion of EV charging capacity in Norway sums up to 4.3 GW in BASE, and there is 3% less capacity expansion in HEAT compared to BASE. After 2040, there is less EV charging capacity developed in NO1 and NO2 in HEAT compared to BASE indicating that building heat flexibility can partly substitute the need for EV charging infrastructure used for flexibility purposes. In other words, increased building heat flexibility increases the opportunity for peak shaving of EV charging profiles.

Load shifting, or optimal timing, of EV charging is increasingly valuable towards 2060 in both BASE and HEAT. Fig. 9 shows an example of one scenario for net charging of EVs in NO2 in a fall week in 2040–2045, and there is less variability in the EV charging in HEAT as the flexibility need is also met through smart building heating. Fig. 9 also shows a net V2G for NO2 in BASE, however, there is no net V2G for all Norwegian nodes in BASE or HEAT.

5.5. Discussion

The EMPIRE model's objective is to minimize total system costs subject

[4] Assuming the space requirement for 'large' hot water tanks ranges from 0.3 m2/MWh to 1.25 m^2/MWh [48]

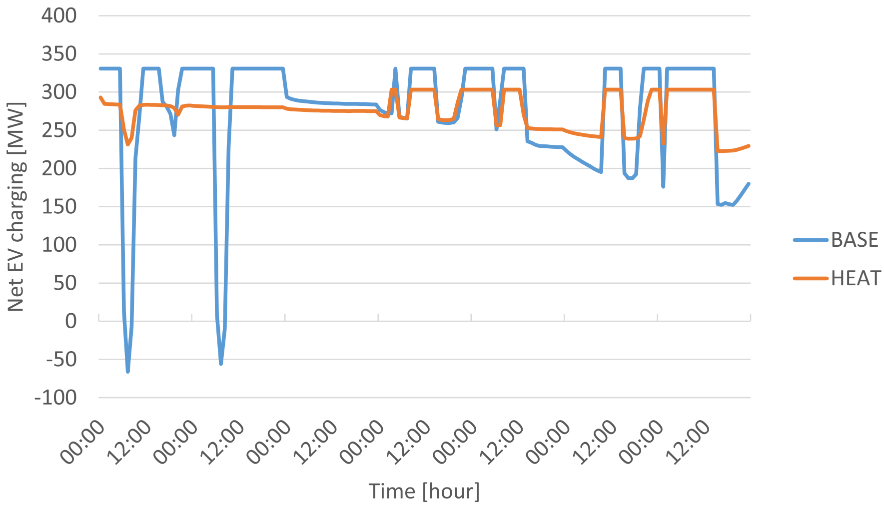


Fig. 9. Net charging of all EVs in NO2 in the same fall week in one stochastic scenario between 2040 and 2045.

to an ambitious European emission cap towards 2060. The output thus represents a simulation of the most cost-efficient decarbonization pathway for Europe as a whole, and does not represent the pathway of minimized emissions nor maximized energy efficiency. As emissions are capped, the difference in expected emissions from HEAT compared to BASE is small for Europe as a whole. However, there is a small increase in Norwegian emissions from WtE plants in HEAT compared to BASE, and this is fully compensated by a decrease in emissions for the rest of Europe in the critical scenarios. Although the increase in Norwegian emissions is small, these results demonstrate an important insight from our analysis: European emissions can cost-efficiently decrease even if national emissions for single European countries increase. This is especially relevant for Norway since Norwegian hydropower is valuable for VRES integration [19,20].

The case study of this paper is conducted within the European power market as we only analyze the development of Norwegian heat systems that are electric today. This is done to compare Norwegian heat system development when it is assumed to be an inflexible load (BASE) and when it can develop freely as building heating assets (HEAT). However, the whole heating market, as well as the gas market, is relevant to consider in multi-sector energy system analyses, especially when considering countries with less electric heating than Norway. Future work includes using the EMPIRE modeling framework to accommodate a larger share of the heating market and thus a larger opportunity for sector coupling.

The EMPIRE modeling framework assumes perfect coordination and resource aggregation within European countries and perfect competition between European countries. Therefore, the EMPIRE model inherently assumes that all energy resources within one node are coordinated, and that all flexibility assets in local energy communities can be provided on a national level within an hour, e.g. through an aggregator role [66]. This poses both technical, regulatory, and even social challenges [67]. Large-scale resource coordination calls for sophisticated metering and a close link between end-users and flexibility markets. Our modeling results indicate that if such coordination can be successful, the utilization of flexible resources at the end-user level could impact the central power system, including capacity expansion of transmission and generation [68].

6. Conclusion

This paper extends the stochastic linear programming model EMPIRE to study sector coupling between the central power system, heat systems in buildings, and flexible charging of EVs under uncertainty of VRES availability, heat pump COP, load, and EV demand. We apply the updated model to a European case study where we analyze decarbonization under uncertainty with and without sector coupling between the central power system and Norwegian building heat systems. Results from our case study indicate that a growth in non-electric heat supply to buildings in Norway is attractive for Europe towards 2060, and that the greatest share of building heat demand should be met with electric building heat solutions dominated by heat pumps coupled with heat storage. The integrated development of the European power system and Norwegian building heat systems increase export of hydropower from Norway to neighbouring countries. More work is needed to realistically represent the uncertain availability and costs related to aggregated local resources like heat systems and EVs. Future work also includes considering building heat and EVs for several European countries to study cost-efficient interactions between building heat systems, electric mobility systems, and the central power system while meeting decarbonization targets.

CRediT authorship contribution statement

Stian Backe: Conceptualization, Methodology, Software, Validation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. **Magnus Korpås:** Conceptualization, Funding acquisition, Supervision, Writing - review & editing. **Asgeir Tomasgard:** Conceptualization, Funding acquisition, Supervision, Writing - review & editing.

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.

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Appendix A. Nomenclature of EMPIRE

A.1. Sets

$\mathcal{G}$: Set of possible generator types,
$\mathcal{B}$: Set of possible storage types,
$\mathcal{R}$: Set of possible electricity-to-heat converter types,
$\mathcal{I} = \{1, 2, ..., |\mathcal{I}|\}$: Set of investment periods,
$\mathcal{H} = \{1, 2, ..., |\mathcal{H}|\}$: Set of operational periods,
$\mathcal{S}$: Set of seasons,
$\mathcal{N}$: Set of nodes,
$\mathcal{A} \subset \mathcal{N} \times \mathcal{N}$: Set of unidirectional interconnectors,
$\mathcal{L} \subset \mathcal{A}$: Set of bidirectional interconnectors,
Ω: Set of scenarios,
$\mathcal{G}_{\mathrm{EL}} \subset \mathcal{G}$: Set of possible electricity generator types,
$\mathcal{G}_{\mathrm{HT}} \subset \mathcal{G}$: Set of possible building heat generator types,
$\mathcal{G}_n \subseteq \mathcal{G}$: Set of possible generator types in node $n \in \mathcal{N}$,
$\mathcal{G}^{\mathrm{Ramp}} \subset \mathcal{G}$: Set of generator types limited by ramping,
$\mathcal{G}^{\mathrm{RegHyd}} \subset \mathcal{G}$: Set of regulated hydro generator types,
$\mathcal{G}^{\mathrm{Hyd}} \subset \mathcal{G}$: Set of all hydro generator types,
$\mathcal{B}_{\mathrm{EL}} \subset \mathcal{B}$: Set of possible electricity storage types,
$\mathcal{B}_{\mathrm{HT}} \subset \mathcal{B}$: Set of possible heat storage types,
$\mathcal{B}_{\mathrm{FX}} \subset \mathcal{B}_{\mathrm{EL}}$: Set of flexible electricity demand,
$\mathcal{B}_n \subseteq \mathcal{B}$: Set of possible storage types in node $n \in \mathcal{N}$,
$\mathcal{B}^{\dagger} \subseteq \mathcal{B}$: Set of storage types with fixed energy and charging ratio,
$\mathcal{R}_n \subseteq \mathcal{R}$: Set of available electricity-to-heat converters in node $n \in \mathcal{N}$,
$\mathcal{H}_s = \{h_s^1, h_s^2, ..., |\mathcal{H}_s|\} \subset \mathcal{H}$: Set of operational periods in season $s \in \mathcal{S}$,
$\mathcal{A}_n^{\mathrm{in}} \subset \mathcal{N} \times \mathcal{N}$: Set of arcs flowing into node $n \in \mathcal{N}$,
$\mathcal{A}_n^{\mathrm{out}} \subset \mathcal{N} \times \mathcal{N}$: Set of arcs flowing out from node $n \in \mathcal{N}$.

A.2. Input data

A.2.1. Costs

$c_{a,i}^{\mathrm{node}}$: Investment cost of asset a $\in \mathcal{G} \cup \mathcal{B} \cup \mathcal{R}$ in period $i \in \mathcal{I}$,
$c_{b,i}^{\mathrm{storCH}}$: Investment cost of charging of storage $b \in \mathcal{B}$ in period $i \in \mathcal{I}$,
$c_{n_1,n_2,i}^{\mathrm{tran}}$: Investment cost of bidirectional interconnection $(n_1, n_2) \in \mathcal{L}$ in period $i \in \mathcal{I}$,
$q_{g,i}^{\mathrm{gen}}$: Operational cost of generator type $g \in \mathcal{G}$ in period $i \in \mathcal{I}$,
$q_{g,i}^{\mathrm{CO2}}$: CO2 emission factor of generator type $g \in \mathcal{G}$ in period $i \in \mathcal{I}$,
$q_{n,i}^{\mathrm{ll,\,EL}}$: Value of lost electric specific load in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
$q_{n,i}^{\mathrm{ll,\,HT}}$: Value of lost building heat load in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
Q_i^{CO2}: CO2 emission ceiling for all generators in period $i \in \mathcal{I}$.

A.2.2. Technology limitations

i_a^{life}: Lifetime of investment in asset $a \in \mathcal{G} \cup \mathcal{B} \cup \mathcal{L} \cup \mathcal{R}$,
γ_g: Ramping factor for generator type $g \in \mathcal{G}_{\text{Ramp}}$,
$\eta_{n_1,n_2}^{\text{tran}}$: Efficiency factor for transmission losses along arc $(n_1, n_2) \in \mathcal{A}$, $\eta_{n_1,n_2}^{\text{tran}} \in (0, 1)$,
η_b^{chrg}: Efficiency factor for charge losses with storage type $b \in \mathcal{B}$, $\eta_b^{\text{chrg}} \in (0, 1)$,
η_b^{dischrg}: Efficiency factor for discharge losses with storage type $b \in \mathcal{B}$, $\eta_b^{\text{dischrg}} \in (0, 1)$,
η_b^{bleed}: Efficiency factor for bleed losses with storage $b \in \mathcal{B}$, $\eta_b^{\text{bleed}} \in (0, 1)$,
ρ_b: Capacity ratio between charge/discharge speed for storage type $b \in \mathcal{B}$,
β_g^{CHP}: Share of electric output per heat output from CHP generator $g \in \mathcal{G}_{\text{EL}}$,
$\forall\, g \notin \mathcal{G}_{\text{EL}} \cap \mathcal{G}_{\text{HT}}$: $\beta_g^{\text{CHP}} = 1$,
β_b^{stor}: Ratio between charging and energy capacity for storage type $b \in \mathscr{B}^\dagger \subseteq \mathcal{B}$,
κ_b: Share of installed energy capacity initially available in storage type $b \in \mathcal{B}$ in each representative time period,
ξ_n^{HydLim}: Max expected annual output from total hydro in node $n \in \mathcal{N}$,
$\bar{x}_{a,n,i}^{\text{node}}$: Initial capacity of nodal asset $a \in \mathcal{G}_n \cup \mathcal{B}_n \cup \mathcal{R}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
$\bar{x}_{b,n,i}^{\text{storCH}}$: Initial capacity of charging of storage $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
$\bar{x}_{n_1,n_2,i}^{\text{tran}}$: Initial capacity of bidirectional interconnection $(n_1, n_2) \in \mathcal{L}$ in period $i \in \mathcal{I}$,
$\bar{X}_{a,n,i}^{\text{node}}$: Max investments in nodal asset $a \in \mathcal{G}_n \cup \mathcal{B}_n \cup \mathcal{R}_n$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
$\bar{X}_{b,n,i}^{\text{storCH}}$: Max investments in charging of storage $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
$\overline{X}_{n_1,n_2,i}^{\text{tran}}$: Max investments in bidirectional interconnection $(n_1, n_2) \in \mathcal{L}$ in period $i \in \mathcal{I}$,
$\bar{V}_{a,n,i}^{\text{node}}$: Max installed capacity of asset $a \in \mathcal{G}_n \cup \mathcal{B}_n \cup \mathcal{R}_n$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
$\bar{V}_{b,n,i}^{\text{storCH}}$: Max installed capacity of storage of charging $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
$\overline{V}_{n_1,n_2,i}^{\text{tran}}$: Max installed capacity of bidirectional interconnection $(n_1, n_2) \in \mathcal{L}$ in period $i \in \mathcal{I}$.

A.2.3. Scenario input

π_ω: Probability of scenario $\omega \in \Omega$,
$\xi_{g,n,h,i,\omega}^{\text{gen}}$: Availability of generator type $g \in \mathcal{G}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,
$\xi_{n,h,i,\omega}^{\text{load}}$: Electric specific load in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,
$\xi_{n,h,i,\omega}^{\text{load, HT}}$: Building heat load in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,
$\xi_{n,s,i,\omega}^{\text{RegHydLim}}$: Max output from regulated hydro in node $n \in \mathcal{N}ins \in \mathcal{S}$, $i \in \mathcal{I}$ and $\omega \in \Omega$,
$\eta_{n,r,h,i,\omega}^{\text{E2H}}$: Efficiency factor for electricity-to-heat converter $r \in \mathcal{R}$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,
$\xi_{n,b,h,i,\omega}^{\text{FX}}$: Energy required by $b \in \mathcal{B}_{\text{FX}}$ in $n \in \mathcal{N}$ by hour $h \in \mathcal{H}$ in $i \in \mathcal{I}$ and $\omega \in \Omega$. ($\xi_{n,h,i,\omega}^{\text{load}}$ is subtracted by the hourly average requirement for each season).

A.3. Variables

A.3.1. Investment decision variables

$0 \leqslant x_{a,n,i}^{\text{node}} \leqslant \bar{X}_{a,n,i}^{\text{node}}$: Investments in asset $a \in \mathcal{G}_n \cup \mathcal{B}_n \cup \mathcal{R}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
$0 \leqslant x_{b,n,i}^{\text{storCH}} \leqslant \bar{X}_{b,n,i}^{\text{storCH}}$: Investments in charging of storage $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
$0 \leqslant x_{n_1,n_2,i}^{\text{tran}} \leqslant \bar{X}_{n_1,n_2,i}^{\text{tran}}$: Investments in bidirectional interconnection $(n_1, n_2) \in \mathcal{L}$ in period $i \in \mathcal{I}$,
$0 \leqslant v_{a,n,i}^{\text{node}} \leqslant \bar{V}_{a,n,i}^{\text{node}}$: Capacity of asset $a \in \mathcal{G}_n \cup \mathcal{B}_n \cup \mathcal{R}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
$0 \leqslant v_{b,n,i}^{\text{storCH}} \leqslant \bar{V}_{b,n,i}^{\text{storCH}}$: Capacity of charging of storage $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
$0 \leqslant v_{n_1,n_2,i}^{\text{tran}} \leqslant \bar{V}_{n_1,n_2,i}^{\text{tran}}$: Capacity of bidirectional interconnection $(n_1, n_2) \in \mathcal{L}$ in period $i \in \mathcal{I}$.

A.3.2. Operational decision variables

$0 \leqslant y^{\mathrm{gen}}_{g,n,h,i,\omega} \leqslant \xi^{\mathrm{gen}}_{g,n,h,i,\omega} v^{\mathrm{node}}_{g,n,i}$: Output by generator type $g \in \mathcal{G}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$0 \leqslant y^{\mathrm{tran}}_{n_1,n_2,h,i,\omega} \leqslant v^{\mathrm{tran}}_{n_1,n_2,i} \vee v^{\mathrm{tran}}_{n_2,n_1,i}$: Electricity transmission from node $n_1 \in \mathcal{N} to n_2 \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$, $(n_1, n_2) \in \mathcal{A}$,

$0 \leqslant y^{\mathrm{chrg}}_{b,n,h,i,\omega} \leqslant v^{\mathrm{storCH}}_{b,n,i}$: Charging of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$, and scenario $\omega \in \Omega$,

$0 \leqslant y^{\mathrm{dischrg}}_{b,n,h,i,\omega} \leqslant v^{\mathrm{storCH}}_{b,n,i}$: Discharging of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$, and scenario $\omega \in \Omega$,

$0 \leqslant w^{\mathrm{stor}}_{b,n,h,i,\omega} \leqslant v^{\mathrm{node}}_{b,n,i}$: Energy content of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$0 \leqslant y^{\mathrm{E2H}}_{r,n,h,i,\omega} \leqslant v^{\mathrm{node}}_{r,n,i}$: Electricity-to-heat conversion by converter type $r \in \mathcal{R}_n$ in node $n \in \mathcal{N}$ in period$h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$0 \leqslant y^{\mathrm{ll,\,EL}}_{n,h,i,\omega} \leqslant +\infty$: Electric specific load shed in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,

$0 \leqslant y^{\mathrm{ll,\,HT}}_{n,h,i,\omega} \leqslant +\infty$: Building heat load shed in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$.

Appendix B. Technology input data

Tables 3 and 4

Table 3
Electricity generator investment options and their assumed capital costs (in €/kW) for future periods. Source: [49].

Technology	Capital cost [€/kW]		
	'20-'30	'35-'40	'45-'60
Lignite (conventional)	1800	1800	1800
Oil (conventional)[a]	–	–	–
Coal (conventional)	1600	1600	1600
Coal (10% bio co-fire)	1600	1600	1600
Combined Cycle Gas	720	690	660
Open Cycle Gas	400	400	400
Nuclear	6000	6000	6000
Bio (conventional)	2000	1800	1700
Geothermal	4970	4586	3749
Hydro (regulated)	3000	3000	3000
Hydro (run-of-river)	2450	2400	2350
Solar Photovoltaic	710	663	519
Waste (electricity-only)	2030	2013	2005
Wave	6100	3100	2025
Wind (offshore)	2778	2048	1929
Wind (onshore)	1295	1161	1010

[a] 'Oil (conventional)' is not considered an investment option, only an existing power generator.

Table 4
Electricity storage investment options and their assumed capital costs for future periods. Source: [69,70].

Technology	Capital cost [€/kW]	
	Charge	Storage
Hydro (pumped storage)	1000	100
Lithium-ion Battery	198 [a]	0 [b]

[a] Capital charge cost is €246/kW for the first investment period (2020 to 2025).
[b] Charge and storage capacity are developed together for lithium-ion batteries, hence no capital storage costs.

References

[1] Lindberg MB, et al. Policies, actors and sustainability transition pathways: A study of the EU's energy policy mix. Res policy 2018.
[2] Lund PD, et al. Review of energy system flexibility measures to enable high levels of variable renewable electricity. Renew Sustain Energy Rev 2015;45:785–807.
[3] Auer H, Haas R. On integrating large shares of variable renewables into the electricity system. Energy 2016;115:1592–601.
[4] Markard J. The next phase of the energy transition and its implications for research and policy. Nat Energy 2018;1.
[5] Li DH, et al. Zero energy buildings and sustainable development implications–A review. Energy 2013;54:1–10.
[6] Wiik MK et al. Zero Emission Neighbourhoods in Smart Cities: Definition, Key Performance Indicators and Assessment Criteria: Version 1.0; 2018. https://fmezen.no/wp-content/uploads/2018/11/ZEN-Report-no-7-Bilingual.pdf [accessed: August 30, 2020].
[7] Taveres-Cachat E, et al. Responsive building envelope concepts in zero emission neighborhoods and smart cities-a roadmap to implementation. Build Environ 2019;149:446–57.
[8] Hancher L, Winters B. The EU Winter Package: Briefing paper. Allen & Overy LLP; February 2017.
[9] Torriti J. The Risk of Residential Peak Electricity Demand: A Comparison of Five European Countries. Energies 2017;10(3):385.
[10] Junker RG, et al. Characterizing the energy flexibility of buildings and districts. Appl Energy 2018;225:175–82.
[11] Cao Y, et al. Optimal scheduling of electric vehicles aggregator under market price uncertainty using robust optimization technique. Int J Electr Power Energy Syst 2020;117:105628.
[12] Ringkjø H-K, et al. A review of modelling tools for energy and electricity systems with large shares of variable renewables. Renew Sustain Energy Rev 2018;96:440–59.
[13] Bloess A, et al. Power-to-heat for renewable energy integration: A review of technologies, modeling approaches, and flexibility potentials. Appl Energy 2018;212:1611–26.
[14] Skar C, et al. The future European power system under a climate policy regime. Energy Conference (ENERGYCON), 2014 IEEE International. IEEE; 2014. p. 318–25.
[15] Skar C et al. A multi-horizon stochastic programming model for the European power system; 2016. https://www.semanticscholar.org/paper/A-multi-horizon-stochastic-programming-model-for-Skar-Doorman/60e07af486807ee3b2426c70cfa5e6d54c8ed15e [accessed: August 30, 2020].
[16] Marañón-Ledesma H, Tomasgard A. Analyzing Demand Response in a Dynamic Capacity Expansion Model for the European Power Market. Energies 2019;12(15):2976.
[17] Le Dréau J, Heiselberg P. Energy flexibility of residential buildings using short term heat storage in the thermal mass. Energy 2016;111:991–1002.
[18] Pasaoglu G et al. Projections for Electric Vehicle Load Profiles in Europe Based on Travel Survey Data. Joint Research Centre of the European Commission; 2013.
[19] Gullberg AT. The political feasibility of Norway as the green battery of Europe. Energy Policy 2013;57:615–23.
[20] Graabak I, et al. Norway as a battery for the future European power system – impacts on the hydropower system. Energies 2017;10(12):2054.
[21] Capros P, et al. European decarbonisation pathways under alternative technological and policy choices: A multi-model analysis. Energy Strategy Rev 2014;2(3–4):231–45.
[22] European Commission. A roadmap for moving to a competitive low carbon economy in 2050; March 2011. https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A52011DC0112 [accessed: August 30, 2020].
[23] Seljom P, Tomasgard A. Short-term uncertainty in long-term energy system models–A case study of wind power in Denmark. Energy Econ 2015;49:157–67.
[24] Spiecker S, Weber C. The future of the European electricity system and the impact of fluctuating renewable energy–A scenario analysis. Energy Policy 2014;65:185–97.
[25] Kristiansen M, et al. A generic framework for power system flexibility analysis using cooperative game theory. Appl Energy 2018;212:223–32.
[26] Kiviluoma J, Meibom P. Influence of wind power, plug-in electric vehicles, and heat storages on power system investments. Energy 2010;35(3):1244–55.
[27] Lund PD, et al. Pathway analysis of a zero-emission transition in the Nordic-Baltic region. Energies 2019;12(17):3337.
[28] Kirkerud JG et al. Modeling the power market impacts of different scenarios for the long term development of the heat sector. Energy Procedia 2014;58:145–51. Renewable Energy Research Conference, RERC 2014.
[29] Henning H-M, Palzer A. A comprehensive model for the German electricity and heat sector in a future energy system with a dominant contribution from renewable energy technologies–Part I: Methodology. Renew Sustain Energy Rev 2014;30:1003–18.
[30] Palzer A, Henning H-M. A comprehensive model for the German electricity and heat sector in a future energy system with a dominant contribution from renewable energy technologies–Part II: Results. Renew Sustain Energy Rev 2014;30:1019–34.
[31] Chen X, et al. Increasing the flexibility of combined heat and power for wind power integration in China: Modeling and implications. IEEE Trans Power Syst 2014;30(4):1848–57.
[32] Li X, et al. Collaborative scheduling and flexibility assessment of integrated electricity and district heating systems utilizing thermal inertia of district heating network and aggregated buildings. Appl Energy 2020;258:114021.
[33] Nuytten T, et al. Flexibility of a combined heat and power system with thermal energy storage for district heating. Appl Energy 2013;104:583–91.
[34] Seljom P, et al. The impact of Zero Energy Buildings on the Scandinavian energy system. Energy 2017;118:284–96.
[35] Ashfaq A, et al. Heat coupling of the pan-european vs. regional electrical grid with excess renewable energy. Energy 2017;122:363–77.
[36] Brown T, et al. Synergies of sector coupling and transmission reinforcement in a cost-optimised, highly renewable european energy system. Energy 2018;160:720–39.
[37] Hörsch J, et al. PyPSA-Eur: An open optimisation model of the European transmission system. Energy Strategy Rev 2018;22:207–15.
[38] Kaut M, et al. Multi-horizon stochastic programming. CMS 2014;11(1–2):179–93.
[39] Backe S, et al. Towards Zero Emission Neighbourhoods: Implications for the Power System. 2018 15th International Conference on the European Energy Market (EEM). IEEE; 2018. p. 1–6.
[40] Hart WE, et al. Pyomo-optimization modeling in Python vol. 67. Springer; 2012.
[41] Luss H. Operations research and capacity expansion problems: A survey. Oper Res 1982;30(5):907–47.
[42] Backe S. OpenEMPIRE: Stochastic linear program for investments in the European power system; 2020. https://github.com/ntnuiotenergy/OpenEMPIRE [accessed: August 30, 2020].
[43] Kall P, Wallace SW. Stochastic programming. Springer; 1994.
[44] Lindberg KB, et al. Modelling electric and heat load profiles of non-residential buildings for use in long-term aggregate load forecasts. Utilities Policy 2019;58:63–88.
[45] European Commission. A Clean Planet for all - A European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy; November 2018. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52018DC0773 [accessed: August 30, 2020].
[46] Eggleston S et al. 2006 IPCC guidelines for national greenhouse gas inventories. Volume 2 Energy. Chapter 2 Stationary combustion. Institute for Global Environmental Strategies Hayama, Japan; 2006.
[47] London Economics. The value of lost load (VoLL) for electricity in Great Britain; 2013. http://londoneconomics.co.uk/blog/publication/the-value-of-lost-load-voll-for-electricity-in-great-britain/ [accessed: August 30, 2020].
[48] Danish Energy Agency and Energinet. Technology Data. https://ens.dk/en/our-services/projections-and-models/technology-data [accessed: August 30, 2020].
[49] De Vita A et al. Technology pathways in decarbonisation scenarios; 2018. https://ec.europa.eu/energy/sites/ener/files/documents/2018_06_27_technology_pathways_-_finalreportmain2.pdf [accessed: August 30, 2020].
[50] Capros P, et al. Outlook of the EU energy system up to 2050: The case of scenarios prepared for European Commission's "clean energy for all Europeans" package using the PRIMES model. Energy Strategy Rev 2018;22:255–63.
[51] Pfenninger S, Staffell I. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. Energy 2016;114:1251–65.
[52] Staffell I, Pfenninger S. Using bias-corrected reanalysis to simulate current and future wind power output. Energy 2016;114:1224–39.
[53] Bosch. Bosch Climate 5000 Ductless Minisplit System: Engineering Submittal Sheet; 2020. https://www.bosch-climate.us/files/Climate_5000AA_engineering_submittal_US.pdf [accessed: August 30, 2020].
[54] Spilde D et al. Rapport nr 22–2019: Strømforbruk i Norge mot 2040. http://publikasjoner.nve.no/rapport/2019/rapport2019_22.pdf [accessed: August 30, 2020].
[55] Spilde D, Skotland C. Hvordan vil en omfattende elektrifisering av transportsektoren påvirke kraftsystemet?; 2015. https://beta.nve.no/Media/4117/nve-notat-om-transport-og-kraftsystemet.pdf [accessed: August 30, 2020].
[56] Line SK, Spilde D. Rapport nr 25–2017: Energibruk i Fastlands-Norge. http://publikasjoner.nve.no/rapport/2017/rapport2017_25.pdf [accessed: August 30, 2020].
[57] European Commission. Clean Power for Transport Infrastructure Deployment. https://op.europa.eu/en/publication-detail/-/publication/1533ba56-094e-11e7-8a35-01aa75ed71a1 [accessed: August 30, 2020].
[58] NOBIL (Norsk Elbilforening). Ladestasjoner i Norge. https://info.nobil.no/statistikk [accessed: August 30, 2020].
[59] Statistisk sentralbyrå (SSB). 18 elbiler per ladepunkt. https://www.ssb.no/transport-og-reiseliv/artikler-og-publikasjoner/18-elbiler-per-ladepunkt [accessed: August 30, 2020].
[60] ENTSO-E. Statistical Factsheet 2018; 2018. https://docstore.entsoe.eu/Documents/Publications/Statistics/Factsheet/entsoe_sfs2018_web.pdf [accessed: August 30, 2020].
[61] Norwegian Ministry of Petroleum and Energy. Meld. St. 25 (2015–2016). Kraft til endring – Energipolitikken mot 2030; 2016. https://www.regjeringen.no/no/dokumenter/meld.-st.-25-20152016/id2482952/sec2 [accessed: August 30, 2020].
[62] Statistisk sentralbyrå (SSB). Avfallsregnskapet. https://www.ssb.no/avfregno [accessed: August 30, 2020].
[63] Statistisk sentralbyrå (SSB). Key figures for the population of Norway. https://www.ssb.no/en/befolkning/nokkeltall/population [accessed: August 30, 2020].
[64] Karmarkar N. A new polynomial-time algorithm for linear programming. In:

Proceedings of the sixteenth annual ACM symposium on Theory of computing; 1984. p. 302–11.
[65] Optimization FX. Xpress-Optimizer Reference manual Release 32.01; 2017. https://www.msi-jp.com/xpress/learning/square/16-optimizer.pdf [accessed: August 30, 2020].
[66] Ottesen SØ, et al. Multi market bidding strategies for demand side flexibility aggregators in electricity markets. Energy 2018;149:120–34.
[67] Inês C, et al. Regulatory challenges and opportunities for collective renewable energy prosumers in the EU. Energy Policy 2019:111212.
[68] Perez-Arriaga IJ. The transmission of the future: the impact of distributed energy resources on the network. IEEE Power Energ Mag 2016;14(4):41–53.
[69] Sullivan P et al. standard scenarios annual report: Us electric sector scenario exploration; 2015. https://www.nrel.gov/docs/fy15osti/64072.pdf [accessed: August 30, 2020].
[70] Cole WJ, et al. Utility-scale lithium-ion storage cost projections for use in capacity expansion models. 2016 North American Power Symposium (NAPS). IEEE; 2016. p. 1–6.

Paper IV

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