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Åse Lekang Sørensen

Energy profiles and electricity flexibility potential in Norwegian apartment buildings with electric vehicle charging

Doctoral thesis

NTNU
Norwegian University of Science and Technology
Thesis for the Degree of Philosophiae Doctor
Faculty of Architecture and Design
Department of Architecture and Technology

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Trondheim, March 2024

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Preface

This PhD thesis is part of the PhD Programme Architecture hosted by the Faculty of Architecture and Design at the Norwegian University of Science and Technology (NTNU). The main supervisor of the thesis was Inger Andresen (NTNU), and co-supervisors were Karen Byskov Lindberg (NTNU/SINTEF) and Igor Sartori (SINTEF).

The candidate is employed at SINTEF Community in the research group Energy and Indoor Environment in Oslo. The PhD is an Institute PhD financed by the Research council of Norway (grant 272402). The work has been carried out during the period January 2018 to August 2023. During this period, the candidate was partly engaged as a researcher at SINTEF.

The PhD project is part of the Research Centre on Zero Emission Neighbourhoods in Smart Cities (FME ZEN). The thesis is article-based, consisting of four main publications, five supplementary publications, and one data publication.

Oslo/Trondheim, October 2023

Åse Lekang Sørensen

“You can have data without information,

but you cannot have information without data.”

– Daniel Keys Moran –

Acknowledgements

During the course of this PhD journey, I've had the privilege to explore the field of energy measurements, learning about the energy use patterns and flexibility potential in apartment buildings with electric vehicle (EV) charging. I am very enthusiastic about this topic, and highly appreciate this opportunity.

I am grateful for being part of the Department of Architecture and Technology at NTNU. Thank you particularly to my main supervisor Inger Andresen, for always being positive, motivating, and available for my questions. Throughout my entire PhD journey, she has provided me with invaluable support and guidance.

The Institute PhD grant from SINTEF Community made it possible for me to become a PhD candidate. I am truly grateful for the confidence and opportunity given to me by Terje Jacobsen, Øystein Fjellheim, and others who have made this possible. I have mainly been situated in the research group Energy and Indoor Environment in Oslo, and I appreciate all the valuable input and engaging discussions with my colleagues. I am especially grateful to my colleagues and co-supervisors, Karen Byskov Lindberg and Igor Sartori, for their significant contributions, which have played an integral role in shaping my research during this period.

The study is an integral part of the Research Centre on Zero Emission Neighbourhoods in Smart Cities (FME ZEN). I am grateful for the support from the ZEN partners and the Research Council of Norway. It is inspiring to be part of such an important research centre.

Throughout this study, I have collaborated closely with housing cooperatives, as well as numerous individuals and companies, who generously shared vital information and data. Notably, the collaboration with Risvollan housing cooperative has been of utmost significance to this thesis. I extend my sincere gratitude to all those who dedicated their time and efforts, as their contributions have been instrumental in shaping the outcomes of this research.

Finally, I would like to greet my family and friends. Especially my two daughters Ragna Ann and Eira, who have spent their formative years alongside my PhD efforts. The great support from my Josephine is highly appreciated – Thank you so much!

Summary

Renewable energy generation and energy efficiency of buildings are central strategies for mitigating emissions, aligned with the objectives of the Paris Agreement. With an increasing share of the energy supply coming from variable sources, the demand for flexible end-use of electricity increases. Energy flexibility in buildings has the potential to reduce grid burden of neighbourhoods. However, despite its potential, the practical implementation of end-user flexibility is challenging. Integrating flexibility solutions with existing automation systems while ensuring occupant satisfaction can be a complex task and remains a main challenge for implementation.

In this context, residential electric vehicle (EV) charging within apartment buildings stands out as a promising solution. Shifting the timing of EV charging from high-demand afternoons to low-load nights can minimize grid strain with little impact on resident comfort. Additionally, in many apartment buildings, EV charging is already part of an energy management infrastructure, which may ease the practical implementation of flexibility solutions. Literature reviews show an increasing research focus on residential EV charging, however there is a need for more real-world data and knowledge on EV charging behaviour and energy use in apartments buildings, and the relationship between them.

This thesis focuses on exploring energy profiles and the electricity flexibility potential in Norwegian apartment buildings with EV charging. A third of the Norwegian population resides in apartments, the residential sector has an increasing demand for EV charging, and a growing solar photovoltaic (PV) utilisation. The study includes the use of comprehensive datasets of energy and EV charging from Norwegian apartment buildings. The main case study is a large housing cooperative with more than 1000 apartments, and EV charging data is analysed from 35 000 EV charging sessions in 12 residential locations in Norway.

Initially, the thesis examines the energy profiles for household energy use and PV generation for apartment buildings, and how the energy profiles are influenced by climate variables such as outdoor temperature and solar radiation. In the main case study, the average annual delivered energy to the apartments was found to be about 138 kWh/m^2 for heating and 51 kWh/m^2 for electricity. Assuming one EV per apartment, the average electricity use for EV

charging was about 25 kWh/m^2, contributing to roughly 12% of the total energy use per apartment.

Next, the research focuses on how user habits of residential EV charging influence the electricity load profiles. The study identified variations in residential charging behaviour between users with private charge points (CPs) at their own parking spaces and those who utilized shared CPs. Users with private CPs had an average connection time of 12.8 hours, whereas those using shared CPs had an average of 6.5 hours connection time. Data from EV charging reports provided information on session energy and plug-in times, which was then used to simulate hourly charging energy at different charging power levels. The study presents how residential charging behaviour and energy flexibility are affected by the battery capacity and charging power for the EVs. Findings indicate a significant opportunity for shifting residential EV charging in time, particularly from late afternoon and evenings to nighttime. The flexibility potential of single EV users grows with increasing charging power, connection frequency, and duration of each connection.

The thesis also explores the effects of grid-connected EV cabin preheating, which is generally recommended in cold climates. EV cabin preheating typically occurs during mornings with cold outdoor temperatures, when the grid is already under pressure. During a trial involving 51 preheating sessions with five representative EV models, it was observed that most EVs used approximately 2 kWh of energy during preheating, with some sessions reaching a maximum of 5 kWh.

Finally, the thesis explores the potential for electricity flexibility from EVs, in relation to non-flexible apartment loads and PV generation, in the Norwegian context. The grid burden of optimised EV charging is affected by different energy/peak tariffs, metering locations, the availability of PV systems, and vehicle-to-grid (V2G) technologies. In the simulated scenarios with apartment electricity loads and optimised EV charging, the peak loads were reduced by around 45% compared to a base case with non-coordinated EV charging. The study found that relatively few EVs were connected to the residential CPs during the day, which limits the self-consumption of PV generation for EV charging. For the simulated scenarios, a maximum of 38% of the energy load in the optimised EV charging was covered by PV generation.

The study offers knowledge relevant for housing associations and building owners regarding their energy use and opportunities for end-use flexibility. Similarly, it provides insights for companies developing end-user flexibility solutions, such as charge point operators (CPOs), energy companies, and aggregators. Additionally, Distribution System Operators (DSOs), can benefit from the knowledge about how end-use flexibility in the residential sector can contribute to reduce the grid burden. Public policymakers and regulatory bodies can leverage this knowledge to drive progress in realizing end-use flexibility and meeting energy and climate objectives.

Sammendrag (Norwegian summary)

Overgangen til fornybar energi og energieffektive bygninger er sentrale tiltak for å redusere utslipp, i tråd med målene i Parisavtalen. En økende andel av energiforsyningen er uregulerbar, noe som igjen øker etterspørselen etter fleksibel sluttbruk av elektrisitet. Energifleksibilitet i bygninger kan bidra til å redusere belastningen på strømnettet i nabolag. Likevel, til tross for potensialet, er det utfordrende å implementere sluttbrukerfleksibilitet i praksis. En av hovedutfordringene er at det kan være komplekst å integrere fleksible løsninger med eksisterende automasjonssystemer, samtidig som man sikrer tilfredse brukere.

Elbillading er en av løsningene med stort potensial for energifleksibilitet. Elbillading kan gjerne flyttes i tid, for eksempel fra ettermiddagen til natten, og slik bidra til å minimere belastningen på strømnettet samtidig som det er til liten ulempe for beboerne. I tillegg finnes det allerede infrastruktur for energistyring av elbillading i en rekke leilighetsbygg, noe som kan gjøre den praktiske implementeringen enklere. Litteraturstudier viser at det er et økende forskningsfokus på elbillading tilknyttet boliger. Det er allikevel fortsatt behov for mer data og kunnskap rundt ladevaner og energiforbruk i leilighetsbygg, samt forholdet mellom dem.

Denne PhD-avhandlingen fokuserer på energiprofiler og potensialet for elektrisitetsfleksibilitet i norske leilighetsbygg med elbillading. En tredjedel av den norske befolkningen bor i leiligheter. Boligsektoren har en økende etterspørsel etter elbillading, og det installeres stadig flere solcelleanlegg på bygninger. Studien inkluderer analyser av større datasett, inkludert energimålinger fra norske leilighetsbygg og laderapporter. Energidataene er i hovedsak fra et stort borettslag (Risvollan) med over 1000 leiligheter, mens ladedataene kommer fra 12 boligområder i Norge med totalt 35 000 ladesesjoner.

I første del av avhandlingen analyseres energiprofiler for energibruk og solenergi i leilighetsbygg, samt hvordan energiprofilene påvirkes av klimavariabler slik som utetemperatur og solinnstråling. Gjennomsnittlig levert energi til Risvollan borettslag var 138 kWh/m^2 til oppvarming og 51 kWh/m^2 til strømbruk i leilighetene. Dersom det antas at hver leilighet har én elbil, er ladebehovet i gjennomsnitt rundt 25 kWh/m^2, som tilsvarer omtrent 12% av den totale energibruken per leilighet.

Den andre delen av avhandlingen fokuserer på hvordan ladevaner for hjemmelading påvirker elektrisitetsprofilene. Studien fant en forskjell i ladevaner når beboerne har lademulighet på sin egen parkeringsplass, sammenlignet med når de bruker en delt lader på en felles parkeringsplass. For lading på egen parkeringsplass var gjennomsnittlig tilkoblingstid 12,8 timer, mens tilkoblingstiden var 6,5 timer for lading på delt parkeringsplass. Informasjon om energi og tilkoblingstider per ladesesjon er tilgjengelig fra laderapporter. Denne informasjonen ble oversatt til energibruk per time, basert på ulike ladeeffekter for elbilene. Studien presenterer hvordan ladevaner og energifleksibilitet påvirkes av batteri- og ladekapasitet for elbilene. Resultatene viser at det er et betydelig potensial for å flytte boligers elbillading i tid, spesielt fra ettermiddag/kveld til nattestid. Fleksibilitetspotensialet for enkeltbrukere av elbiler øker med høyere ladeeffekt, hyppigere tilkoblinger og lengre tilkoblingstider.

Avhandlingen undersøker også konsekvensene av nett-tilkoblet forvarming av elbiler, som generelt anbefales i kalde klima. Forvarming av elbiler skjer vanligvis om morgenen når det er kaldt, samtidig som strømnettet allerede har høy belastning. Under en forsøksperiode med 51 forvarmingssesjoner for fem typiske elbilmodeller, var energiforbruket for forvarming opptil 2 kWh for de fleste elbiler, med en maksimal verdi på 5 kWh.

I den siste delen av avhandlingen utforskes potensialet for fleksibilitet fra elbiler i norske leilighetsbygg, sett i forhold til ikke-fleksibel strømbruk i leilighetene og solenergi. Elbilladingen ble optimalisert, og belastningen på nettet ble vurdert for ulike energi/effekttariffer, plasseringer av AMS-målere, solcellesystemer og toveis elbillading (V2G). De simulerte scenarioene, med strømbruk i leiligheter og optimalisert elbillading, reduserte effekttoppen med rundt 45%, sammenlignet med strømbruk i leiligheter og elbillading direkte ved tilkobling. I studien var relativt få elbiler tilkoblet hjemmeladeren i løpet av formiddagen, noe som begrenser egenforbruket av solenergi til elbillading. For de simulerte scenarioene ble maksimalt 38% av ladingen dekket av solenergi.

Avhandlingen har spesiell relevans for borettslag, sameier og byggeiere, og gir kunnskap om energibruk og muligheter for energifleksibilitet. Den kan også være nyttig for bedrifter som utvikler løsninger for energifleksibilitet hos sluttbrukere, som ladeoperatører, energiselskaper og aggregatorer. I tillegg kan kunnskapen om hvordan boligsektoren kan bidra til å avlaste strømnettet være til fordel for nettselskaper. For offentlige beslutningstakere og regulatoriske myndigheter kan kunnskap om energibruk og fleksibilitetspotensial i leilighetsbygg bidra til å fremme løsninger hos sluttbrukere, og slik bidra til å oppfylle energi- og klimamål.

Abbreviations

AMS	Advanced Metering System
Apt	Apartment
BEV	Battery Electric Vehicle
CET	Central European Time
CEST	Central European Summer Time
COP	Coefficient of Performance
CP	Charge Point
CPO	Charge Point Operator
DH	District Heating
DHW	Domestic Hot Water
DSO	Distribution System Operator
DR	Demand Response
DST	Daylight-Saving Time
EB	Electric Boiler
EMS	Energy Management System
ET	Energy-Temperature
EV	Electric Vehicle
FAIR	Findability, Accessibility, Interoperability, and Reusability
FME ZEN	The Research Centre on Zero Emission Neighbourhoods in Smart Cities
GHI	Global Horizontal Irradiation
GSHP	Ground Source Heat Pump
KPI	Key Performance Indicator
MILP	Mixed Integer Linear Programming
PHEV	Plug-in Hybrid Electric Vehicle
PV	PhotoVoltaic
RQ	Research Question
SoC	State of Charge
SUB	Heating SUBstations
UTC	Coordinated Universal Time
V2G	Vehicle-to-Grid

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A. Dissertation

(Norwegian "kappe")

1. Introduction

In this chapter, the background and research context of the thesis is presented, followed by the problem statement and the research questions, the publication overview, and the structure of the thesis.

1.1 Background and research context

Buildings account for approximately 40% of Europe's energy consumption [1]. The energy system is currently undergoing a transition driven by various factors, including increasing renewable energy integration, evolving technology trends, and the pursuit of sustainability goals. Energy efficiency and renewable energy generation within buildings stand as pivotal strategies for emissions reduction, in alignment with the objectives of the Paris Agreement [2]. The adoption of solar photovoltaic (PV) generation situated behind the building's energy meter is on the rise, strengthened by the European Union's solar energy strategy [3]. Electric vehicles (EVs) form a crucial part of the solution to attain carbon emissions reduction targets, and the global market share of EVs is steadily increasing [4]. On the other hand, increased PV generation and demand for EV charging can challenge the grid infrastructure [5].

As the proportion of variable energy sources in the energy supply continues to grow, the demand for flexible electricity end-use becomes increasingly important [6]. IEA EBC Annex 67 defines energy flexibility in buildings as [7]:

"The energy flexibility of a building is the ability to manage its demand and generation according to local climate conditions, user needs and grid requirements."

Technologies with energy flexibility potential in buildings include appliances and control strategies related to space heating, domestic hot water (DHW) tanks, washing machines, batteries, and EVs [8–10]. Owners and occupants of buildings may have several motivations for utilizing energy flexibility, such as reduced costs, mitigation of power peaks, curbing CO_2-emissions, and increased self-consumption of locally produced energy. However, real-life implementation of energy flexibility in buildings has not yet been fully realized. One reason may be that it can be quite complex to achieve energy flexibility in buildings. For example, as stated by [9], the integration with existing automation systems can be challenging, and the operation must be in line with occupant comfort and satisfaction.

Buildings can provide energy flexibility services to distribution system operators (DSOs) or district heating (DH) companies through demand response (DR) to a signal. Mechanisms to provide DR from buildings can be classified as 'implicit', i.e., with time-varying energy prices or network tariffs, or 'explicit' with consumers participating in energy markets and receiving payments in return for load variations [11]. In the residential sector, implicit DR programmes have been the most common, since they are easier to implement [11]. With a more mature flexibility market, customers that are participating in the implicit DR markets may move to explicit DR markets, e.g., through aggregators that acquire flexibility from several smaller customers.

This thesis focuses on the energy performance and flexibility potential of apartment buildings with EV charging. Per 2022, about 32% of Norwegian residents lived in apartment buildings, either in multi-dwelling buildings or in linked houses with at least 3 dwellings [12]. Load profiles of Norwegian buildings are previously studied by Pedersen [13], Lindberg [14], and Kipping [15], where apartments were one of the considered building categories. Pedersen [13] provided heat and electricity load profiles for a combination of single-family houses and apartments. The load profiles specified by Pedersen formed the basis for residential buildings in the tool PROFet developed by Lindberg [14], which generates aggregated load forecasts for heating and electric loads in buildings. The PROFet heat load profiles for apartments were validated in [16], including DH data from 43 apartment blocks. Kipping and Trømborg [17] studied hourly electricity consumption in Norwegian households including 84 attached dwellings, and disaggregated the data into space heating and other electric appliances.

Heating is a large share of the energy use in the Norwegian building stock. At the national level, it is estimated that about 78% of the total energy use in households is for space heating and DHW [18]. As per 2012, 31% of the apartments in multi-dwelling buildings were connected to a common central heating system, whereof 13% by DH [19]. Electricity provides about 70 to 80% of the residential heating energy use [18], and the residential electricity use is therefore highly temperature dependent. The daily energy profiles for residential buildings show a higher energy use in households during mornings and afternoons [13]. This coincides with high load hours in the national grid, which is typically in the morning and afternoon during cold winter days [20].

In apartment buildings, the energy use is typically metered by a combination of private apartment meters and common energy meters. As stipulated by regulations (§ 13-1 i in [21]), electricity use within apartments is metered separately using hourly Advanced Metering System (AMS) measurements. Common energy use includes energy use in common areas such as corridors, basements, outdoors, central heating if relevant, and EV-charging. Cho et al. [22] highlighted that the energy management systems for apartment buildings are not fully understood, noting the distinct structural differences between energy systems in apartment buildings and detached houses, where apartment buildings have energy demands in both apartments and in common facilities. A complex ownership structure can be a barrier for developing smart energy communities [23]. For example, the Norwegian regulations did not allow sharing of PV generated electricity across AMS meters until October 2023 [24]. At the same time, the flexibility available in the common energy use tends to be more accessible than the energy consumption within individual apartments, particularly because the common energy is often equipped with an energy management system (EMS).

Among potential flexibility solutions in Norwegian apartment buildings, EV charging stands out. Norway is a frontrunner within EV adoption, and EVs contributed to almost 80% of the passenger car sales in 2022 [25]. Residents in apartment buildings have, under certain conditions, a statutory right to charge at home [26], which can challenge the local grid infrastructure to the buildings. Therefore, a common infrastructure for EV charging is often installed in Norwegian apartment buildings, along with an energy management system that limits the maximum power for simultaneous EVs charging. A high share of the EV charging occurs in the afternoons and evenings, and coincides with other residential electricity use. Since the EVs are normally connected to the charge point (CP) for a longer time period than the actual charging time, there is a potential to shift the EV charging load in time. For example, residential charging loads can be shifted from high load hours in the afternoon to low load hours in the night. This can be done with minimal consequences to comfort and without active involvement of residents.

Residential EV charging flexibility is gaining attention in the research world. Nevertheless, there are research gaps that have been identified by various research groups. Fachrizal et al. [27] did a review of smart charging strategies with PV generation and electricity consumption, and concluded that more studies should evaluate EV smart charging schemes in different latitudes, for different climates, and for different occupancy patterns. A majority of flexibility case studies in literature are based on simulations [9]. According to [28], flexibility studies focussing on EV charging should incorporate realistic driving and plug-in behaviour. Amayri et al. [29] emphasized the necessity for additional publicly available datasets with EV charging in residential buildings to enhance load forecasting and flexibility predictions. Additionally, Calearo et al. [30] noted that data concerning EVs for studies related to smart grids, are limited. Vermeulen et al. [31] acknowledged the scarcity of research on the impact of battery capacity on EV charging behaviour. Shahriar et al. [32] performed a review of machine learning approaches for EV charging behaviour, and stated that the key challenges included lack of public charging datasets and lack of high dimensional data.

For the practical realization of end-user flexibility in apartment buildings, an increased understanding of the energy use is needed, including how EV charging loads can be shifted in time. Ideally, this understanding should be rooted in real-world data.

1.2 Problem statement and research questions

The main objective of this thesis is to investigate how residential EV charging in apartment buildings can contribute to energy flexibility. To achieve this, it is essential to understand the energy use in apartment buildings in relation to the user habits of residential EV charging. Analysis of real-world energy demand and EV charging data forms the basis for this understanding.

Based on these objectives, the research questions (RQs) of this thesis are:

Main research question:

> What are the energy profiles and electricity flexibility potential in Norwegian apartment buildings with electric vehicle charging?

Sub-questions:

1. What are the energy profiles for household energy use and PV generation for apartment buildings, and how are the energy profiles influenced by climate variables?
2. How does the user habits influence the electricity load profiles of residential EV charging, and how is the electricity load affected by EV cabin preheating?
3. What is the potential for electricity flexibility from EVs, in relation to non-flexible apartment building loads and PV generation, in the Norwegian context?

1.3 Publications overview

1.3.1 Main topics of publications

Table 1 illustrates the relationship between the research questions and the publications in this thesis. The publications are listed in Section 1.3.2.

Table 1 *Main topics of publications.*

	Supplementary articles	Main article I	Main article II	Main article III	Main article IV	Data articles *(D* denotes planned articles)*
RQ1: What are the energy profiles for household energy use and PV generation for apartment buildings, and how are the energy profiles influenced by climate variables?	S I. Electricity S II. Heat-DHW S III. DHW S IV. PV				Main IV. Energy profiles	D* IV. Data Main IV
RQ2: How does the user habits influence the electricity load profiles of residential EV charging, and how is the el. load affected by EV cabin preheating?	S V. Stochastic EV charging	Main I. EV charging	Main II. EV charging	Main III. EV cabin preheating		D I. Data Main I D* II. Data Main II D* III. Data Main III
RQ3: What is the potential for electricity flexibility from EVs, in relation to non-flexible apartment building loads and PV generation, in the Norwegian context?					Main IV. Flexibility	

1.3.2 List of papers

Main publications

I. **Å.L. Sørensen**, K.B. Lindberg, I. Sartori, I. Andresen, Analysis of residential EV energy flexibility potential based on real-world charging reports and smart meter data, Energy Build. 241 (2021) 110923. https://doi.org/10.1016/j.enbuild.2021.110923.

II. **Å.L. Sørensen**, I. Sartori, K.B. Lindberg, I. Andresen, A method for generating complete EV charging datasets and analysis of residential charging behaviour in a large Norwegian case study, Sustain. Energy, Grids Networks. 36 (2023). 101195. https://doi.org/10.1016/j.segan.2023.101195.

III. **Å.L. Sørensen**, B. Ludvigsen, I. Andresen, Grid-connected cabin preheating of Electric Vehicles in cold climates – A non-flexible share of the EV energy use, Appl. Energy. 341 (2023). 121054. https://doi.org/10.1016/j.apenergy.2023.121054.

IV. **Å.L. Sørensen**, B.B. Morsund, I. Andresen, I. Sartori, K.B. Lindberg, Energy profiles and electricity flexibility potential in apartment buildings with electric vehicles – A

Norwegian case study, Energy Build. 305 (2024), 113878. https://doi.org/10.1016/j.enbuild.2023.113878.

Supplementary publications

S I. **Å.L. Sørensen**, I. Sartori, K.B. Lindberg, I. Andresen, Electricity analysis for energy management in neighbourhoods: Case study of a large housing cooperative in Norway, in: J. Phys. Conf. Ser., IOP Publishing, EPFL Lausanne, Switzerland, 2019: p. 012057. https://doi.org/10.1088/1742-6596/1343/1/012057.

S II. **Å.L. Sørensen**, K.B. Lindberg, H.T. Walnum, I. Sartori, U.R. Aakenes, I. Andresen, Heat analysis for energy management in neighbourhoods: Case study of a large housing cooperative in Norway, in: IOP Conf. Ser. Mater. Sci. Eng., 2019. https://doi.org/10.1088/1757-899X/609/5/052009.

S III. **Å.L. Sørensen**, H.T. Walnum, I. Sartori, I. Andresen, Energy flexibility potential of domestic hot water systems in apartment buildings, in: E3S Web Conf. Vol. 246, Cold Clim. HVAC Energy 2021, 2021. https://doi.org/10.1051/e3sconf/202124611005.

S IV. **Å.L. Sørensen**, I. Sartori, K.B. Lindberg, I. Andresen, Analysing electricity demand in neighbourhoods with electricity generation from solar power systems: A case study of a large housing cooperative in Norway, in: IOP Conf. Ser. Earth Environ. Sci., IOP Conference Series, 2019. https://doi.org/10.1088/1755-1315/352/1/012008.

S V. **Å.L. Sørensen**, M.C. Westad, B.M. Delgado, K. Byskov, Stochastic load profile generator for residential EV charging, E3S Web Conf. 362 (2022) 1–8. https://doi.org/10.1051/e3sconf/202236203005.

Data publications

D I. **Å.L. Sørensen**, K.B. Lindberg, I. Sartori, I. Andresen, Residential electric vehicle charging datasets from apartment buildings, Data Br. 36 (2021). https://doi.org/10.1016/j.dib.2021.107105.

The published data article is connected to Main I. Additionally, there are three related data articles planned for submission. The planned data articles are indicated with a star, as they are not included in the thesis:

D* II. **Å.L. Sørensen**, et. al. Complete EV datasets, related to Main II.

D* III. **Å.L. Sørensen**, et. al, Preheating and EV charging data, related to Main III.

D* IV. **Å.L. Sørensen**, et. al, Data from the main case study (2019-2022), related to Supplementary I, Supplementary II, and Main IV.

Additional publications

The following articles were published during the doctoral research but is not included in the thesis:

Work related to the Research Centre on Zero Emission Neighbourhoods in Smart Cities:

- **Å.L. Sørensen**, I. Sartori, I. Andresen, Smart EV Charging Systems to Improve Energy Flexibility of Zero Emission Neighbourhoods, in: Cold Clim. HVAC 2018, Springer International Publishing, Cham, 2019: pp. 467–477. https://doi.org/10.1007/978-3-030-00662-4_39.
- S. Backe, **Å.L. Sørensen**, D. Pinel, J. Clauß, C. Lausselet, Opportunities for Local Energy Supply in Norway: A Case Study of a University Campus Site, in: Nord. ZEB Conf., 2019. https://doi.org/10.1088/1755-1315/352/1/012039.
- H.T. Walnum, M. Bagle, **Å.L. Sørensen**, S.M. Fufa, Cost optimal investment in energy efficiency measures and energy supply system in a neighbourhood in Norway, in: E3S Web Conf. Vol. 246, Cold Clim. HVAC Energy 2021, 2021. https://doi.org/10.1051/e3sconf/202124605005.

Work related to the research project "Energy for domestic hot water in the Norwegian low emission society" (VarmtVann2030):

- H.T. Walnum, **Å.L. Sørensen**, B. Ludvigsen, D. Ivanko, Energy consumption for domestic hot water use in Norwegian hotels and nursing homes, IOP Conf. Ser. Mater. Sci. Eng. 609 (2019). https://doi.org/10.1088/1757-899X/609/5/052020.
- D. Ivanko, N. Nord, **Å.L. Sørensen**, I. Sartori, T.S.W. Plesser, H.T. Walnum, Prediction of DHW energy use in a hotel in Norway, in: IOP Conf. Ser. Mater. Sci. Eng., 2019. https://doi.org/10.1088/1757-899X/609/5/052018.
- D. Ivanko, N. Nord, **Å.L. Sørensen**, T.S.W. Plesser, H.T. Walnum, I. Sartori, Identifying typical hourly DHW energy use profiles in a hotel in Norway by using

statistical methods, in: E3S Web Conf., 2019. https://doi.org/10.1051/e3sconf/201911104015.

- K. Stråby, H.T. Walnum, **Å.L. Sørensen**, Pipe sizing based on domestic hot water consumption in Norwegian hotels, nursing homes, and apartment buildings, in: IOP Conf. Ser. Mater. Sci. Eng., 2019. https://doi.org/10.1088/1757-899X/609/5/052016.
- D. Ivanko, **Å.L. Sørensen**, N. Nord, Selecting the model and influencing variables for DHW heat use prediction in hotels in Norway, Energy Build. 228 (2020) 110441. https://doi.org/10.1016/j.enbuild.2020.110441.
- D. Ivanko, H.T. Walnum, **Å. L. Sørensen**, N. Nord, Analysis of monthly and daily profiles of DHW use in apartment blocks in Norway, E3S Web Conf. 172 (2020) 1–7. https://doi.org/10.1051/e3sconf/202017212002.
- D. Ivanko, **Å.L. Sørensen**, N. Nord, Splitting measurements of the total heat demand in a hotel into domestic hot water and space heating heat use, Energy. 219 (2021) 119685. https://doi.org/10.1016/j.energy.2020.119685.
- H.T. Walnum, K. Stråby, **Å.L. Sørensen**, Measurement of domestic hot water consumption in hotel rooms with different basin and shower mixing taps, in: E3S Web Conf. Vol. 246, Cold Clim. HVAC Energy 2021, 2021. https://doi.org/10.1051/e3sconf/202124604002.
- H.T. Walnum, **Å.L. Sørensen**, K. Stråby, Measurement data on domestic hot water consumption and related energy use in hotels, nursing homes and apartment buildings in Norway, Data Br. 37 (2021). https://doi.org/10.1016/j.dib.2021.107228.

1.3.3 Author contributions

My contributions to the publications are listed in Table 2. I am the main author of all the publications included in the PhD thesis. I have been the initiator of the publications, have collected the data needed (except Supplementary III), and have had the main role in writing and publishing the manuscripts.

My main supervisor Inger Andresen (I.A.) and co-supervisors Karen Byskov Lindberg (K.B.L) and Igor Sartori (I.S.) have provided beneficial support and comments to the publications. They have been involved in early discussions about concepts and methodologies, as well as given valuable input to the manuscripts.

For the publication with practical experiments (Main III), I planned the experiments, secured funding for equipment from FME ZEN (charger and metering equipment), was responsible for purchasing the equipment, recruited EV owners, and had the main responsibility for the trials. Bjørn Ludvigsen (B.L.) provided valuable support regarding the equipment and laboratory work.

The two MSc students, Maria Claire Westad (M.C.W., Supplementary V) and Balder Bryn Morsund (B.B.M., Main IV), were both supervised by Karen Byskov Lindberg and co-supervised by me. Maria Claire Westad developed the stochastic load profile generator in her MSc thesis, while Balder Bryn Morsund developed the optimization model for smart EV charging. Their models were important contributions for the two articles. Both MSc-theses were based on background information and data from the PhD work. I had the main responsibility for writing the publications, including the introduction, analyses, discussions, and conclusions.

Table 2 *Author's (ÅLS) and co-authors' contributions to articles.*

Publication		**ÅLS contribution**	**Co-author contribution**
Main	I	ÅLS: Conceptualization, Methodology, Investigation, Data curation, Writing - original draft, Writing - review & editing.	K.B.L., I.S., I.A.: Conceptualization, Writing - review & editing, Supervision.
	II	ÅLS: Conceptualization, Methodology, Investigation, Data curation, Writing - original draft, Writing - review & editing.	I.S., K.B.L., I.A.: Conceptualization, Methodology, Writing - review & editing, Supervision.
	III	ÅLS: Conceptualization, Methodology, Investigation, Data curation, Writing - original draft, Writing - review & editing.	B.L.: Conceptualization, Investigation, Writing - review & editing. I.A.: Writing - review & editing, Supervision.
	IV	ÅLS: Conceptualization, Methodology, Data curation, Validation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing.	B.B.M.: Methodology, Software. K.B.L.: Conceptualization, Methodology, Writing - review & editing, Supervision. I.A., I.S.: Writing - review & editing, Supervision.
Suppl.	S I	ÅLS: Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing.	I.S., K.B.L., I.A.: Conceptualization, Methodology, Writing - review & editing, Supervision.
	S II	ÅLS: Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing.	K.B.L., I.S., I.A.: Conceptualization, Methodology, Writing - review & editing, Supervision. U.R.A.: Data curation. H.T.W.: Methodology, Writing - review & editing.
	S III	ÅLS: Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing.	H.T.W.: Methodology, Data curation, Writing - review & editing. I.S., I.A.: Writing - review & editing, Supervision.
	S IV	ÅLS: Conceptualization, Methodology, Data curation, Software, Formal analysis, Visualization, Writing - original draft, Writing - review & editing.	I.S., K.B.L., I.A.: Conceptualization, Methodology, Writing - review & editing, Supervision.
	S V	ÅLS: Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing.	M.C.W.: Conceptualization, Methodology, Software, Data curation, Formal analysis, Visualization, Writing - original draft. B.M.D.: Software. K.B.L.: Conceptualization, Methodology, Writing - review & editing, Supervision.
Data	D I	ÅLS: Conceptualization, Methodology, Investigation, Data curation, Writing - original draft.	K.B.L., I.S., I.A.: Conceptualization, Writing - review & editing, Supervision.

1.4 Structure of the thesis

The structure of the remaining thesis is:

In Chapter 2, the methods are introduced, including the research process, the apartment building cases, and the data collection, cleaning, analyses, and modelling.

Chapter 3 presents and discusses the results of the publications in the thesis, and how they are linked to the research questions. The chapter also includes limitation of the study and further work.

Finally, Chapter 4 provides the conclusions and future perspectives.

The publications of the thesis are included after Chapter 4, including the four main publications, the five supplementary publications, and one data publication.

2. Methods

This chapter introduces the methods of the thesis, i.e., the research process (2.1), the apartment building cases (2.2), the data collection, cleaning, and sharing (2.3), and the data analysis and modelling (2.4). Further details of the methods used can be found in the publications.

2.1 The research process

Figure 1 illustrates the main steps in the research process for my PhD thesis. The process involved conducting a literature review, treating data, and performing analysis and modelling to address the research questions.

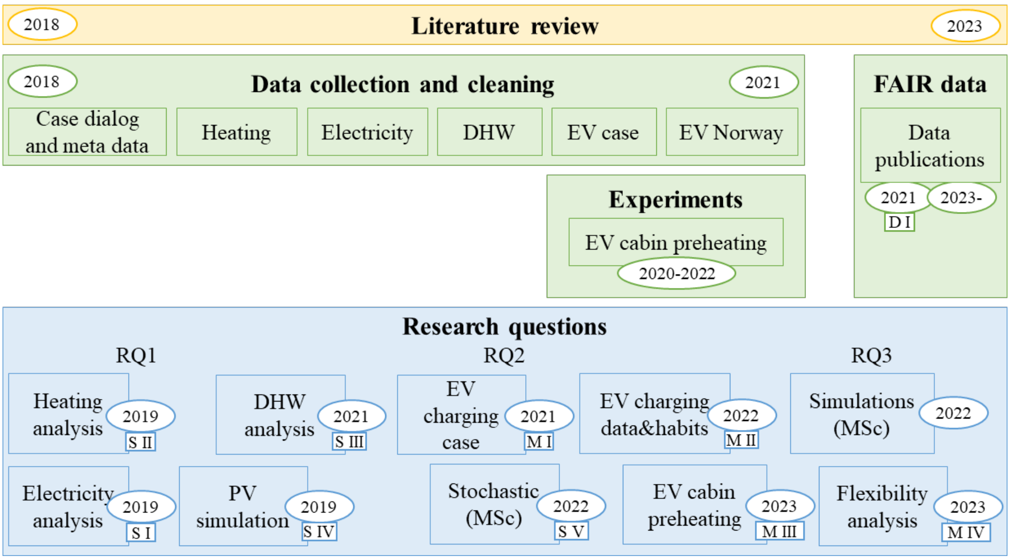


Figure 1 *The research process of the PhD thesis. Numbers in circles denote the year (period) when the research was conducted, starting from 2018 to the left in the figure, and ending in 2023 to the right. The small boxes below the circles include the publication numbers, as described in section 1.3.2.*

2.2 Apartment building cases

2.2.1 Main case study

The case study selected for this work is Risvollan housing association, which is a large housing association constructed in the 1970th, located in Trondheim. It includes in total 1058 apartments in 121 low-rise apartment buildings. Photos of some of the buildings are shown in Figure 2. The floor area of the apartments varies from 53 to 107 m^2 (1 to 4 bedrooms), whereof 78% of the apartments have 2 or 3 bedrooms. The total floor area for the entire stock of apartments is 93,713 m^2. In 2018, the housing association had 2,321 residents.

District heating (DH) provides space heating and DHW to the apartments. There are 20 heating substations (SUBs) in the housing association area, metering delivered heat hourly. Each SUB serves between 25 and 74 apartments with space heating and DHW. Electricity is provided to common areas/garages and apartments. In total, 114 AMS meters measure common electricity use in garages (25 meters) and other common areas (89 meters). Common infrastructure is installed for charging EVs. In total it is possible to activate up to 764 CPs on the parking spaces which are used by residents from 1113 apartments. EV charging reports describe energy and time information for the EV charging sessions per EV user. Figure 3 shows a map with the 20 SUB areas of the case study, with metering locations for common electricity and heating meters. The metering structure is illustrated based on information from Risvollan housing association and the EMS-provider Enoco. In addition, AMS meters in each apartment measure electricity use in apartments.

***Figure 2** Photos of apartment buildings in the case study.*

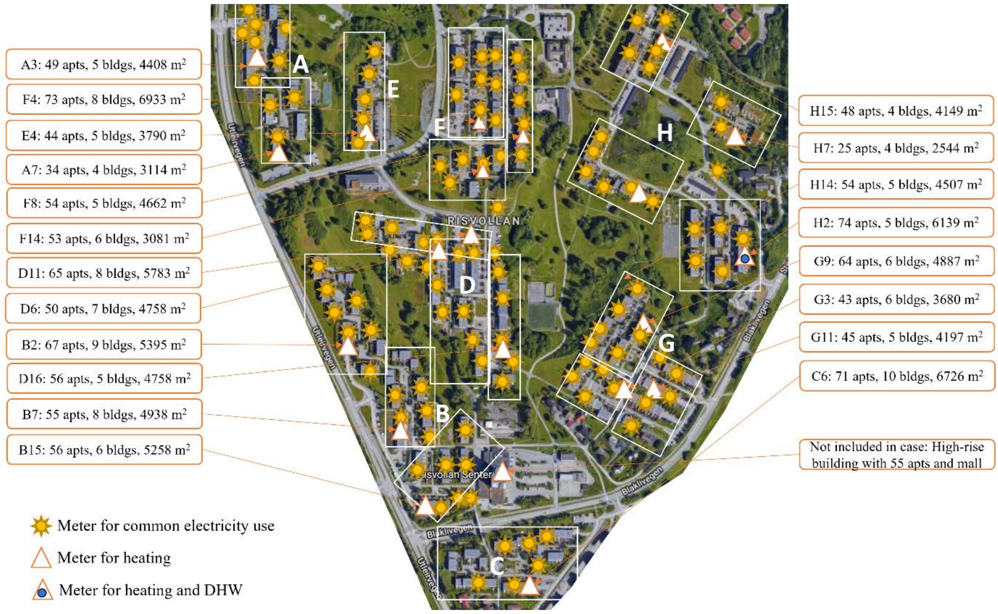


Figure 3 *Case study area, with metering structure for common electricity and heating meters (Map: google maps).*

Data from the main case study has formed the basis for the energy analyses within the thesis. This includes analysis and modelling of electricity use, heating, PV generation simulations, EV charging, and energy flexibility. The primary data period is from 2018 and therefore predates the COVID-19 pandemic.

2.2.2 Representativeness of the main case study

In the PhD thesis, we aimed to select a case study which was representative for a major share of Norwegian apartments. This section presents information about apartments in the Norwegian building stock, together with information about the selected case study. Energy data from a range of housing associations are compared to the data of the case study, including heat data from 29 other locations and electricity data from 4 other locations, based on measurements collected in the research centre FME ZEN [35], and the project COFACTOR [36]. Lastly, in this section, the representativeness of the EV charging and PV generation data is discussed.

Apartments in the Norwegian building stock

Per 2022, about 32% of Norwegian residents (1.7 million) live in apartments, defined as either multi-dwelling buildings or linked houses with at least 3 dwellings [12]. Such apartments represent 37% of the dwellings in the Norwegian residential building stock [37]. The remaining residents mainly live in detached houses or houses with two dwellings. A comparison between apartments in the Norwegian building stock and the selected case study can be found in Table 3.

Table 3. *The Norwegian building stock and the selected case study.*

	Apartments in the Norwegian building stock	**Selected case study**
Building category	Multi-dwelling buildings or linked houses with at least 3 dwellings: 37% [37]	Low-rise apartment buildings with an average of 8.7 dwellings per building
Construction year	Before 1970: 35%, between 1971 and 2000: 31%, after 2001: 33% [37]	1970-1973. Renovations 1993-1998 (insulation and windows) [38]
Floor space area	70% have floor space between 50 and 120 m^2 [39]	In average 88.6 m^2 per apartment
Number of residents	In average 1.8 residents per household [12]	In average 2.2 residents per household

Residents

In 2018, the housing association had 2,321 residents, with 53% being female and 47% male. Of the residents, 24% were under 20 years old, 40% were aged between 20 and 50, and 36% were 50 years old and above [33]. Figure 4 illustrates the gender and age distribution of the residents, alongside with the corresponding distribution for Norway [34]. The age and gender distribution of the residents is similar to the wider Norwegian population.

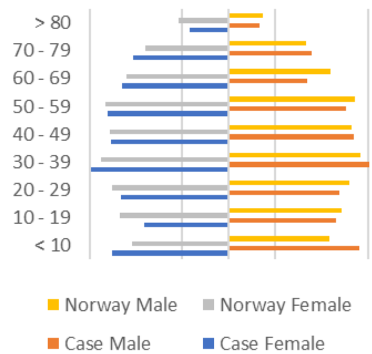


Figure 4 *Gender and age distribution of the residents in the main case study and for the Norwegian population.*

Space heating and domestic hot water

In the case study, space heating and DHW constitute approximately 72% of the total delivered energy, when not including EV charging. The heating share is close to the national average estimation for households of about 78% [18].

The energy use for space heating and DHW in the case study is compared with 29 other Norwegian apartment housing associations with central heating systems, whereof 25 with DH, 2 with electric boilers (EBs), and 2 with ground source heat pumps (GSHP). The delivered energy for space heating and DHW is based on meter readings, as defined by EN

15378-3:2017 [40]. The specific delivered energy is calculated as the total delivered energy for the housing associations, divided by the floor area in the apartments. The specific delivered energy therefore includes delivered energy for heating common areas, such as staircases or basements, and is not directly comparable with energy use in apartments with individual heat technologies such as electric panel heaters or air-to-air heat pumps. For such apartments, the energy for heating of common areas is typically metered by common AMS meters.

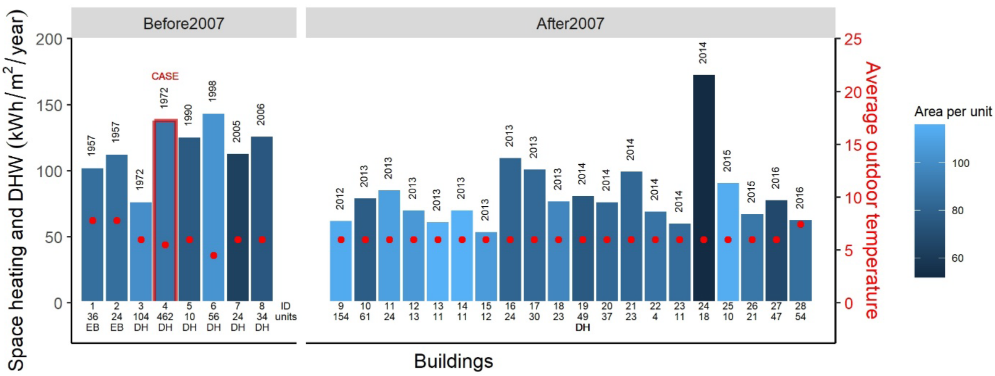
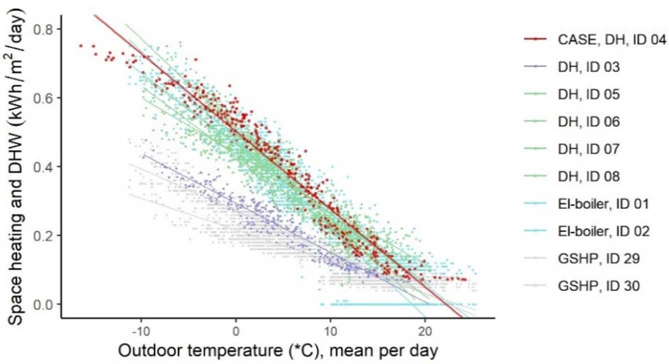


Figure 5 *Specific delivered energy for space heating and DHW in 28 housing associations with common central heating systems (DH and EB), divided into construction year before or after 2007. The numbers below the bars show ID no, number of units (apartments) in the housing associations, and type of heating system (DH or EB). Heated floor area is between 50 and 120 m^2 per apartment. The case study (Risvollan) has ID no 4.*

Figure 5 shows the annual delivered energy for space heating and DHW in the 28 housing associations with DH (25+case Risvollan) and EBs (2). The data presented in the figure is not corrected for climate or use, but for comparison, the annual average outdoor temperatures for the building locations are also shown in Figure 5. The measurement period is three years for housing associations 1 and 2, and one year for housing associations 3 to 28. The apartments have floor areas between 50 and 120 m^2. The number of apartments in the housing associations vary from 4 to 462 units, as shown in Figure 5. The construction year of the apartment buildings span from 1957 to 2016. It is expected that the energy performance improves with construction year, since newer apartment buildings have stricter energy requirements. This is e.g. shown in simulations presented by the projects Tabula and Episcope [41,42], where the energy performance for apartment archetypes of different construction years were simulated. In Norway, energy requirements for new buildings were introduced in the building codes of 1997, 2007, 2010 and 2017 [43]. In Figure 5, the apartments are separated by construction year before and after 2007, since the 2007-revision of the building code introduced the most significant step in the requirements for energy use in buildings. For the apartment buildings in Figure 5, the buildings with construction year before 2007 have a higher specific delivered energy for space heating and DHW (in average 117 kWh/m^2), compared to the buildings constructed after 2007 (in average 81 kWh/m^2). For the 8 buildings constructed before 2007, we did not find a clear relationship between construction year and the annual delivered energy for heating. Delivered DH to the case study apartments (Risvollan) was 138 kWh/m^2 in 2018.

Energy use for heating is affected by e.g. building and energy system efficiencies, user behaviour, and climate [44]. Figure 6 illustrates the relationship between daily delivered heat and outdoor temperatures for 10 housing associations constructed before 2007. The construction year of the buildings vary from 1953 to 2006. All the buildings have central heating systems, whereof 2 have EBs, 6 have DH (including the case study), and 2 have GSHPs. The comparison shows that the delivered heat to housing associations with EBs and DH are in the same range, with Apt ID 3 as an exception. As expected, the delivered heat is lower for the two housing associations with GSHPs, due to the Coefficient of Performance (COP) of the heat pump systems being higher than 1.



Model evaluation metrics

	MAE	MSE	RMSE
Training	0.054	0.005	0.071
Case	0.052	0.004	0.063

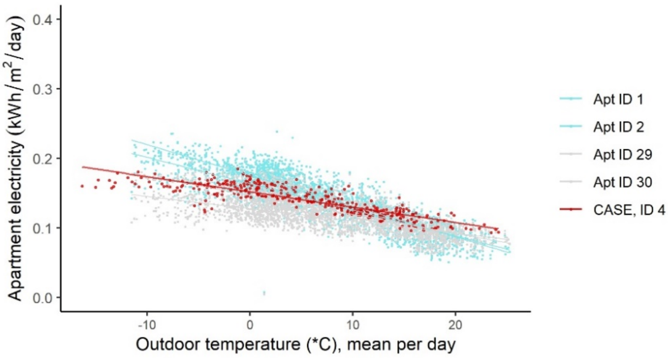
Figure 6 *Specific delivered energy for space heating and DHW in 10 housing associations, as a function of outdoor temperature.*

A linear regression model was employed to assess whether the energy use for heating in the case study (Risvollan) can be considered representative of apartment buildings with DH or EB constructed before 2007. The model described the linear relationship between daily energy use for heating and outdoor temperatures. The training data for the model were from the apartment buildings with EBs (Apt. ID 1 and 2) and DH (Apt. ID 3, 5, 6, 7, 8). The same model was then tested on the case data (Apt. ID 4). Evaluation metrics, including MAE (Mean Absolute Error), MSE (Mean Squared Error), and RMSE (Root Mean Squared Error), are presented in Figure 6. These metrics indicate that the model's predictions on the case study data have slightly lower errors, both in terms of magnitude and dispersion, compared to the training data. This suggests a similar or slightly improved fit.

To sum up, we conclude that the delivered heat to the case study can be considered representative for apartment buildings with DH or EB, constructed before 2007.

Electricity in apartments

Apartments in Norway generally have their own meter for delivered electricity, metering hourly values [45]. Figure 7 compares daily specific delivered electricity to apartments in five housing associations, where Apt. ID 4 is the selected case study (Risvollan), together with the average daily outdoor temperatures. The daily delivered electricity values are average values for the apartments in each housing association. All the apartments are connected to a central heating system, supplying heat to both space and DHW. Still, the figure shows a seasonal difference in electricity use, with higher energy use with cold temperatures. Thus, we may assume that the difference is partly caused by electric floor heating, which is typical in Norwegian bathrooms, and partly caused by higher electricity use for lighting during the winter.



Model evaluation metrics

	MAE	MSE	RMSE
Training	0.017	0.0005	0.022
Case	0.011	0.0002	0.014

***Figure** 7 Electricity use in apartments in 5 housing associations, as a function of outdoor temperature.*

Figure 7 shows that the electricity uses in the five housing associations are in the same range. For Apt. ID 1, 2, 29, and 30, the average electricity use in the apartments varied from 37 to 53 kWh/m^2/year from 2019 to 2022, corresponding to 2868- 4551 kWh per apartment. For the apartments in our selected case study (Risvollan), the specific delivered energy for electricity was 51 kWh/m^2 in 2018, or 4527 kWh per apartment (average values, 505 units). This is in line with results in [46], which assumed an average electric load of 4500 kWh for all apartments in Norway, independent of their construction year.

A linear regression model was employed for the daily electricity use and outdoor temperatures, to assess the representativeness for the case study (Risvollan). The model was created based on training data (Apt. ID 1, 2, 29, 30), and the same model was then tested on the case data (Apt. ID 4). Figure 7 shows the evaluation metrics, which suggests a similar or slightly improved fit for the case data compared to the training data.

To sum up, the evaluation suggests that the apartment electricity use in the case study can be considered representative for apartment buildings.

Residential EV charging

The share of EVs in the Norwegian car park is increasing, and by July 2023 there was about 30% EVs, including both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) [47].

In the main case study, an EV charging infrastructure was installed in December 2018. This infrastructure allows for the installation and activation of CPs on demand, and up to 764 CPs can be activated in the 24 garages. These CPs are either shared among all residents or designated for use on individual residents' private parking spaces. Between December 2018 and January 2020, the number of CPs increased from zero to 70, with 12 CPs designated for shared use and 58 for private use. The charging infrastructure is designed to balance the EV charging loads in each garage, ensuring that the aggregated charging power remains below a specified limit.

In Norway, residential customers are typically connected to a 230 Volt IT system [48]. When it comes to residential EV charging, the available charging power is commonly 2.3 kW when utilizing a household power plug (10 A) and 3.6 kW or 7.4 kW when using a Type 2 connector (16 A or 32 A). Certain charging systems offer the capacity to enable 3-phase charging on a 230V IT system, which results in increased charging power for specific EV models. In the context of the case study, all customers have access to 7.4 kW charging power, and this can be increased to 11 kW by activating 3-phase charging. The actual charging power for an EV is also dependent on the onboard charger capacity for the EV.

In addition to the EV charging data collected from the main case study, an extended database was utilized for EV charging analysis within this thesis, as detailed in section 2.2.3. Figure 8 displays plug-in times, plug-out times, connection durations, and energy charged for 12 residential EV data locations. The main case study location is denoted as "TRO_R" in the figure, and the EV charging patterns observed in the main case study align with those in the other locations. For more details of the EV charging habits in the 12 locations, please refer to article Main II.

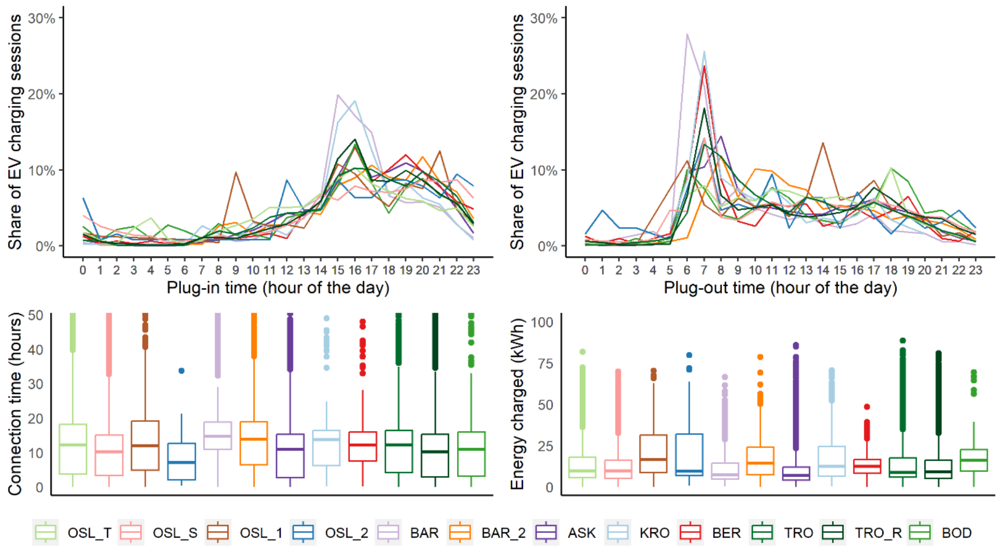


Figure 8 *Plug-in times, plug-out times, connection times, and energy charged in the 12 residential EV data locations (from article Main II).*

PV generation

PV generation in apartment buildings vary with PV size, location, and weather conditions. As there are no PV systems connected to the buildings in our case study, we have simulated the generated PV electricity for various installed capacities. The PV generation is simulated for roof and façade mounted PV systems in Trondheim. Hourly measurements for global horizontal irradiation (GHI) in Trondheim from 2018 [49] are utilized for the simulation. GHI represents the total solar radiation on a horizontal surface. Annual GHI measured by weather stations in Trondheim and Oslo for the years 2016 to 2022 is shown in Figure 9. The GHI in Trondheim in 2018 (870 kWh/m^2) is higher than the Trondheim average from 2016-2022 (827 kWh/m^2), but lower than the Oslo average (953 kWh/m^2) [49]. Dobler et al. [50] conducted a solar resource assessment in Norway, finding that the highest GHI values occurred in high mountain areas (about 1000-1100 kWh/m^2) and southern coastal sites (1000 kWh/m^2). In contrast, lower GHI values were observed on the west coast (700-800 kWh/m^2) and in northern Norway (600-700 kWh/m^2). The annual GHI value used in our simulation (870 kWh/m^2) falls within the mid-range of values typical for Norway. In general, there are few examples of PV systems on Norwegian apartment buildings, since the regulations did not allow for sharing of electricity across AMS meters until 2023. The residential PV systems currently installed in Norway are therefore mainly installed on detached houses. A histogram with installed capacities for residential PV systems in Norway is shown in Figure 10, as registered in the national database elHub by December 2022 [51]. The data is registered by the DSOs, and represent a mix of installed inverter capacity (kW AC) and installed PV capacity (kW$_p$ DC). It can be seen that the systems mainly range between 3 and 12 kW installed capacity.

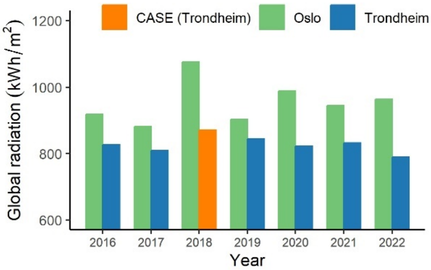


***Figure 9** Global GHI in Trondheim and Oslo 2016-2022.*

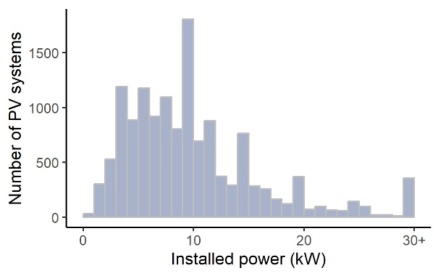


***Figure 10** Installed power for residential PV systems in Norway* [51].

Representativeness of the main case study

To conclude, we have evaluated the main case study to be representative for a major share of Norwegian apartment buildings with EV charging. The apartment buildings include apartments of diverse floor sizes, accommodating households of varying sizes, as well as a range of gender and age demographics. The average floor area and resident count per household align with typical Norwegian apartment statistics. In terms of energy use, the delivered heat to the case study can be considered representative for apartment buildings with DH or EB, constructed before 2007. The electricity use in the case study can be considered representative for apartment buildings in general. The EV charging data from the main case study corresponds with data from 11 other residential locations included in this thesis. For PV generation simulations, the GHI values utilized falls within the mid-range of values typical for Norway.

2.2.3 Other case studies

Besides using data from the Risvollan housing cooperative, the articles in the thesis also include analyses of data from other locations. For the DHW analysis in Supplementary article III, an apartment building in Oslo is the case study. The apartment building has 56 apartments and a shared DHW system. Detailed DHW data was available from the research project VarmtVann2030 [52].

For the EV charging analyses in Main articles II and IV, EV charging data from 12 residential locations in Norway was used (including the location of the main case study). The EV charging data was based on EV charging reports with energy and time information for 35.000 EV charging sessions and 271 EV users. Various CPOs and housing associations provided access to the data. The EV charging data is described with further details in article Main II.

2.3 Data collection, cleaning, and sharing

To address the research questions of this thesis, it was crucial to obtain access to comprehensive data describing energy use in apartment buildings, EV charging data, climate data, and relevant metadata. This section describes the data collection and data cleaning procedures.

Access to real-world energy data provides the basis for research within a number of fields, such as energy use analysis, modelling, and simulations. Still, it can be challenging for researchers to access suitable data. Data sharing has therefore been an important part of this thesis, aiming to share findable, accessible, interoperable, and reusable data according to the FAIR principles [53].

2.3.1 Data collection

A number of stakeholders have been contacted during the time period of this thesis, and have been invited to contribute with data. The major data collection steps are listed in Table 4. Before processing personal data, notification forms were sent to the NSD – Norwegian Centre for Research Data (since 2022: Sikt – Norwegian Agency for Shared Services in Education and Research). Information letters were sent to the participants, providing information about the project and their rights. When only collecting anonymous data, such notifications were not needed.

Table 4. *Data collection in the thesis.*

	Stakeholders/owners of data	**Type of data**	**Source**
Apartment building energy use	Risvollan housing cooperative, NTE Marked (energy company), Enoco (EMS-provider), Fosen Innovasjon (partner), and Statkraft varme (DH company)	Meta data and energy system information	Dialog
	Enoco (EMS-provider)	Heating and DHW data (hourly)	EMS of the housing cooperative
	DSO TrønderEnergi Nett	Electricity data from cooperative meters (hourly). Coupled with meta-data	Data files
	DSO TrønderEnergi Nett	Electricity data from apartments (hourly). Anonymous data	Data files
	National registry in Norway	Resident information (number, age and gender)	Data on request [54]
	Other research projects, especially VarmtVann2030 [52] and COFACTOR [36]	Energy data	Data files
EV charging data	Risvollan housing cooperative, NTE Marked (energy company)	EV charging reports. Coupled with electricity data	Data files
	Housing cooperatives in Bærum and Tveita, Current Eco AS, Kople AS, and Mer Norway AS	EV charging reports	Data files
	Residents in housing cooperatives in Risvollan and Bærum	Data about EVs and charging habits	Questionnaire
	The Norwegian EV Association	Charging habits in Norway	Questionnaire "Elbilisten 2022" [55]
EV cabin preheating	Experimental study. Data was collected in two sites, where volunteering EV owners charged and preheated their EVs	Power loads for grid-connected preheating of EV cabins	Trial meters and charging reports
PV capacity data	NVE and Statnett/ Elhub	Data on grid-connected PV systems in Norway [51]	National database Elhub
Climate data	Norwegian Centre for Climate Services	Climate data from public weather stations [49]	Data files

2.3.2 Data cleaning

The data cleaning process was performed using the statistical computing environment R [56]. This section presents a summary of the key insights gained during the data cleaning process in the thesis, primarily focusing on time series with hourly resolution. Data cleaning of the time series is further described in the publications, especially Supplementary I and II. For a detailed description of data cleaning of EV charging reports, please refer to the publications Main I, Main II, and Data I. The thesis has limited utilization of data series involving "change of value" (COV) [57], with the exception of some EV sessions in Main I and Main III, which is not covered in this summary.

Understanding the energy system and metering location

When analysing energy data, it is essential to have some information about the energy system and metering location. For instance, meter readings for space heating and DHW usually represent delivered energy, including heat losses. As a result, they might not be directly comparable to Norwegian energy performance requirements, which generally represent energy use for space heating and DHW, excluding energy losses. In cases where a building has multiple energy meters, it is necessary to be aware of the metering structure, encompassing main meters, sub-meters, etc. For heating systems with multiple heat sources, consideration should be given to whether all relevant heat flows are metered.

Evaluation of data quality

Typically, data cleaning handles missing values, resolves inconsistencies, and detects and removes outliers [58]. To get an overview of missing data per time series, the number of measurements within the data period can be counted (either overall or on a monthly basis if required). As a quality assurance measure, this process can also be repeated after data treatment. Data quality can be evaluated through data analyses and visual evaluation, including zero-values (evaluate if values truly are zero or in fact missing data), negative values, too high values, and periods with unchanged values (may be average values for the period, due to missing data). Out-of-range checks, such as negative and too high values, are described by [59] based on the cleansing of a large database with energy data from 750 000 buildings. Their data cleansing involved confirming that the data values were within reasonable or researched limits. In our analysis, we also found that values estimated by the energy companies should be critically evaluated. E.g., in article Supplementary I, we removed estimated values from peak load analysis, since they represented the maximum values for some time series. In the same article, we included the estimates in the annual energy values, since only a minor share of the hourly values was estimates (99% for apartments and 98% for common areas).

The measurement resolution of the data should be considered, to evaluate if the data are suitable for the purpose. Typically, AMS meters (electricity) have relatively high resolution (e.g. 1 Wh/h), while thermal (sub-)meters have low resolution (e.g. 10 or 100 kWh/h for the SUBs at Risvollan, as described in article Supplementary II). With low measurement resolution, hourly loads may be shifted to the subsequent hour. In Supplementary II, we therefore included only SUBs with 10 kWh/h resolution when analysing daily heat load profiles and peak values. All the SUBs were included when analysing annual energy values.

Time stamps in the time series

Diverse time series handle time stamps differently, encompassing factors such as whether time stamps are logged before or after the measurement period, as well as considerations related to time zones and daylight-saving time (DST). Additionally, there can be errors in the time stamps. Table 5 provides examples of the variations observed in the time stamps of some received data series. Norway follow Central European Time (CET) from October to March (UTC+1) and Central European Summer Time (CEST) from March to October (UTC+2).

Table 5 *Examples of time stamps used in time series.*

Electricity/AMS-data – Example from DSO TrønderEnergi Nett (per 2020)	▪ Timestamps show the time AFTER measurement period. ▪ Norwegian time-zone without DST ("normal time", UTC+1).
Electricity/AMS-data – Example from Elhub user portal "minside" (per 2023)	▪ Timestamps show start and end time. ▪ Norwegian time-zone with DST (UTC+1/UTC+2). ▪ DST: All values, with 23 hours in March, 25 hours in October.
Electricity/AMS-data – Example from DSO Elvia user portal "minside" (per 2023)	▪ Timestamps show the time BEFORE measurement period. ▪ Norwegian time-zone with DST (UTC+1/UTC+2). ▪ DST: 24 hours in March, with zero-value for DST-hour. 24 hours in October, with summarized value for DST-hour.
Heating/ EMS-data – Example from EMS-provider Enoco (per 2019)	▪ Timestamps show the time BEFORE measurement period. ▪ Norwegian time-zone with DST (UTC+1/UTC+2).
Heating/EMS-data – Example from EMS-provider Dråpe (per 2022)	▪ Timestamps show the time AFTER measurement period. ▪ Norwegian time-zone with DST (UTC+1/UTC+2). ▪ DST: 24 hours in March, with NA-value for DST-hour. 24 hours in October, with average value for DST-hour.
Weather-data from seklima.met.no	▪ Timestamps show the time BEFORE measurement period. ▪ Norwegian time-zone without DST ("normal time", UTC+1).

To enhance confidence in the accuracy of the timestamps, the following steps may be considered during the data treatment. Firstly, the data provider should provide information about the time stamps of their data series. During data treatment, time stamps in all the data series should be changed to the same format, e.g., standard time for the location when DST is not in use (UTC+1 in Norway). For clarity during data handling, two columns can be used for the time series, showing start and end time for each time step. Especially the hourly data for the dates with change in DST should be carefully considered (in October and March). For example, aggregated values for the DST-hour in October can provide peaks which are not real. When visually presenting data, it can be an advantage to include DST. In R [56], the time zone of the figures can be defined separately. Finally, to ensure the quality of the resulting time stamps, a comparison of average daily profiles for both summer and winter, or even for each month, can be conducted. Thereafter, the alterations in the peaks can be evaluated, for e.g., solar radiation and energy loads.

2.4 Data analysis and modelling

Table 6 provides an overview of the main methods used in the publications. The methods are briefly explained in this chapter, with data analysis in section2.4.1, key performance indicators (KPIs) in section 2.4.2, and main modelling methods in 2.4.3. The methods are further described in the publications presented in Chapter 3.

The main tool for the analyses and modelling has been the statistical computing environment R [56]. In addition, the two MSc students used Python [60] for the stochastic model (Maria Claire Westad, Supplementary V) and optimization of EV charging (Balder Bryn Morsund, Main IV).

Table 6 *Overview of main methods used in the publications.*

Publications	**Data analysis**	**Modelling** (ref. section 2.4.3)
RQ1		
S I	Electricity use	Data analysis emphasised; no modelling included
S II	Heating	Linear regression model for heat and DHW
S III	DHW use	Rule based control of delivered DHW
S IV	PV generation	Simulation of electricity from PV systems
RQ2		
Main I	EV charging and flexibility potential	Data analysis emphasised; no modelling included
S V	Generalisation of EV charging	Stochastic model for EV charging
Main II	Complete EV charging datasets and charging behaviour	Data analysis emphasised; no modelling included
Main III	EV cabin preheating	Linear regression model for cabin preheating
RQ3		
Main IV	Energy profiles for apartment buildings with EV charging	Optimization of EV charging in apartment buildings

2.4.1 Data analysis

The case study data is analysed to increase the understanding of the energy performance in Norwegian apartment buildings with EV charging and is essential for addressing the research questions. In the articles, the energy uses (electricity, heating, and EV charging) are described with both absolute and specific values (per area, per apartment, or per EV). Visual representation of the data is important for the analysis, and includes:

- **Time series**, which illustrates how the hourly energy loads changes during a period (e.g., seasonal differences in thermal energy, and increase of EV charging use over time).
  Figure 11 shows an example of the use of time series from Article S II (heating), addressing RQ1. Time series are also included in Article S I, S III, S IV, Main I, S V, and Main IV.

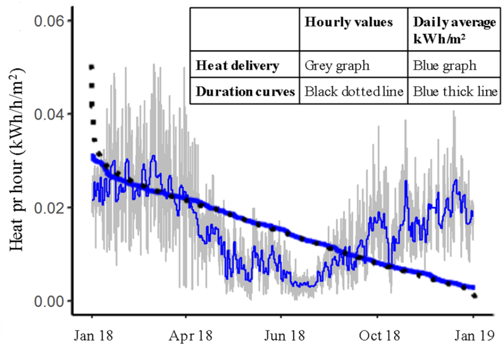


Figure 11 *Examples of "Time series" and "Duration curves" from Article S II. Area specific values for delivered heat is presented on hourly and daily basis.*

- **Daily average load profiles**, which show how the average hourly energy loads change during the day. Load profiles can also show the difference between workdays and weekends, and can be segmented by different seasons.
  Figure 12 shows an example of daily average load profiles from Article S I (electricity use), addressing RQ1. Daily average load profiles are also included in Article S II, S III, S IV, Main I, S V, Main II, Main III, and Main IV.

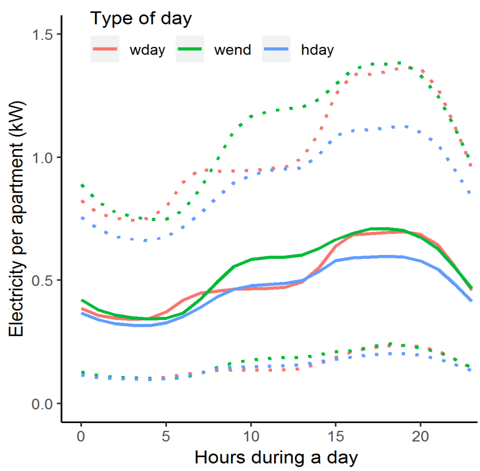


Figure 12 *Example of "Daily average load profiles" from Article S I, for electricity use in apartments (average for 1009 apartments, and for the 10% with less/most annual electricity use).*

- **Energy signatures** (ET diagrams) with hourly or daily values, reflecting the relationship between energy use and different outdoor temperatures. Figure 13 shows an example of an ET diagram from Article Main III (EV cabin preheating), addressing RQ2. ET curves are also included in Article S I, S II, and Main IV.

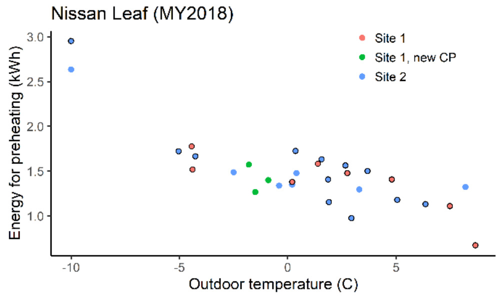


Figure 13 *Example of Energy-Temperature diagram from Article Main III, showing energy use during preheating sessions for a Nissan Leaf.*

- **Load duration curves** with hourly (or daily) loads over a specified period, sorted by their magnitude. The duration curves illustrate the duration of different load conditions, which is valuable insights when e.g., dimensioning the capacity of heating systems and storage.
  Figure 14 shows an example of the use of load duration curves from Article S IV (PV), addressing RQ1. Load duration curves are also included in Article S I, S III, and S IV.

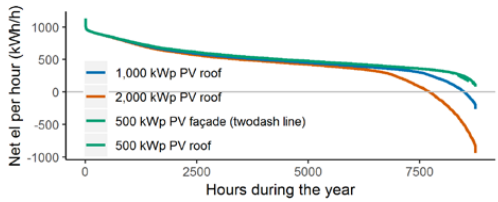


Figure 14 *Example of load duration curves from Article S IV. Hourly duration curves are shown, for net electricity load for apartment buildings with 4 PV system scenarios (positive values: import from grid, and negative values: export to grid).*

- **Histograms and boxplots**, which visually display data distribution, indicating variations among users (apartments, EVs, etc.) in for example annual energy use or maximum power. Histograms use bins to show frequency of values, while boxplots represent quartiles and highlight outliers.

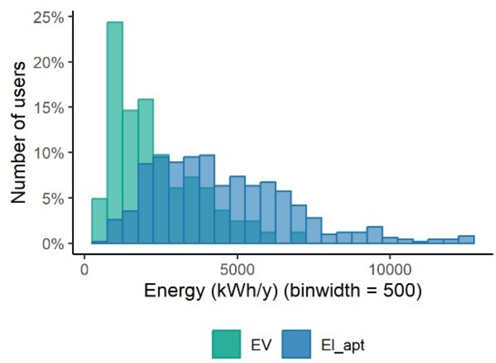


Figure 15 *Example of histogram from Article Main 1V, showing annual energy use for 505 apartments and 271 EVs.*

Figure 15 shows an example of a histogram from Article Main IV (flexibility), addressing RQ1 and RQ3. Histograms are also included in Articles S V, and Main II.

Figure 16 shows an example of boxplots from Article Main II (EV charging), addressing RQ2. Boxplots are also included in Article S I and Main I.

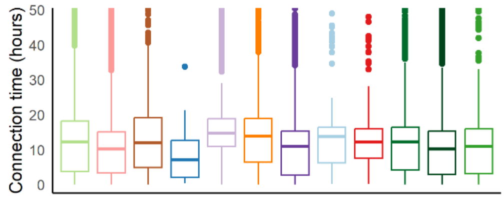


***Figure 16** Example of boxplots from Article Main II, showing the variation in connection times per EV session in 12 residential locations.*

- **Aggregated peak loads** can for example be illustrated in figures where the aggregated peak load is shown per user (e.g., per EV) for an increasing number of users.

  Figure 17 shows an example of aggregated peak loads from Article S V (EV charging), addressing RQ2. An aggregated peak power figure is also included in Article Main I.

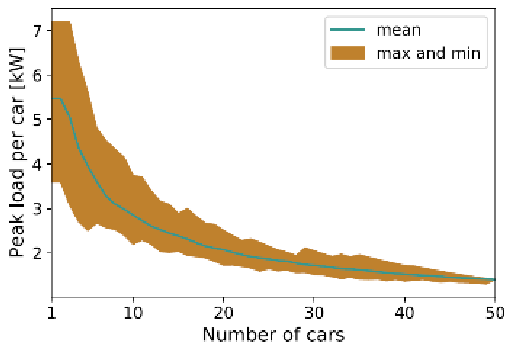


***Figure 17** Example of aggregated peak loads from Article S V, showing how the average peak load decreases for an increasing number of EVs (for base scenario, with EV mix similar to original data).*

2.4.2 Key performance indicators

Different KPIs have been developed and proposed to quantify the energy flexibility of buildings [9,61–63]. Energy, power, and duration are commonly included in the properties of energy flexibility. Cost, comfort, and emission are other properties which are frequently considered. To activate the energy flexibility, a penalty signal is often introduced (e.g. price) [64]. When quantifying flexibility, there is usually a reference case for the energy use, representing 'business-as-usual' [9]. Kathirgamanathan et al. [62] concluded that different stakeholders such as end-users, aggregators, and grid operators require different kinds of flexibility indicators. While end-users often aim to reduce their total energy costs, grid operators need to know the aggregated flexibility potential of a building stock. Aggregators need knowledge of the DR technical specifications such as DR power, rebound energy, and response time. Li et al. [65] emphasized that a generic energy flexibility characterization methodology should be simple to apply and usable by different stakeholders. Since there is a lack of consensus and standardization in literature when it comes to quantification of energy flexibility in buildings [62,65,66], [65] recommends that several methodologies should be tested when quantifying energy flexibility for a specific case study.

To increase the understanding of the data and outcomes, a combination of several KPIs is utilized in the thesis. KPIs are featured across all the publications, with a particular emphasis in the article Main IV. KPIs used in the thesis include:

- **Energy**
    - Annual values for delivered energy and energy use (in kWh), per apartment, per resident, per EV, and per area.
    - Energy use during stress hours (in kWh).
    - Flexibility factor, which is the loads (e.g. EV loads) during low load (or low price) hours versus high load (or high price) hours.
- **Peak power**
    - Maximum hourly loads (e.g. during a year), and peak power difference between different scenarios (in kWh/h or kW).
    - Coincidence factors, describing the ratio between maximum load for the accumulated measurements studied and the aggregated maximum load.
- **EV charging**
    - Battery capacity (kWh/EV user), charging power (kW/EV user), start SoC of battery (%), time for charging, connection to CP, and non-charging idle time (hours per session), energy charged (kWh/session), idle energy capacity (kWh/session), weekly charging sessions (per user), time between charging sessions (hours).
- **PV generation**
    - Self-consumption: Share of the on-site generation that is used by the buildings or behind the billing meter.
    - Self-generation: Share of the energy use that is covered by on-site generation.
    - Generation multiple factor: Ratio between exported and imported peak powers.
- **Costs**
    - Annual operational costs (in NOK), and operational cost difference.

2.4.3 Modelling

The main modelling methods used in this thesis is explained in the following.

Multiple linear regression analysis is a statistical technique employed to examine the relationships between a response variable and various independent predictor variables. This method proves valuable for understanding energy data and forecasting future energy loads in buildings. The method provides a reasonable accuracy and relatively straightforward application compared to alternative methods [59]. Within this thesis, multiple linear regression analysis is implemented for heating data in the article Supplementary II and for cabin preheating data in article Main III. In these two publications, multiple linear regression is used to investigate the relationships between energy use and multiple independent variables like outdoor temperature.

PV simulations are performed in Supplementary IV, and the resulting data series serve as inputs for the analyses conducted in Supplementary IV and Main IV. PVsyst [67] was used to simulate generated electricity time series with hourly resolution, using climate data from local weather stations [68]. PVsyst is a widely used simulation tool for modelling and designing solar PV systems [69]. It offers numerous options for system configuration, including size, tilt, orientation, seasonal soiling losses, etc. Additionally, PVsyst can import climate data, and for this analysis, climate data from the main case study region was used, aligning it with the available energy data for the corresponding years. This approach was important for ensuring that parameters such as self-consumption and self-generation, which are central to the analyses in this thesis, were based on realistic values.

The stochastic load profile generator, as described in Maria Claire Westad's MSc thesis [70] and Supplementary V, employs a methodology similar to the one presented by Fischer et al. in [71]. This generator produces EV charging load profiles based on probabilistic factors, capturing the stochastic nature of EV charging. This stochastic nature arises from the fact that the timing of EV charging and the charging need per EV session depend on user behaviour.

To create this generator, we used the EV charging dataset in Main I and Data article I. Initially, we estimated car sizes (small or large EVs) for the EV users, which allowed us to categorize the dataset. Subsequently, we derived stochastic model parameters from probability distributions related to: 1) weekly charging frequency, 2) charging need per session, and 3) plug-in and 4) plug-out time of session.

The advantage of using the generator when addressing RQ2, in addition to analysing the EV charging data directly, was especially its ability to generate time series for specific user groups (small or large EVs). This provided insights into how user habits and car sizes influence the electricity load profiles of residential EV charging. Moreover, since the generator can provide time series for any number of EVs, it allowed us to create coincidence factors and aggregated peak loads for an increasing number of EVs.

The optimization model for smart EV charging, as described in Balder Bryn Morsund's MSc thesis [72] and the publication Main IV, utilizes Mixed Integer Linear Programming (MILP) [73]. MILP is a widely employed tool for modelling optimal control of energy use in buildings [74]. The main objective of this optimization is the minimization of energy costs during the operational phase.

The reference scenarios for the results illustrate uncontrolled EV charging in the apartment buildings. In the simulated scenarios, the electricity use within the apartments is static, while the EV charging can be shifted in time. The model handles each EV charging session individually, optimizing it in accordance with real-world values, including energy demand for charging sessions and associated plug-in and plug-out times.

The optimization model is important in addressing RQ 3 in this thesis, when investigating and quantifying the potential for electricity flexibility from EVs in relation to non-flexible apartment building loads and PV generation. Specifically, the model allows us to investigate how the electricity flexibility KPIs of optimised EV charging in apartment buildings are affected by different energy tariffs, PV, V2G, and the location of the billing meters.

3. Results and discussions

In chapters 3.1-3.3, the results of the publications are presented along with explanations of how they are linked to the research sub-questions. Chapter 3.4 presents how the contributions answer the main research question. Chapter 3.5 describes limitations of the study and provides suggestions for further work.

3.1 RQ1: What are the energy profiles for household energy use and PV generation for apartment buildings, and how are the energy profiles influenced by climate variables?

3.1.1 Article Supplementary I. Electricity analysis for energy management in neighbourhoods: Case study of a large housing cooperative in Norway

Supplementary I investigates the energy profiles for electricity use in apartment buildings. The case study of the work is the housing association Risvollan, with 1,058 apartments. Hourly data from the year 2018 was analysed, divided into electricity use in apartments (1,009 AMS-meters), electricity to common areas (89 AMS-meters), and electricity use in garages (25 AMS-meters). The data was linked with outdoor temperatures and calendar data. In 2018, the average specific delivered electricity to apartments and common areas was 56.7 kWh/m^2 heated apartment area. The apartments had an average annual electricity use of 4,362 kWh and reached an average maximum hourly load of 3.2 kW. The electricity coincidence factor for the 1,009 apartments was 0.316. This factor is calculated as the ratio between the aggregated maximum hourly load for all apartments during the year and the sum of each of the apartment's individual maximum hourly load. Time series and duration curves show the electricity use during the year, where Christmas Eve and New Year's Eve have the highest annual electricity peaks. The reason for this is the high coincidence for electricity use in apartments during these dates, together with low outside temperatures. The relationship between electricity use and outdoor temperatures was illustrated by ET curves, showing that the temperature dependency for the electricity use was rather small, since the housing cooperative is connected to district heating. This temperature (or seasonal) dependency is explained by heating (e.g. floor heating in the bathrooms), lighting, and other increased electricity use during the colder season. Daily electricity load profiles for apartments, garages, and other common areas were illustrated separately. The studies showed that both apartments and garages have an afternoon/evening peak in delivered electricity, i.e., from about 3 pm to 9 pm (in average 7.5 W/m^2 for apartments), while the lowest electricity use happens during night (in average 4 W/m^2 for apartments).

3.1.2 Article Supplementary II. Heat analysis for energy management in neighbourhoods: Case study of a large housing cooperative in Norway

Supplementary II investigates the energy profiles for heat use in apartment buildings, with data from the main case study Risvollan. DH provides space heating and DHW to the apartments, with sub-meters in 20 SUBs, covering 25 to 74 apartment units per SUB. The supply temperature for the space heating system is controlled according to an outdoor temperature compensation curve, and is turned off at 18.0°C. Average specific delivered heat was 139 kWh/m^2 heated apartment area.

A linear regression model was developed, modelling specific heat delivered to the apartments as a function of different climate variables. The model was tested with the climate variables outdoor temperature, wind speed, wind direction, solar radiation, and minutes of sun each hour. Among these, outdoor temperature and average outdoor temperature the last 18 hours were selected for the final model. This model, with an outdoor temperature breakpoint at 19.0°C, demonstrated a strong fit to the training data with an adjusted R^2 value of 0.8438. Including wind speed and solar radiation led to a slight increase in the adjusted R^2 (to 0.8515), however, these parameters were omitted due to the unreliable nature of hourly wind and solar data in the Risvollan area. By focusing on outdoor temperature alone, the model was found to have greater robustness against missing input data and errors.

The linear regression model was also used for separating energy for DHW from the total delivered heat, by setting an outdoor temperature of 19°C every hour of the year. This resulted in a modelled delivered heat for DHW of 25.1 kWh/m^2, which was 18% of the delivered heat. Daily heat load profiles were presented for delivered heat during weekdays and weekends in the annual seasons, with holidays separated. The daily peaks were primarily linked to DHW use, and appeared in the morning hours.

3.1.3 Article Supplementary III. Energy flexibility potential of domestic hot water systems in apartment buildings

Supplementary III provides energy profiles for DHW use in apartment buildings. The case study for the work is 56 apartments in Oslo with a shared DHW system. Energy measurements, with minute or hourly resolution during 23 to 50 days (January to March

2019), included data on consumed hot water, hot water circulation, and energy supplied to the DHW tanks. During this measurement period, daily DHW heat use averaged approximately 96 Wh/m^2, while the daily delivered heat for DHW was around 148 Wh/m^2. The total heat losses were about 35% of the supplied energy. Assuming these daily DHW values are representative for the entire year, the estimated annual heat use and delivered heat for DHW would be 35 and 54 kWh/m^2, respectively (2,360 and 3617 kWh/apartment).

The daily profiles in Supplementary III display hourly average values for consumed hot water, hot water circulation, heat losses, and energy supplied, with their individual 90% confidence interval. Morning and afternoon peaks were evident in the hot water consumption, with average hourly values peaking at up to 8.4 W/m^2 in the morning and 6.1 W/m^2 in the afternoon. Additionally, DHW usage remained relatively high during other daytime hours, typically falling within the range of 3.5 to 4.3 W/m^2. The study also investigates the impact of different rule-based control options on DHW energy profiles. These options include "power limitation," "spot price savings," "flexibility sale," and "solar energy.".

To evaluate the DHW values presented in Supplementary III, the daily energy profiles and annual values are compared with data from other case studies that became available after publication. The energy data from the Oslo case described above were sourced from the VarmtVann2030 project [52]. In [75,76], the data from this apartment building in Oslo (referred to as "AB3") was presented alongside data from three other apartment buildings. The daily energy profiles and energy use in AB3 was similar to another housing cooperative presented ("AB4"), but had a lower daytime DHW use compared to the two examples with social housing ("AB1" and "AB2"). AB1 and AB2 were smaller (average 40 m^2) than AB3 and AB4 (average 60-70 m^2), and one of the conclusions from VarmtVann2030 was that DHW use depends on number of residents not apartment area [76]. It is therefore advisable to compare DHW use per apartment instead of area.

In 2022, delivered heat for DHW was also accessible for 74 apartments in the main case study, Risvollan. For these apartments, annual delivered heat for DHW was 35 kWh/m^2 (2,900 kWh/apartment), which is 35% lower than delivered heat for DHW in the Oslo case (20% lower per apartment). This variation underscores the need for additional DHW data from various apartment buildings before drawing conclusions on typical values. Moreover, delivered energy for DHW is likely influenced by outdoor temperatures, as colder input water temperatures are common during the winter. In [76], monthly data from the Oslo case is presented, indicating how delivered energy to DHW has a seasonal dependency. While this aspect hasn't been a primary focus of this thesis, it presents an opportunity for further investigation in future studies.

3.1.4 Article Supplementary IV. Analysing electricity demand in neighbourhoods with electricity generation from solar power systems: A case study of a large housing cooperative in Norway

In Supplementary IV, electricity generation from PV systems were simulated for the main case study Risvollan. The electricity generation from PV systems with different orientations and capacities were analysed in combination with data on electricity loads from Supplementary I. It was found that the PV systems mounted on the south-facing building facade generated approximately 5-6% more electricity annually compared to east-west oriented rooftop PV systems. The reason for this difference was that the façade mounted PV systems generated more electricity in the spring and autumn. Various KPIs, such as self-generation, self-consumption, and self-generation multiple, were calculated based on hourly values. Considering Norway's national tariff structure, the self-consumption factor is considered to be the most important KPI for the housing cooperative. A PV capacity of about 1 kW_p per apartment gave a self-consumption factor of 97% for a rooftop system, based on 2018 electricity and climate data.

The article also investigated the impact of billing meter location on various energy and economic KPIs. From the housing cooperative's standpoint, aggregating electricity loads for common areas and individual apartments was found to be financially advantageous since it enabled a greater portion of the generated electricity to be utilized by the cooperative. Prior to October 2023, Norwegian regulations allowed PV electricity generated behind a billing meter to be used directly behind the same meter or be exported. However, with new regulations [24], PV electricity behind a billing meter can now also cover electricity use behind other meters on the same property. This is an advantage for housing associations, since PV electricity can be used in both common areas and apartments.

The article's results demonstrate how the capacity and orientation of a PV system can influence the daily and annual energy profile for PV generation, which, in turn, affects self-consumption in the apartment building. This information is valuable when planning PV systems; for example, an east-west oriented system can be considered to maximize electricity generation during morning or afternoon hours, when there is also a high demand for electricity in the apartments.

3.1.5 Article Main IV. Energy profiles and electricity flexibility potential in apartment buildings with electric vehicles – A Norwegian case study

Article Main IV provides energy profiles for household energy use, residential EV charging, and PV generation for Norwegian apartment buildings. This study analyses hourly measurements for electricity and heat consumption in approximately 500 apartments (from the main case study Risvollan). The household energy data is combined with a substantial dataset of residential EV charging (involving 271 EV users) and simulated PV electricity generation. Daily average energy profiles and energy KPIs for the case study were presented. While the articles in section 3.1.1 to 3.1.4 provide detailed discussions of electricity, heating, DHW, and PV generation, article Main IV offers a complete overview of energy usage in apartment buildings. Additionally, the article highlights the significant role of EV charging in relation to the total power and energy consumption within these buildings. Further details on this are provided in section 3.4.

3.2 RQ2: How does the user habits influence the electricity load profiles of residential EV charging, and how is the electricity load affected by EV cabin preheating?

3.2.1 Article Main I. Analysis of residential EV energy flexibility potential based on real-world charging reports and smart meter data

Article Main I focuses on charging habits, electricity load profiles, and flexibility potentials of EV charging in apartment buildings. Data from the main case study Risvollan was used as input to the work: EV charging reports with 6878 individual charging sessions and AMS data for the garages. These data sources are generally accessible for apartment buildings in Norway, making it feasible to widely implement this methodology.

The study involved an analysis of EV charging habits, which included an examination of the daily distribution of EV plug-in and plug-out times on weekdays and weekends, as well as the creation of histograms illustrating connection times and energy charged. Furthermore, the study compared charging behaviours in residences with private CPs at individual parking spaces to those using shared CPs accessible to all residents. Notably, a distinction emerged in residential charging patterns based on CP ownership. For those with private CPs, the average connection time averaged 12.8 hours, whereas it was 6.5 hours for those using shared CPs. Information about energy and plug-in times from the EV charging reports were translated into hourly charging energy, assuming two different levels of charging power (3.6 kW and 7.2 kW). In real life, the charging power is limited by the onboard charger capacity for the EVs, up to the CP capacity limitation (7.4 kW in our study). Comparing the calculated hourly loads to AMS measurements per garage, the AMS data fell within the range of the two calculated load profiles.

The article illustrates how user habits, particularly regarding CP plug-in times and charging needs, impact the electricity load profiles of residential EV charging. Most EVs are typically connected to the CPs in the afternoon and evenings, with, for private CPs during weekdays, roughly 80% of connections occurring between 15:00 and 23:00. Consequently, with immediate EV charging, the charging loads are concentrated in the evenings. For private CPs in the case study, approximately 82% of the weekday charging occurred between 15:00 and 01:00, assuming 7.2 kW charging power. However, a large share of the EVs remain connected to the CP overnight, offering a potential for shifting the EV charging load to nighttime hours.

3.2.2 Article Main II. A method for generating complete EV charging datasets and analysis of residential charging behaviour in a large Norwegian case study

Article Main II introduces a methodological framework designed to offer what is defined as "complete EV charging data" by [30]. This framework incorporates realistic estimations of battery capacities, charging power, and plug-in battery state of charge (SoC) for individual EVs and their respective charging sessions. These estimations were integrated into datasets containing plug-in/plug-out times and energy charged. The development of these methods involved a combination and further enhancement of existing methodologies found in the literature, utilizing data from a case study with more than 35,000 charging sessions from residential buildings in Norway.

The generated EV charging dataset enabled a detailed analysis of how residential charging behaviour, electricity load profiles, and energy flexibility were influenced by EV battery capacity and charging power. Behaviour data, including energy charged, start SoC values, idle energy capacity, and charging frequency, were provided separately for users with "small" (small to medium-sized batteries and lower charging power) and "large" (larger batteries and higher charging power) EVs. On average, users charged approximately 6.2 kWh per day. Users with large EVs where charging about 1.6 times more than those with small EVs. The average charging time was less than 3 hours, while, on average, EVs remained connected to the CPs for 12 hours. This confirms the potential for shifting residential EV charging in time, especially from the afternoon and evening to nighttime.

3.2.3 Article Supplementary V. Stochastic load profile generator for residential EV charging

Supplementary V describes a stochastic bottom-up model for residential EV charging, taking outdoor temperatures into account. The model was based on charging data from the main case study (articles Main I and Data I). The load profile generator is described in more detail in section 2.4.3. The generator provides hourly charging loads for EVs, assuming immediate charging after CP connection. Hourly load profiles were simulated for 1000 EVs in three EV mix scenarios: BASE (a mix of "small" and "large" EV types and charging power), LOW ("small" EVs with 3.6 kW charging power), or HIGH ("large" EVs with 7.2 kW charging power).

Coincidence factors and peak loads per EV were calculated for the three EV mix scenarios. This analysis was conducted for an increasing number of EVs, from 1 to 50, by randomly drawing single load profiles from a fleet of 100 load profiles. The procedure was repeated 50 times to understand how the mean, minimum, and maximum values changed per EV. Our findings indicate that the average peak load per EV descended to approximately 1.4 kW for BASE, 1.3 kW for "small" EVs, and 1.9 kW for "large" EVs.

3.2.4 Article Main III. Grid-connected cabin preheating of Electric Vehicles in cold climates – A non-flexible share of the EV energy use

Article Main III focuses on grid-connected preheating of EV cabins. In cold climates, it is generally recommended to utilize grid electricity for preheating the EV cabin before using the car, to extend driving ranges, ensure passenger comfort, and for safety. The energy required for this purpose is typically non-flexible regarding timing, as it is typically directly delivered from the grid, not from the vehicle's battery. A significant portion of these preheating sessions occurs during the winter's morning hours, when there is also a high demand for other energy use. Consequently, it becomes important to understand the power loads associated with grid-connected EV cabin preheating.

The work presented an experimental study involving 51 preheating sessions of five representative EV models, conducted under various outdoor temperature conditions. The study reported the energy and power consumption associated with these preheating sessions. It also involved the development of multiple linear regression models, to investigate the relationship between various variables and the energy use during preheating. Lastly, the study compared the hourly energy loads for EV cabin preheating with other energy loads within apartment buildings, using data sourced from the main case study.

The study showed that various factors influenced the power and energy loads for preheating EV cabins, including the specific EV, the charge point, the preheating duration, the temperature conditions, and user habits. In our trial, we observed preheating energy use of up to 2 kWh for most EVs, with occasional examples reaching 5 kWh. While this can result in a significant energy and power demand at the apartment level, our study found that preheating had a relatively minor impact when aggregated for a residential neighbourhood. In our study, the average morning load during winter increased by 0.5-2% due to cabin preheating, accounting for all apartment energy and EV charging loads. To mitigate the strain on the grid caused by EV cabin preheating, EV batteries can provide energy for preheating on days where extended driving ranges are not required.

3.2.5 Data article I. Residential electric vehicle charging datasets from apartment buildings

Data article I presents residential EV charging datasets from apartment buildings in the main case study. The data article refers to the article Main I. Several datasets are provided, such as: 1) The initial EV charging reports (6,878 charging sessions), 2) Calculated charging loads with hourly resolution, 3) AMS data for a main garage with 33% of the charging sessions, 4) Local hourly traffic density in 5 nearby traffic locations. The open data serves to enhance the understanding of residential EV charging and can prove valuable for tasks such as forecasting energy loads, assessing flexibility, and aiding in planning and modelling activities.

3.3 RQ3: What is the potential for electricity flexibility from EVs, in relation to non-flexible apartment building loads and PV generation, in the Norwegian context?

3.3.1 Article Main I and II. Flexible and non-flexible EV charging loads

Articles Main I and Main II also target RQ3 of the thesis, in addition to RQ2 as described in section 3.2.1 and 3.2.2. Article Main I focuses on the potential for electricity flexibility from EVs in apartment buildings. The hours that the EVs are connected to a CP without charging (non-charging idle times) were translated into energy flexibility potential, or idle energy capacity. The study uncovers considerable potential for flexibility in residential EV charging, particularly in cases where private parking spaces are equipped with CPs. While the average charging load for the private CPs was 5.7 kWh per user during weekdays, the hourly charging capacity for connected EVs during night hours (23:00 to 07:00) was in average about 2.5 kW per user (assuming 7.2 kW charging power). In principle, most of the daily charging load may therefore be covered by night charging.

In Article Main II, the flexibility of EV charging was further investigated. It was analysed how the idle energy capacity were affected by EV battery capacity and charging power. The charging sessions were divided into flexible or non-flexible sessions, where the non-flexible sessions had idle times of less than 1 hour. The majority of non-flexible charging took place in the afternoon and evening. Nevertheless, the findings demonstrate a considerable potential for shifting the timing of residential EV charging, particularly from afternoon/evenings to night-time. On workdays, the daily averaged connected energy capacity was over four times higher than the energy charged during the day. The ability of single EV users to shift EV charging in time increases with greater EV charging power, more frequent connections, and longer connection durations. Comparing users with larger batteries and higher charging power (L_High) with users with small to medium-sized batteries and lower charging power (SM_Low), the EV charging power of L_High was 2.4 times higher than for SM_Low. At the same time, SM_Low had 1.8 times more frequent connections, compared with L_High. Since the connection times were quite similar for the two groups, the average daily idle energy capacity for L_High was 1.3 times higher than for SM_Low. In the future, the flexibility potential may change with advancements in technologies, such as higher charging power or V2G capabilities, and changing charging habits, like longer connection times and more frequent connections, possibly due to end-user payment for energy flexibility.

3.3.2 Article Main IV. Energy profiles and electricity flexibility potential in apartment buildings with electric vehicles – A Norwegian case study

Article Main IV focuses on how the electricity flexibility KPIs of optimised EV charging in apartment buildings are affected by different energy tariffs, PV-generation, V2G-technology, and the location of the billing meters. The case study included electricity use in 117 apartments, EV charging from 82 EV users (0.7 EVs per apartment), and energy generation from a 117 kW_p rooftop PV system (1 kW_p per apartment). An optimization model was used to simulate all the individual EV charging sessions separately, taking the real-world values for energy demand into account, as well as plug-in and plug-out times for the charging sessions. The optimization model is further described in section 2.4.3. The main objective of the optimization was to minimize the energy costs in the operational phase. Optimised scenarios used in the case study is shown in Figure 18, including two tariff options (energy tariff and peak per month), two billing meter locations (everything under one meter, or apartments measured separately), and energy options (with or without PV-generation and V2G-technology).

Finally, the article discusses how coordinated EV charging in apartment buildings can affect the aggregated grid load and the self-consumption of PV electricity in residential neighbourhoods. In the case study, the annual peak load for apartment buildings with EV charging (baseline) was 219 kW, whereof uncontrolled EV charging accounted for 48%. Implementing optimal charging according to energy tariffs increased the annual peak by up to 37%, but shifted the peak to nighttime when there is typically less pressure on the grid. With peak per month tariffs, the grid peak was reduced by up to 39% compared with the baseline. Investigating the potential for EV flexibility in relation to PV generation, about 18% of the uncontrolled EV charging was covered by PV electricity, increasing up to 38% with optimized EV charging. EV charging was mainly shifted to periods with PV-generation in the scenarios where the shared energy systems (PV, EV, V2G) were metered separately from the apartments. When also apartment energy loads were behind the billing meter, the self-consumption of PV-generated electricity was nearly 100%, thus eliminating the need to shift the EV charging.

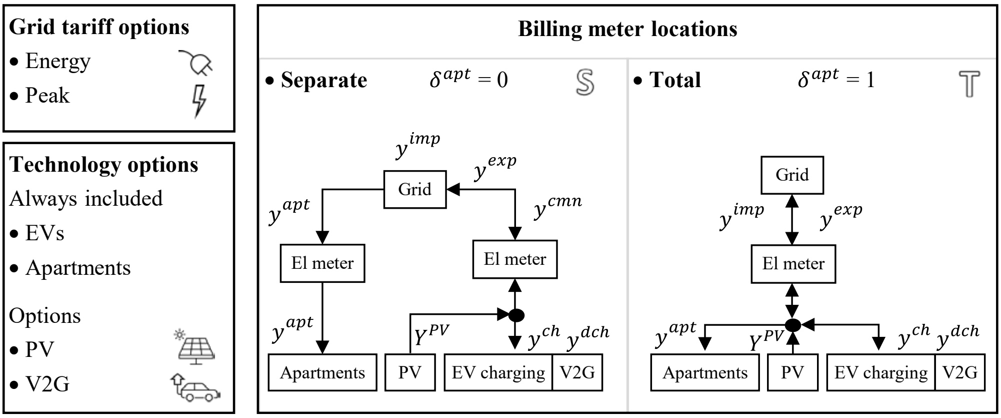


Figure 18 *Overview of the options in the optimization scenarios considered in Article Main IV. Further details are provided in the article.*

3.4 Main RQ: What are the energy profiles and electricity flexibility potential in Norwegian apartment buildings with electric vehicle charging?

This thesis examined the energy profiles for household energy use and PV generation for apartment buildings in Norway. For an average apartment with one associated EV in the case study, we found that 63% of the delivered energy was for space heating and DHW, 24% for electricity use in apartments, 12% for EV charging, and 1% for other common electricity use. The daily average energy profiles are illustrated in Figure 19, displayed for the summer period (June to August) and the winter period (December to February), and segmented by workdays and weekends. There are average daily peaks in the household energy use during mornings and afternoons, and these periods coincide with high load hours in the national grid, especially during wintertime. For heating, the energy use is spread quite evenly during the day (in average 2.1 kW from December to February), but with a DHW-related morning peak at around 08:00 during weekdays (in average 2.9 kW). Electricity use in apartments is highest in the afternoon and evenings (from 15:00 to 19:00, the average daily values are 0.8 kW from December to February). Table 7 summarizes energy KPIs for the apartments (from Main IV), which are described further in the following.

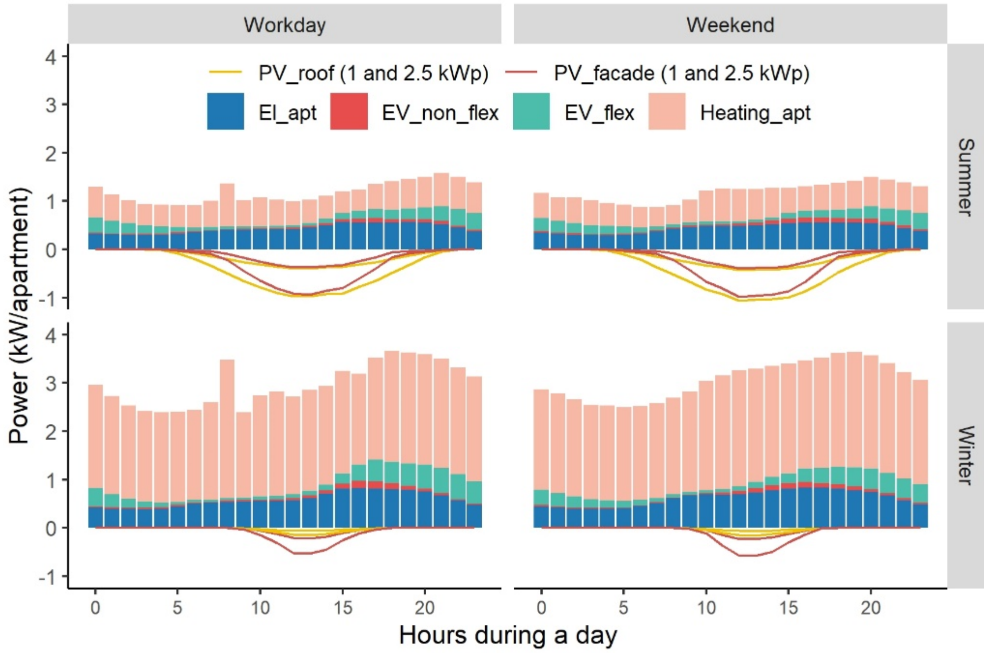


Figure 19 *Daily average energy profiles for Norwegian apartment buildings, with 1 EV per apartment (from Main IV).*

Table 7. *Energy KPIs for the apartment building of the case study (from Main IV).*

	Delivered energy (kWh/apt/year)	Delivered energy (kWh/m2/year)	Energy share
Space heating and DHW	12 200	138	63%
Electricity use in apartments	4 527	51	24%
EV charging (1 EV/apartment)	2 314	25.5	12%
Other common electricity use	250	2.8	1%
	Energy generation (kWh/apt/year)	Self-consumption (Self-sufficiency): PV to Apt and EV	Self-consumption (Self-sufficiency): PV to EV only
PV roof 1 kW_p /apartment 2.5 kW_p /apartment	754 1 885	98% (11%) 75% (21%)	51% (17%) 29% (24%)
PV façade 1 kW_p /apartment 2.5 kW_p /apartment	799 1 998	96% (11%) 65% (19%)	43% (15%) 23% (21%)

The presented heating and electricity use in apartments are based on data from the main case study Risvollan. The average delivered energy in 2018 was about 138 kWh/m^2 for heating and 51 kWh/m^2 for electricity use in apartments. The delivered heating is considered to be representative for Norwegian apartment buildings constructed before 2007 with heat supply from EBs or DH. The electricity use is considered to be representative for Norwegian apartments in general.

For residential EV charging, the energy profiles and KPIs are based on an extended dataset for EV charging, including residential EV charging data from 12 residential locations in Norway (ref. Main I and Main II). The EV charging profile presented in Figure 19 is based on uncontrolled charging, and divided into flexible and non-flexible EV charging. The flexible EV charging has in average 9.3 hours idle time, and the charging load may therefore be shifted to other hours within the connection period, without necessitating changes in user behaviour. About 25% of the EV charging sessions have idle times of less than 1 hour and may consequently be considered as non-flexible EV charging. In addition, electricity for grid connected preheating of EV cabins is part of the non-flexible electricity demand for EVs (not included in Figure 19), as described in section 3.2.4.

An essential aspect of our analysis is the interplay between electricity consumption in apartments and energy use for EV charging. By examining various combinations of these factors, we gain insights into how they influence total energy consumption. When we added the average EV charging to the average electricity use in apartments, we observed that energy consumption increased by a factor of 1.5, excluding heating. In Figure 15, we present a histogram illustrating variations in annual energy use for 505 apartments and 271 EVs. For example, adding the 75th percentile EV charging to the 25th percentile electricity use in apartments resulted in an increase of 2.1 times in electricity use, while the reverse situation, adding 25th percentile EV charging to 75th percentile electricity use in apartments, led to an increase of 1.2 times. If we include heating in the calculations of average values, total energy use increased by a factor of 1.1. In more energy efficient apartment buildings, assuming 66 kWh/m^2 energy use for heating[1] and maintaining the same levels of electricity use and EV charging as in the case study, we found that the total energy use would increase by a factor of 1.2.

The average maximum power for apartments without EV charging was 1.4 kW. If adding EVs with charging powers of 3.5 kW to 11 kW to the apartment loads, the maximum power increased to 3.5 to 8.6 times the original. In the case study described in Main IV, we found

[1] Calculation is based on the energy requirements for new apartment buildings (95 kWh/m^2 energy demand) [77], subtracted standard values for equipment and lighting electricity (30 kWh/m^2) [78].

that uncontrolled EV charging accounted for 48% of the annual peak load in apartment buildings with EVs (heating excluded).

For apartments with PV generation, the self-consumption and self-sufficiency values shown in Table 7 were calculated based on hourly values for PV-generation, electricity use in apartments, and EV charging. For a roof-mounted PV system with 1 kW_p capacity per apartment, the self-consumption is nearly 100% and the self-sufficiency 11%, given that the electricity can be used to cover electricity demand in the apartments and for EV charging. If the PV electricity is used for uncontrolled EV charging only, the self-consumption is reduced to 51%, meaning that half of the generated electricity is exported to the grid. Still the self-sufficiency of PV generation for EV charging is only 17%, since a relatively small number of EVs are charging during the day.

To avoid significant power increases during peak hours and enhance self-consumption of PV generation, flexible EV charging should be shifted in time. In Main IV, flexible EV charging is analysed together with static electricity use in apartments combined with PV generation. The EV charging is optimised according to different energy/peak tariffs, metering locations, PV systems, and V2G technologies, and the resulting grid burden is analysed. Our simulations indicate that combining optimized EV charging with peak tariffs, V2G technology, and PV generation, led to peak load reductions of up to 45% compared to a base case of non-coordinated EV charging and apartment electricity loads. By implementing quite simple management strategies for EV charging based on energy tariffs, the energy consumption during peak hours may be reduced by 20% compared to non-coordinated EV charging and apartment electricity loads. This is due to a shifting of the EV charging to nighttime hours. The nighttime peak can be avoided by aligning EV charging with peak tariffs. In the scenarios in Main IV, a maximum of 38% of the EV charging was covered by PV generation. The PV-to-EV self-consumption is limited by the number of EVs which are connected to the CP during daytime. In the case study, most of the PV-to-EV therefore happens during the weekends when the EVs are more frequently connected during the day.

3.5 Limitations of the study and further work

This thesis investigates the energy profiles and electricity flexibility potential in Norwegian apartment buildings with electric vehicle charging. The analysis is grounded in real-world energy and EV charging data, aiming at understanding the energy use in apartment buildings and the relation to user habits of residential EV charging. Given the breadth of this subject, there are many aspects which can be studied further, and some identified possibilities are highlighted below. Moreover, specific topics for further research are pinpointed in the individual articles.

When collecting energy data, data cleaning is an important and often time-consuming task. In this thesis, the data cleaning leaned towards manual methods, yet more automatic data cleaning techniques can be utilized to analyse and identify errors or outliers. Such data cleaning techniques should encompass error detection in the time stamps, e.g., related to DST or unsynchronized time series.

The analyses can be extended to cover more apartment buildings with different energy systems and building standards, and also to other building categories. Preferable, data series should be available for different types of energy use and generation, such as electricity use, EV charging, space heating, DHW use, and PV generation. If such data are made available, additional aspects can be analysed, such as seasonal / temperature dependency of DHW and energy flexibility potentials of other energy uses besides EV charging.

Analysis of EV charging and the use of V2G technology can be extended to cover different types of commercial and public buildings, and specific user groups. CPO reports are becoming more and more frequently accessible for energy management and billing. An increased availability of such studies will enable the analysis of variations in EV charging behaviour based on building categories and user demographics. For example, in an office building with PV generation, the EV charging behaviour, grid impact, and PV self-consumption, will be different from EV charging in the residential sector. It is also relevant to study the interaction between different building categories, where for example EV users can charge PV electricity in an office building during the day, before discharging energy to their home using V2G technology in the evenings.

Also, for residential EV charging, it would be relevant to collect more detailed data. For example, real-world values for charging power, battery capacity, and session start SoC can be used to validate and improve the method for generating complete EV charging datasets suggested in Main II.

For EV cabin preheating in cold climates, further research is needed. This research should, e.g., include real-world testing of different EVs under various conditions, an examination of user behaviours, and analyses of how both EV cabin and battery preheating can influence the power use in buildings, along with their aggregated impact on the grid loads. Further, it would be interesting to investigate how the EV batteries can be used to preheat the EV cabin and battery, and the advantages / disadvantages of using the battery for preheating compared to using electricity from the grid.

The energy profiles and flexibility potential of apartment buildings with EV charging can be further investigated in various modelling and simulation activities, based on the open data available from the thesis. Datasets for energy use in apartment buildings from the main case study (from 2019-2022) will be published, providing the basis for in depth analysis and modelling activities. Datasets for EV charging is partly published already, and can e.g. be used for evaluating current and prospective EV charging patterns, developing data-driven assessments of energy flexibility, and modelling EV charging loads alongside the integration of EVs into power grids. Furthermore, the stochastic load profile generator for EV charging can be improved, to make the model more robust and reflect more general conditions. This includes creating new probability distributions based on a larger dataset, in addition to other improvements suggested in article supplementary V.

Finally, the knowledge and data from the thesis can form basis for real life testing, implementation and upscaling of smart and robust energy and EV charging solutions in apartments buildings.

4. Conclusions and future perspectives

The significance of energy use, generation, and flexibility within buildings is on the rise, driven by changes in the energy system and global climate objectives. The end-users can play a more important role by shifting their electricity use to periods of low grid demand or when unregulated renewable energy is abundant. To realize the potential for end-user flexibility, knowledge about the actual energy use and flexibility potential is needed. This thesis investigates energy use in apartment buildings, with a special focus on the flexibility potential of residential EV charging.

Flexible EV charging has the potential to significantly reduce energy use during peak grid load hours with minimal disruption to user routines. This holds particularly true for residential EV charging conducted at private parking spaces. Improving the tariff structure is essential to encourage end users to adjust their charging habits according to grid demands. At present, the practical application of smart EV charging often revolves around shifting charging loads to periods of low spot prices or to mitigate peaks behind the garage energy meters. However, this approach might not always align with local grid capacity or the availability of PV generation.

Although individual EV charging sessions are stochastic in nature, their aggregated behaviour is predictable. Aggregators can strategically shift charging loads across a large EV fleet, guided by e.g., price signals and knowledge of charging behaviour. The end-user flexibility potential can be realised with minimal investments and may be integrated into existing energy management systems. Promoting V2G-technologies is also important, as this will increase the flexibility potential for EV charging. V2G-technologies also provide the opportunity for energy exchange between locations, where energy charged in one location (e.g. from PV generation) can be discharged in another location (e.g. to reduce energy use during peak hours). In regions with weak grids, integrating stationary batteries alongside EV charging and PV generation might be necessary. However, given the current environmental and economic challenges of batteries, the top priority should ideally be to realize end-user flexibility without stationary batteries.

In the current situation where the building sector is experiencing escalating energy costs, a growing demand for residential EV charging, and increasing PV adoption, there is a golden opportunity to implement scalable end-user flexibility solutions. The thesis confirms that residential EV charging may be a frontrunner in implementing end-user flexibility. This opens new possibilities for residents and building owners to engage in flexibility markets, for energy and grid enterprises to experiment with and implement end-user flexibility solutions, and for regulatory bodies to advance their progress toward achieving energy and climate goals.

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B. Main publications

Main article I

Analysis of residential EV energy flexibility potential based on real-world charging reports and smart meter data

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Table: The paper's context in the thesis.

	Supplementary articles	Main article I	Main article II	Main article III	Main article IV	Data articles *(D* describes planned articles)*
RQ1: What are the energy profiles for household energy use and PV generation for apartment buildings, and how are the energy profiles influenced by climate variables?	S I. Electricity S II. Heat-DHW S III. DHW S IV. PV				Main IV. Energy profiles	D* IV. Data Main IV
RQ2: How does the user habits influence the electricity load profiles of residential EV charging, and how is the el. load affected by EV cabin preheating?	S V. Stochastic EV charging	Main I. EV charging	Main II. EV charging	Main III. EV cabin preheating		D I. Data Main I D* II. Data Main II D* III. Data Main III
RQ3: What is the potential for electricity flexibility from EVs, in relation to non-flexible apartment building loads and PV generation, in the Norwegian context?					Main IV. Flexibility	

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Analysis of residential EV energy flexibility potential based on real-world charging reports and smart meter data

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ABSTRACT

The increase in the number of electric vehicles leads to an increased demand for residential charging. While EV electric loads can have a negative impact on the power grid, they also represent a large potential for energy flexibility. This study proposes a methodology to describe charging habits, electricity load profiles, and flexibility potentials of EV charging in apartment buildings. The input data used for the method are generally available for buildings with multiple EV charge points: EV charging reports with individual charging sessions and aggregated smart meter data. The case study is a large housing cooperative in Norway, with a combination of private and shared charge points for the residents. The study compares two charging power assumptions of 3.6 kW and 7.2 kW. The flexibility potential increases with higher charging power. The study reveals a significant potential for residential EV charging flexibility when private parking spaces have EV charge points.

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1. Introduction

1.1. Background

Electric mobility is growing rapidly, with China being the leading electric vehicle (EV) market, followed by Europe and the United States [1]. In terms of EV shares, Norway was the global leader in 2019, with 13% EVs of the total stock and 56% market share [1]. The growth in the number of EVs has led to an increased demand for residential charge points (CPs). Access to CPs has therefore become a topic of discussion in many Norwegian apartment buildings. In a survey from 2019, 94% of the EV owners living in single houses state that they charge at home weekly or more frequently, while 67% of the residents in apartment buildings state the same [2]. The Norwegian government has proposed to give apartment owners in housing cooperatives a statutory right to charge at home, under certain conditions [3]. However, local power grid capacity can be a limiting factor for new charging infrastructure. Facilitating for charging in housing cooperatives has become a grid capacity challenge, but also an opportunity for charge point operators (CPOs) with electricity load sharing possibilities [4].

EV electric loads represent a large potential for energy flexibility [5,6] and EVs are frequently considered in demand side management (DSM) systems [7]. With DSM, it is possible to affect the end-use of energy in a number of ways, by reducing (peak shaving), increasing (valley filling) or rescheduling (load shifting) the energy demand [8]. Knezovic [9] defines EV flexibility services as a power adjustment maintained from a particular moment for a certain duration at a specific location, characterised by the direction, the power capacity, the starting time, and the duration of the charging. If the EV is not vehicle to grid (V2G) capable, the flexibility direction is always the same. For residential DSM, it is essential that the comfort of the users is maintained [10]. Load shifting of EV-charging should therefore preferably not reduce the access to the cars, when needed by the residents.

EV charging infrastructure for residents in apartment blocks is often situated at common parking facilities. Typically, the residents share the general responsibility for the infrastructure. Even if the operating costs are eventually paid for by the residents using the CPs, the energy use is part of the common energy use in the housing cooperative, unlike energy use in apartments which usually are metered and paid for individually. EV charging in housing cooperatives is therefore more easily available for energy flexibility since it can be controlled by a single operator, compared to the energy loads in apartments.

Current knowledge of the characteristics of residential EV load profiles is limited [11,12]. More knowledge on charging habits, energy charged, and charging power, will make buildings owners more capable of utilizing the flexibility potential of EV charging, e.g. to reduce power peaks. This knowledge is also useful for distribution system operators (DSOs) and transmission system operators (TSOs), when evaluating the need for and alternatives to

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Nomenclature

AMS	Advanced Metering System, Smart meters	EV	Electric Vehicle
BEV	Battery Electric Vehicle	IT230V	230 Volt IT system (distribution grid)
CCF	Cross-Correlation Function	PHEV	Plug-in Hybrid Electric Vehicle
CP	Charge point	SoC	State of Charge of the battery
CPO	Charge point operator	V2G	Vehicle to Grid
DSM	Demand side management	#	Number of
DSO	Distribution System Operator		

future grid capacity expansions [13]. This paper proposes a methodology for analysis of residential EV energy flexibility potential that can use input data that are generally available for building owners with multiple EV CPs. CPOs are often involved when there is a pool of public or private CPs from one or more manufacturers. EV charging reports are typically made available for the charging infrastructure owner, for the purposes of invoicing and data management. The reports include information such as plug-in time, plug-out time, and energy charged, all linked to a user and a CP. It is less common that the Norwegian charging reports contain information on actual charging time or charging power. Smart meter data is another available data source. In Norway, all DSOs have been obliged to install advanced metering system (AMS) for all customers by the Norwegian regulator (NVE) by 1.1.2019 [14]. This makes hourly electricity meter readings easily available.

The main research question of this work is: How can EV charging reports and smart meter data describe charging habits, electricity load profiles, and flexibility potential of EV charging in apartment buildings? The paper is structured as follows. Section 1.2 provides a brief literature review of real-world EV charging data analyses, while Section 1.3 describes the contribution of this work. Section 2 introduces the case study, and describes EV charging power and charge characteristics of EV batteries. The methodology is described in Section 3, while Section 4 presents the results and a discussion of the findings with respect to EV charging habits, EV energy loads and EV charging flexibility. Finally, the conclusion of the paper is drawn in Section 5.

1.2. Literature review

A number of studies have analysed real world EV charging data based on EV charging reports from CPOs. Other data sources also form the basis for charging data analyses, including mobility datasets (e.g. [15–18]) or Global Positioning System (GPS) data from the EVs (e.g. [19,20]). In addition, some articles have based their work on charging assumptions or expected values for EV charging habits (e.g. [21]), or EV information available from questionnaires (e.g. [22,23]).

The studies [24–26,12] analyse EV charging and flexibility based on EV charging reports from public charging stations in the Netherlands. The research in these studies are based on charging session-information with plug-in and plug-out times, charging times, connection times, idle times with no charging, as well as energy or power information. Sadeghianpourhamami et al. [24] have clustered the arrival and departure time combinations for nearly 400,000 charging sessions, with the three clusters "Park to charge", "Charge near home" and "Charge near work". The cluster "Charge near home" has arrivals in the afternoon/evening with departures mostly in the morning the next day. This cluster was therefore identified as the best candidate for moving charging demand to nighttime. Gerritsma et al. [25] have categorized anonymous EV IDs for 8223 charging sessions according to local or visiting EVs, where the local users charge more frequently and with longer connection times. Analysing flexibility, the researchers found that 59% of the aggregated EV demand could be delayed for more than 8 h. Furthermore, they found that local EVs charge longer and have a larger potential for flexibility, compared to visiting EVs, especially when it comes to moving the evening peak to the night. Flammini et al. [26] analysed 400,000 charging sessions in publicly accessible charging stations. 1213 of the 1744 charging stations were found to be localized next to roads categorized as residential, while the remaining charging stations were located by four other road classifications with higher vehicle capacity. The study found that connection and non-charging idle times were higher for EV charging in residential areas, where the average connection time was about 7 h, compared to the other road classifications. They also found that chargers in residential areas had a higher utilisation rate, which suggests that drivers prefer charging close to their home. Both [24,25] point out that there are few examples from literature where EV flexibility has been analysed or quantified, e.g. by finding the difference between connection times and charging times.

Research groups in other countries have also analysed EV charging reports. Xydas et al. [27] (UK) describe an EV study, providing a cluster analysis of 22,000 charging sessions from 255 public charging stations. The study investigates the charging impact on the distribution network. They conclude that DSM of EV charging can be designed for charging habits in specific areas, e.g. dependent on if the EV charging load is high during peak times or more randomly distributed. The research by Quirós-Tortós et al. [28] is not based on typical charging reports, since the available data are from a research trial with onboard monitoring in EVs, but still with similar type of data available, such as plug-in and plug-out times, as well as initial and final state of charge (SoC). The research presents monitoring of 221 EVs and reports data from 68,000 residential charging sessions, together with other residential electricity use. Neaimeh et al. [29] combine charging data from onboard monitoring in 44 EVs with data from nearly 9000 residential smart meters, to study the impact of EVs on electricity distribution networks. Khoo et al. [30] describe charging reports from a trial in Australia, involving 121 households and 57 corporate participants. The study found that each charging session in the households lasted in average 2.5 h and consumed 6 kWh. The researchers in [31] present data from 2000 non-residential EVs in California, US, with plug-in/plug-out times corresponding with typical working hours. The study compares the benefits of smart charging from an EV charging service provider's perspective to the benefits from a DSO's perspective.

Several researchers have analysed EV charging based on energy measurements. Studies such as [32] (US), [33] (US) and [34] (Norway/US) quantify EV charging and flexibility using a top-down approach, analysing electricity metering data for many households with or without EVs. However, few bottom-up analyses are identified, where hourly meter values are combined with other data sources available for the building owner. Apartment buildings typically have several AMS-meters measuring electricity use in common areas [6], where it is not unusual that a meter measure aggregated EV charging mainly.

1.3. Contribution of this work

Even though several articles recognize the flexibility potential of residential EV charging, few studies analyse real data from residential EV charging in apartment buildings. This paper aims to fill this gap, by proposing a methodology that combines information which is commonly available for building owners: EV charging reports from the CPO and hourly smart meter data from the DSO. These data sources are generally available for apartment buildings in Norway, which makes wide scale use of this methodology possible. Specifically, the methodology introduced in this work provide:

- Flexibility potential of residential charging:
  The bottom-up analysis of EV charging and flexibility uses commonly available data sources. Daily profiles for charging load and flexibility are provided per user, which is useful e.g. when estimating future charging loads with an increasing number of EVs or charging loads in other locations.
- Distinctions of ownership of chargers:
  EV charging is analysed for users with their own CPs at individual parking spaces or shared CPs available for all the residents. How charging habits depend on CP location and ownership has not been studied in the literature identified in the review.
- Correlation between plug-in/plug-out times and local hourly traffic data:
  A link between plug-in/plug-out times and local hourly traffic data is analysed, and thus provides new possibilities for planning and simulations of residential charging. The review of the literature has not identified other bottom-up studies focussing on this link.

2. Introduction to case study, EV charging power and charge characteristics of EV batteries

2.1. Introduction to case study: Risvollan housing cooperative

Norway has a high share of EVs, compared to the EV share in other countries [1]. EV charging experiences and data from Norway can therefore be useful also for other countries in Europe and worldwide. This is especially relevant for apartment buildings, where there is a lack of data on aggregated residential charging in the literature, even though the flexibility potential is recognized. Besides serving as s a case study for the developing a new methodology, the numeric findings from the case study may also be useful in a wider context. The case study chosen represents apartment buildings with newly installed EV charging infrastructure, and an increasing number of EV users. With an increasing share of EVs worldwide, lessons learned from this case study may be relevant for many other building estates in a similar situation.

The case study is located in Trondheim, Norway, in a suburb that is located 6 km from the city centre. Risvollan housing cooperative has about 2400 residents living in 1113 apartments, where 95% of the apartments are located in 121 similar apartment blocks (Fig. 1). Space heating and domestic hot water (DHW) are provided by district heating. Table 1 summarizes building data and information about energy use in Risvollan housing cooperative, based on an energy analyses of 95% of the apartments in 2018 [6,35].

During the first 11 months of 2018, it was possible to charge approximately 55 EVs in the garages of the housing cooperative. A new infrastructure for EV charging was installed in December 2018, making it possible to activate up to 764 CPs in the garages. The charging infrastructure balances the EV loads in each garage, to make sure the aggregated charging power is below the power limit. The CPO registers all charging sessions including plug-in times, plug-out times, and charged energy. From December 2018 to January 2020, 6878 charging sessions were registered by 97 different user IDs; 82 of these IDs appeared to be still active at the end of the period. The EVs were parked in 24 different parking locations, each with an AMS-meter measuring the aggregated EV-

Fig. 1. Example of apartment blocks in case study.

Table 1
Key information on the case study.

# Apartments	1113
in 121 building blocks	1058
in 1 tall building block	55
# Residents in 121 building blocks	2321
Total heated apartment area (m^2)	96,254
Specific electricity use (kWh/m^2)	56.7
Share, el use in common areas/apartments	13%/87%
Specific heat delivery (kWh/m^2)	139

charging at that location. Table 2 summarises charging information available from Risvollan. Fig. 2 shows hourly energy use aggregated in 22 of the 24 garages. The number of EV users is increasing from zero to 82 during the period, with in average 53 users. The number of EV users shown is EV users registered per day, with new EV users added and inactive users deactivated (see Section 3.1). For January 2020, the figure shows the total number of EV users active during the last month, which is 82.

The price structure for charging in the case study is not expected to influence charging habits or timing. The users pay for the electricity charged, using the same spot-market-based electricity tariffs as for the electricity use in the housing cooperative (this varies typically between 1 and 1.5 NOK/kWh). The energy cost for charging at shared and private CPs is the same, but residents using shared CPs are encouraged to park for <3 h. Typically, home charging has a lower price, compared to paid non-residential charging. However, workplace charging can be free of charge, but is often limited.

2.2. EV charging power and energy

For residential charging of EVs, both the onboard charger in the EV and the available AC power can be limiting factors for the EV charging power. Fig. 3 shows nominal onboard charger capacity (kW AC) for battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) on the market, based on an overview of EVs from [36,37]. The plot includes new models of BEVs and PHEVs as well as earlier models for the most typical BEVs on the Norwegian market. There are five typical levels for the onboard charger capacities: 3 to 3.7 kW, 6.6 to 7.4 kW, 11 kW, 16.5 kW and 22 kW. Charging capacity for most BEVs is between 3.3 and 11 kW. For PHEV, the onboard charger capacity is typically between 3.3 and 3.7 kW.

In Norway, residential customers are normally connected to a type 230 Volt IT system. Power use during residential EV charging is typically 2.3 kW when using a household power plug (10 A) and 3.6 kW or 7.4 kW when using a Type 2 connector (16 or 32 A). For some charging systems, it is possible to activate 3-phase charging on IT230V, increasing the charging power. In the case study, 7.4 kW is available for all customers and 11 kW is available if activating 3-phase charging.

Fig. 3 also shows typical gross battery capacities for BEVs and PHEVs. For BEVs on the market from 2018 to 2020, most batteries

Table 2
Data sources for EV charging information.

AMS-meters	Hourly electricity measurements in 22 locations (kWh/h)								
EV charging report from CPO	Per address/charger ID/user ID: Plug-in time, Plug-out time, Charged energy (kWh)								
Data collection period	From December 21, 2018 to January 31, 2020								
# addresses/garages	24								
Ownership of the CPs	Private			Shared			Total		
	Dec18	Jan20	average	Dec18	Jan20	average	Dec18	Jan20	average
# CPs	0	58	25	0	12	8	0	70	33
# User IDs	0	58	35	0	24	18	0	82	53
# Charging sessions	5466			1412			6878		

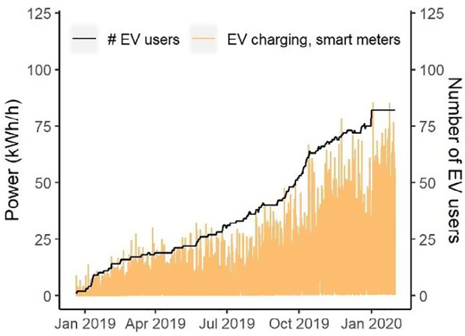

Fig. 2. Hourly energy use in 22 of the 24 garages (aggregated) and the increasing number of EV users during the period.

have nominal capacities between 40 and 100 kWh. Due to charging efficiency, energy use for charging is higher than the charged energy. The efficiency vary, and [38,39] have found energy losses between 12% and 40%.

2.3. Charge characteristics of EV batteries

Later in this study, it is assumed that the energy charged each hour is constant, independent of type of EV, battery SoC, etc. However, this is a simplification, and this section gives an introduction to charge characteristics of EV batteries.

Lithium-ion (Li-ion) batteries are the market leader for use in EVs, mainly because of their high specific energy cycle life and high efficiency [40]. The Li-ion battery pack in an EV consists of a large number of single battery cells, arranged in serial, parallel or hybrid forms [41]. Typical charging characteristics for a single battery cell is shown in Fig. A1 in the Appendix, described as constant current – constant voltage (CC-CV). The charging capacity is gradually increasing with a constant current, until the battery reaches the maximum charging voltage. The current then drops to maintain this charging voltage while preventing overcharging the cells [43]. A battery management system is needed to monitor, manage and protect the Li-ion battery charging [44]. Charging and discharging within the ideal operating range of the SoC, i.e. 20%-90%, is a topic within such management [42].

Fig. A2 in the Appendix shows charging characteristics of two example charging sessions by two EVs in the case study. The car types for the two EVs are marked in Fig. 3, as example EV mid-range and long-range. The nominal onboard charger capacity of the cars is 7.2 kW for the mid-range EV and 11 kW for the long-range EV. However, since 3-phase charging is not activated for the cars, the long-range EV is limited to 1-phase charging power of 7.4 kW. The nominal battery capacity is 36 kWh for the mid-range EV and 75 kWh for the long-range EV. The charging sessions last for about three hours, where both of the EVs charge around 20 kWh. The current for both cars is reduced by about 8% during the charging sessions, while the voltage is constant. The reduction in current is less than presented as typical charging characteristics in Fig. A1. However, the current reduction is EV and SoC dependent. For the long-range EV, the constant current could be explained by the owner's statement that the charging is normally discontinued automatically at 80% battery capacity. For the middle-range EV, [22] found that for this type of EVs, the charging ends instantly when the battery has reached its full charged level.

3. Methodology

The suggested methodology in this article is developed to describe charging habits, electricity load profiles and flexibility potential of EV charging in apartment buildings. The main data sources are: EV charging reports with 6878 individual charging sessions, hourly AMS data from 22 garages, and local hourly traffic data. The data was collected from 21 Dec 2018 to 31 Jan 2020.

A flow chart of the methodology is shown in Fig. 4. First, EV charging reports are used for analysing charging habits. Secondly, EV charging and flexibility potential are estimated. The results are validated using hourly AMS data. The data are analysed using the statistical computing environment R [45].

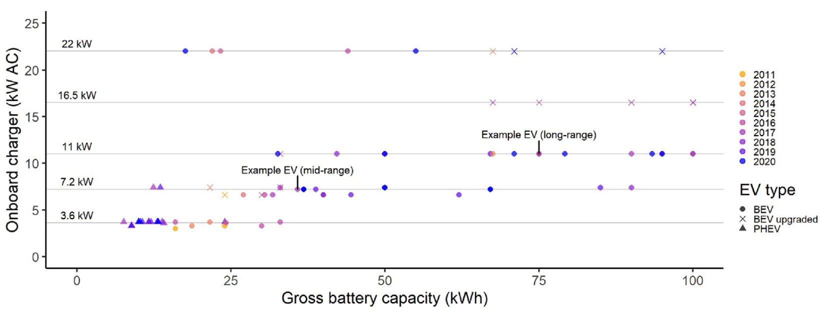

Fig. 3. Nominal onboard charger capacity and gross battery capacity for BEVs and PHEVs on the market.

3.1. Data preparation

The EV charging reports include plug-in times, plug-out times, and charged energy per charging session. Each charging session is connected to a user ID, a charger ID, and an address. The charger IDs are either private or shared, since the CPs are either located on the residents' private parking spaces or on shared parking areas available for all residents. The original charging reports have 7245 charging sessions. The main steps of initial data cleaning include removing unrealistic charging sessions (1 charger with 29 charging sessions removed) and charging sessions with no energy charged (338 charging sessions removed). If the plug-out time is too early when compared to energy charged and maximum 11 kW charging power available, the plug-out time is removed (set to NA), since this indicates that the value is incorrect (relevant for 34 charging sessions). Further, there is quality assurance to assure correct data time zones/daylight saving time (DST), before calendar data is added, such as weekdays and months.

Hourly electricity data from 22 of the 24 AMS-meters in the garages are provided by the DSO. The two missing AMS-meters are connected to four EV users only, with in total 4500 kWh charging energy from 353 charging sessions (5% of all charging sessions). Each of the AMS-meters measures the aggregated EV-charging on that location. Hourly energy estimates provided by the DSO are removed from the data (4% of the hourly values), since inaccurate hourly values may influence the results.

Hourly traffic data from five nearby locations are provided by [46]. Hourly counts are available for vehicles with different sizes. The hourly count of small cars (<5.6 m) is used in the analysis, as an average of the traffic measured by the five nearest traffic stations.

3.2. Analysing EV charging habits

EV charging habits are analysed showing the daily distribution of EV plug-in and plug-out times during weekdays and weekends, and histograms for connection times (related to plug-in time) and energy charged (related to plug-in time and connection time). EV charging habits are analysed separately for private and shared CPs.

The daily distribution of plug-in and plug-out times is compared to hourly traffic data from nearby locations. The correlation between plug-in/plug-out times and local hourly traffic data is explored by using the cross-correlation function (CCF), which is a function used to evaluate the correlation between time series. CCF is a "wrapper" function calling the autocorrelation function (ACF), as described by [47], page 390–392]. To find the correlation, the function ccf() is used in R [48]. CCF examines the cross-correlation between the number of plug-ins or plug-outs each hour and the hourly number of cars, where the maximum value for correlation is 1. Before calculating the CCF, the dataset is split into charging sessions using private and public CPs, respectively.

3.3. Estimating EV energy load and flexibility potential

The energy loads and flexibility potential of EV charging are estimated as follows. The differences between the plug-in and plug-out times of the charging sessions provides the duration of the EV connection time (Eq. (1)). The actual charging times and charging power are not known. In the method, two alternative charging powers ($P_{charging}$) are assumed: 3.6 or 7.2 kWh/h, representing typical levels for the onboard charger capacities as described in Section 2.2. The assumed charging power is the average charging power during an hour. When estimating hourly EV energy loads for a specific charging session, the synthetic charging time is first calculated, by dividing the actual charged energy ($E_{charged}$ from the EV charging report), on the assumed charging power (Eq. (2)). The hourly charging loads equal the assumed charging power multiplied by time (Eq. (3)). For the first hour, the maximum charging time is calculated as the number of minutes after the plug-in time. For full hours after the initial hour, the hourly charging load equals the assumed charging power. For the last hour, the charging load equals the remaining energy difference, so total energy charged during the charging session equals the actual charged energy, known from the EV charging report. The method provides a synthetic charging time and energy load, given immediate charging after plug-in. Average daily charging load profiles are shown for different weekdays and holiday periods.

$$\text{EV connection time: } t_{connection} = t_{plug-out} - t_{plug-in} \tag{1}$$

$$\text{EV charging time: } t_{charging} = E_{charged}/P_{charging} \tag{2}$$

$$\text{EV load hour } i\text{: } E_{load(i)} = t_{(i)} \cdot P_{charging} \text{ where } \sum (E_{load(i)}) = E_{charged} \tag{3}$$

$$\text{EV idle time: } t_{idle} = t_{connection} - t_{charging} \tag{4}$$

$$\text{EV idle capacity hour } i\text{: } E_{idle(i)} = t_{idle(i)} \cdot P_{charging} \tag{5}$$

The difference (non-charging *idle time*) between the EV connection time and the synthetic charging time reflects the flexibility potential for the charging session (Eq. (4)). The *idle capacity* is the energy which could potentially have been charged during the non-charging idle times. The idle capacity is analysed for the assumed charging power of 3.6 and 7.2 kWh/h. To calculate the hourly idle capacities for hours with non-charging idle time, the hourly idle times are multiplied by the assumed charging power (Eq. (5)).

Initially, the database includes synthetic estimates for all charging sessions separately. Only hours with charging loads or idle capacities are included. An hourly aggregated database is created by grouping the data per hour. Hours with no charging or idle capacities are added to the aggregated database, to assure a full hourly timeseries for the period, from mid-December 2018 to end-January 2020.

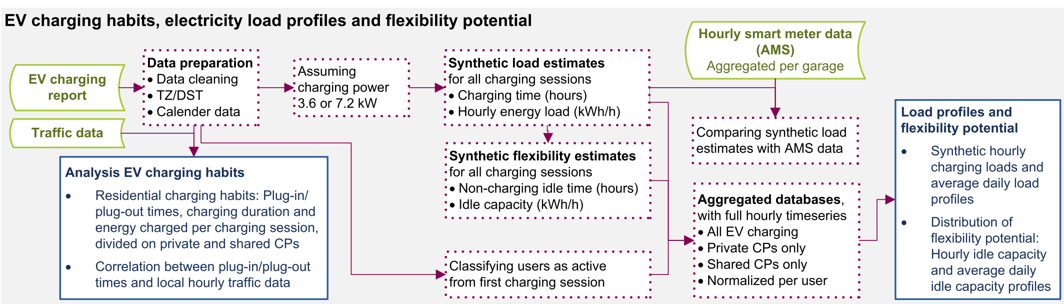

Fig. 4. Flow chart outlining the methodology. Green boxes show data sources, red boxes show processes, and blue boxes show results. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Since the number of EV users is increasing during the measurement period, energy and power results are also presented normalized per user. The users are classified as active from the date of their first charging session (user has value NA before and 1 after first connection). In addition, some users become inactive, if they for example move or if a user with shared CP becomes a user with private CP. Users with NA values towards the end of the measurement period are classified as inactive and not included in the number of EV users. The change of classification takes place after their last charging session, from their first inactive date. However, during the last month (January 2020), only users not charging at all during the month were classified as inactive, to avoid wrong classification of users that are travelling, etc.

The classification of active users makes it possible to divide the hourly aggregated values for charging loads and idle capacities on the current number of users, to get e.g. typical average load profiles per user. When analysing selections of the dataset, such as users with private/shared CPs, hours with no charging are added to the data to assure full hourly time series. Before their first charging session (and after their last charging session, if becoming inactive), energy values are set to NA during hours with no charging, while energy values are zero after the first charging session. This is done to assure correct average values.

3.4. Validation of the methodology

The synthetic hourly EV energy loads are compared to AMS data per garage. AMS data are available from 22 of the 24 garages (95% of the charging sessions). Some differences between the total AMS data and the total charging energy from the charging reports can be expected, since there may also be other electricity use metered in the garages. For 20 of the garages in the case study, the total energy charged is <10% different from the AMS data in the specific garage, while the AMS data is 20% higher in one garage. For the last garage, the AMS data is 50% higher, but this garage includes the user which was removed in the initial data cleaning. It can therefore be concluded that in the case study garages, there is little electricity use measured by the AMS-meters other than EV charging.

The charging infrastructure in the case study has the possibility to balance the EV loads in each garage, when the aggregated EV load is high. However, a similar load balance is not included in the synthetic loads. Some differences may therefore be expected in the hourly aggregated loads per garage, especially when the loads are high.

Fig. 5 shows an example from a garage (Bl2) for four days, where synthetic hourly EV energy loads are compared to AMS data. For the garage shown, the total AMS data is 28.2 MWh during the measurement period, which is only 4% higher than the total charging energy reported for the same garage. The figure highlights examples of individual charging sessions, marked with a square. When there is one charging session only, the highlighted charging sessions in the figure show an agreement between the hourly measured charging power and the hourly estimates, with a charging power close to 7.2 kW (November 2nd) and 3.6 kW (November 5th). When there are several charging sessions aggregated, the measured charging power is often between the two estimates.

4. Results and discussion

4.1. EV charging habits

This section aims to answer how EV charging reports can describe EV charging habits for residents. Figs. 6 and 7 show how the plug-in and plug-out times are distributed during weekdays and weekends, for private and shared CPs, as well as the daily distribution of cars in near-by traffic. The plug-in time for the charging (Fig. 6) is mainly in the afternoons during workdays, both for the private and the shared CPs. There is a peak around 16:00, with around 15% of the plug-ins during the day, which corresponds to when the workdays typically end in Norway. An afternoon peak is also present in the near-by traffic density. During the weekends, the plug-ins are more evenly distributed during the day, corresponding to the nearby traffic. For plug-out times (Fig. 7), private CPs have a peak in the morning, between 07:00 and 08:00, corresponding to the start of a typical workday. This peak is also present in the traffic density. For shared CPs, the morning peak is less substantial, indicating that the users move their car sooner after finishing the charging. The residents using the shared CPs are encouraged to charge for <3 h.

The case study results indicate that the hourly plug-in/plug-out times correspond well to local traffic data. Fig. 8 describes the CCF values between the number of plug-in (left) or plug-out (right) times each hour and the hourly number of cars. Each lag is equivalent to 1 h. In the figure, a seasonality of h = 24 is observed, with a strong dependence between the plug-in/plug-out times and the local traffic. The CCF correlation coefficients at lag 0 and 1 are 0.296 and 0.363 respectively for plug-in/local traffic and 0.345 and 0.278 for plug-out/local traffic. Such correlations provide possibilities for developing new models to estimate EV charging loads at different locations, where local hourly traffic data can be used as input.

The histograms in Fig. 9 show connection times for charging sessions. The histograms confirm that residents using shared CPs often have shorter connection times than residents with private CPs. For private CPs, the average connection time is 12.8 h, while 90% are connected for <22.6 h. For shared CPs, the equivalent connection times are 6.5 h on average, and 14.3 h for 90% of the charging sessions. The histograms show a twin peak in the connection times, which can be explained by the plug-in time for the charging sessions. The first peak occurs for charging sessions with <5 h of connection time, where typically the plug-in time is in the daytime, afternoon, or early evening. The second peak is for charging sessions with connection time between 8 and 15 h (longer for private CPs), with plug-in time typically in the evening and connection through the night. The average connection time differs according to the weekday when the charging started, where especially Sundays stand out for residents with private CPs. When plugged in during weekdays, 73% of the charging sessions are longer than three hours. The corresponding share for plug-in during Sundays, is 84%.

Figs. 10 and 11 show histograms for energy charged per charging session, divided according to private and shared CPs. The histograms are the same, but the colours in Fig. 10 are related to plug-in time, while the colours in Fig. 11 are related to connection time. The average energy charged per session is 11.2 kWh for users using private CPs and 14.7 kWh for shared CPs. For 90% of the charging sessions, energy charged is below 22.0 kWh per session for the private CPs and 39.5 kWh per session for the shared CPs. The explanation for why users with shared CPs charge more energy, may be that these users wait to charge until the battery has a lower SoC compared to users with private CPs at their own parking space, and the shared CP users therefore charge less frequently. This is confirmed by the average number of daily charging sessions per user: The users with private CPs have an average of 4.4 charging sessions per week, which is a factor of about 3.5 higher than the users with shared CPs, where the average is 1.2 charging sessions per week. Fig. 11 shows that there is no direct relationship between energy charged and connection time. Private CPs often have a longer connection time than shared CPs, for the same amount of energy charged. The outcome of this is a longer non-charging idle time for private charging sessions, which results in a higher potential for flexibility.

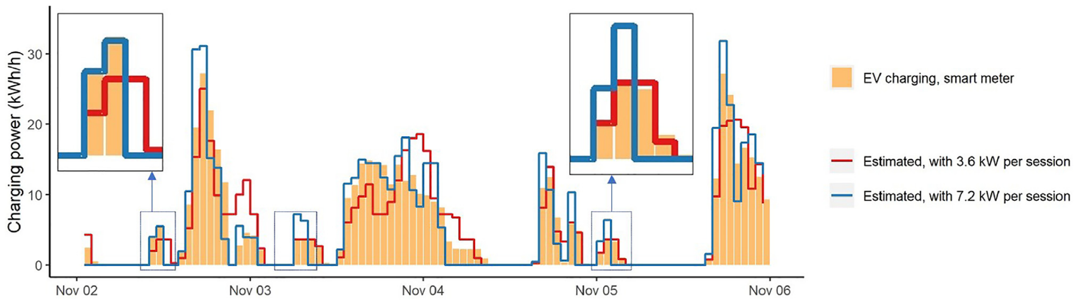

Fig. 5. Validating the methodology for four days in garage Bl2. Synthetic hourly EV energy loads are compared to smart meter data. Three individual charging sessions are highlighted with grey squares.

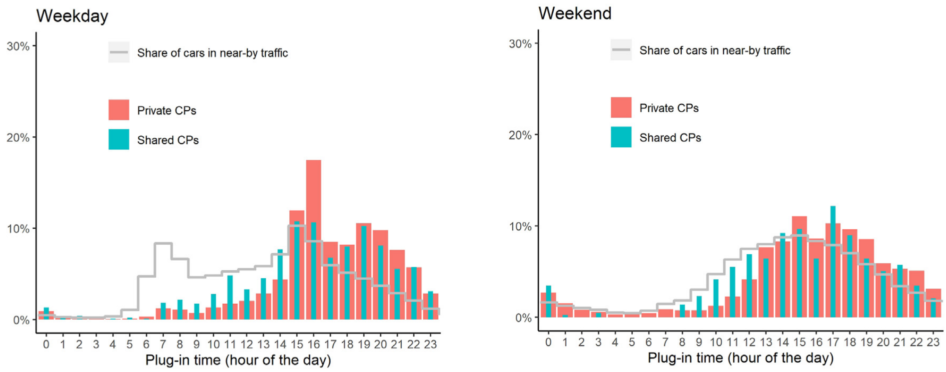

Fig. 6. Plug-in times: Average daily distribution of EV plug-in times during weekdays (left) and weekends (right), for private and shared CPs, as well as average daily distribution of cars in near-by traffic.

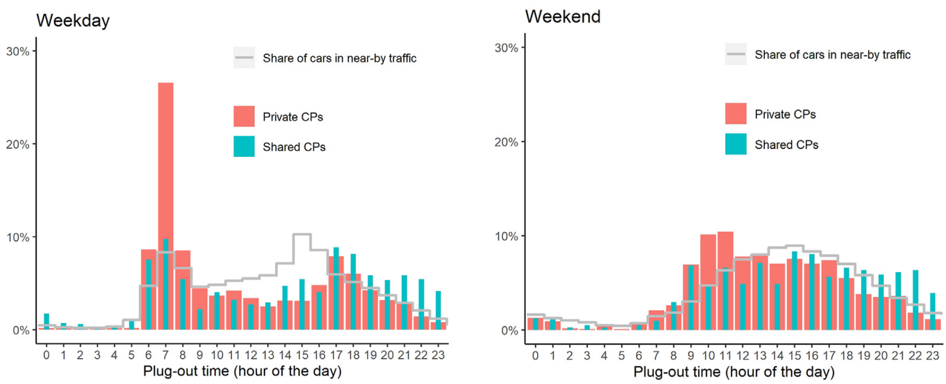

Fig. 7. Plug-out times: Average daily distribution of EV plug-out times during weekdays (left) and weekends (right), for private and shared CPs, as well as average daily distribution of near-by traffic.

4.2. EV energy load

This section aims to answer how information in EV charging reports can be translated into synthetic hourly EV energy loads. To answer this question, information about plug-in times and energy charged from the charging reports is combined with charging power assumptions.

The monthly energy charged per user is estimated from January 2019 to January 2020, as shown in Fig. A3 in the Appendix. For the monthly distribution, a charging power of 3.6 kW is assumed. The charging power assumption is especially relevant for charging sessions with a plug-in time late in a month and a plug-out time in the following month. Since monthly energy charged vary between the users, the results are shown in boxplots. In the boxplots, 50% of the monthly values are in the boxes within the first (Q1) and third (Q3) quartile, with the median monthly value in the middle. The vertical lines represent the least and greatest monthly value excluding outliers. Black dots show outliers, which are defined as values

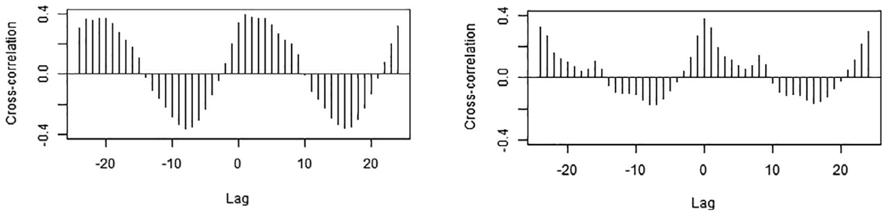

Fig. 8. CCF between the number of plug-ins and number of cars in nearby traffic (left) or plug-outs and number of cars (right) each hour.

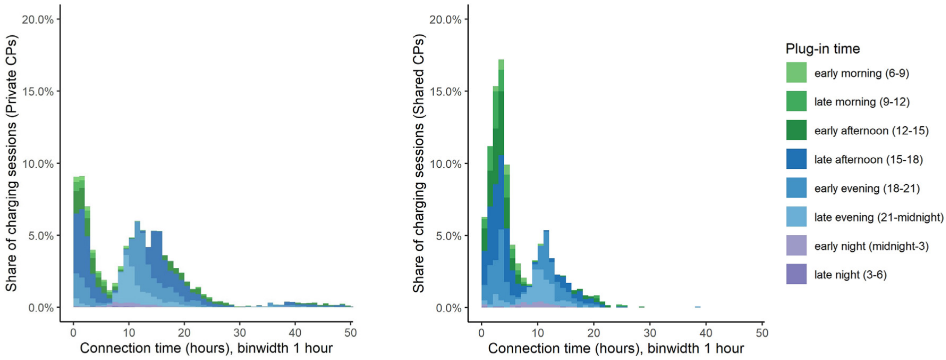

Fig. 9. Histogram for connection time related to plug-in time, for private (left) and shared (right) CPs. Binwidth is 1 h, showing the first 48 h only.

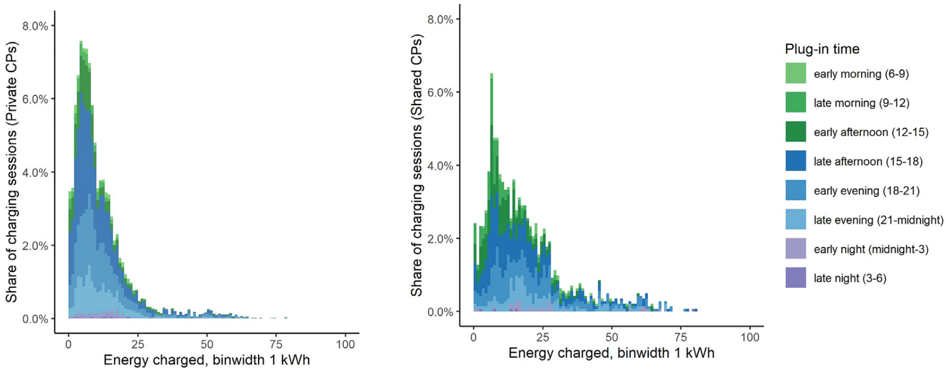

Fig. 10. Histogram for energy charged related to plug-in time, for private (left) and shared (right) CPs. Binwidth is 1 kWh.

extending 1.5 times the interquartile range (IQR = Q3-Q1) out from the box. The red dots represent the average values. The data are divided into users with private or shared CPs. For users with private CPs, the monthly values during the first two months are lower than the average. The reason for this may be that a large share of the users is registered in the middle of the month, resulting in less monthly days available for charging. There are also values that are lower than average in July, which is the main holiday month in Norway.

For users with private CPs, the average monthly energy use during the period is 179 kWh per user, or about 2150 kWh per year. For users with shared CPs, the average monthly energy use is 125 kWh per user, or about 1500 kWh per year. Assuming an average driving efficiency of 5 km/kWh, this corresponds to, on average, 10,700 km for users with private CPs or, on average, 7500 km for users with shared CPs. As a comparison, the average yearly driving distance for EVs in Norway was 12,631 km in 2019 [49]. However, as stated in the introduction, it is expected that the EVs are not being charged at their home address only. The estimated annual driving distances confirm an expectation that users with shared CPs charge less at home, compared to users with private CPs at their parking space.

The synthetic hourly aggregated peak power values each month are shown in Fig. 12, assuming a charging power of 3.6 kW and 7.2 kW, respectively. The figure shows the hourly aggregated max peak loads per month, as well as the 99th and 90th percentiles of the hourly load values. The total aggregated power is increasing during the period (left figure), since also the number of users is increasing. However, the peak power per user is reduced with increasing number of users (right figure), due to a lower coincidence factor. The coincidence factor is defined as the ratio between maximum load for the aggregated data studied and the sum of each users' maximum load [50]. For example, for the 20 users in March 2020, the coincidence factor was 0.43, decreasing to 0.25 for the 82 users in January 2020, assuming charging power 3.6 kW.

For the aggregated load (left figure), the monthly max. peak for the charging power of 7.2 kW is a factor 1.1 to 1.5 higher than the

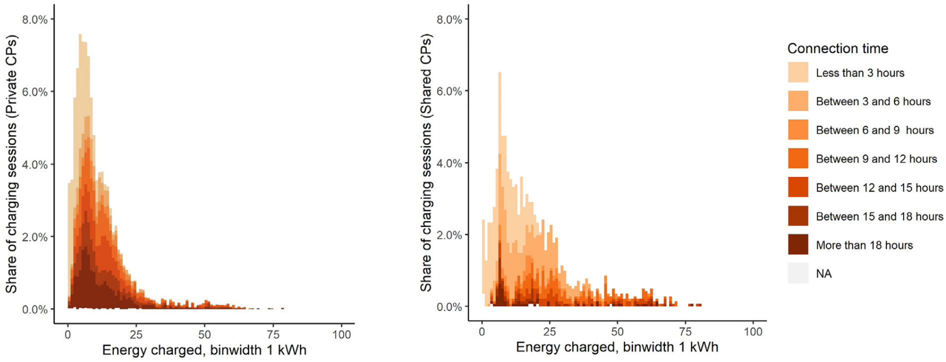

Fig. 11. Histogram for energy charged related to connection time, for private (left) and shared (right) CPs. Binwidth is 1 kWh.

max. peak for the charging power of 3.6 kW. The max. power peaks are not so frequent, shown by the difference between the peak loads, 99th and 90th percentiles. For the charging power of 7.2 kW, the max. peak power each month is a factor 1.6 to 3.3 higher than the 90th percentile. Equivalent, for the 3.6 kW charging power, the max. peak power each month is a factor 1.6 to 2.2 higher than the 90th percentile. When utilizing the potential EV charging flexibility, the operator often wishes to reduce the highest aggregated EV power peaks, getting values closer to the 99th percentile, the 90th percentile, or even lower, towards the average power.

The average load profile for weekdays shows an increased energy use in the afternoons and evenings, with the highest load occurring from about 16:00 to midnight. The weekend profile is quite similar, but without the afternoon peak. For the average values, the hourly load for the 7.2 kW charging power is up to a factor 1.3 higher than for 3.6 kW charging power. This happens during afternoons/evenings when many users have recently plugged in their EVs, with the largest difference occurring from 15:00 to 17:00 on weekdays, and from 13:00 to 20:00 on weekends. During the night/morning, from 23:00 to 12:00, the hourly load for the 3.6 kW charging power is higher than for the 7.2 kW charging power, since the cars with higher charging power finish charging earlier.

The average values shown in Fig. 13 do not illustrate how EV charging typically varies during the year. For example, holiday periods tend to deviate from the average values. Assuming a charging power of 3.6 kW, Fig. 14 shows the average daily charging load profiles for an average weekday, Saturday and Sunday. The average charging need during the week is 37.5 kWh per user. Most weekdays have similar charging needs, with Tuesdays somewhat lower (−7%) and Thursdays (+4%) and Fridays (+5%) somewhat higher than the weekly mean values. Saturdays have −13% lower and Sundays +8% higher values, compared to the weekly mean values. Fig. 14 also illustrates the daily load profiles during holiday periods. During July, the energy demand is lower than for the average profile (ref. Fig. A3), but otherwise quite similar to the average. For the holiday week in October, the charging need at Sunday evenings increase when residents come home from travelling. For Christmas, there is an increased charging need during the day before Christmas (Monday 23 December), while the residents charge earlier on Christmas Eve (Tuesday 24 December) than on an average Tuesday. The charging power is shown per number of users during the different periods: 57 users in average, 33 in July, 59 in October and 75 during Christmas 2019.

In addition to charging the battery, EVs can use energy to preheat the battery and cabin. This is not taken into account in the methodology, but it is not expected to significantly affect the daily charging load profiles in the case study, since most EVs are parked in garages.

4.3. EV charging flexibility

This section aims to answer how non-charging idle times can be translated into energy flexibility potential. From the charging reports, the EV connection times (the difference between plug-in and plug-out times) and charged energy are known per charging session. Two alternative EV charging times are calculated, assuming different levels of charging power (3.6 or 7.2 kW). The non-charging *idle time* between the EV connection time and the charging time reflects the flexibility potential for a charging session. Fig. 15 shows an example of a single charging session, with charging power 3.6 or 7.2 kW. Energy charged and connection time is the same in both figures (11.3 kWh and 13.5 h connection time), and has quite typical values as shown in Figs. 9 and 10. The flexibility potential in the figures, termed *idle capacity*, is the energy which could potentially have been charged during the non-charging idle times. However, since the actual energy charged dur-

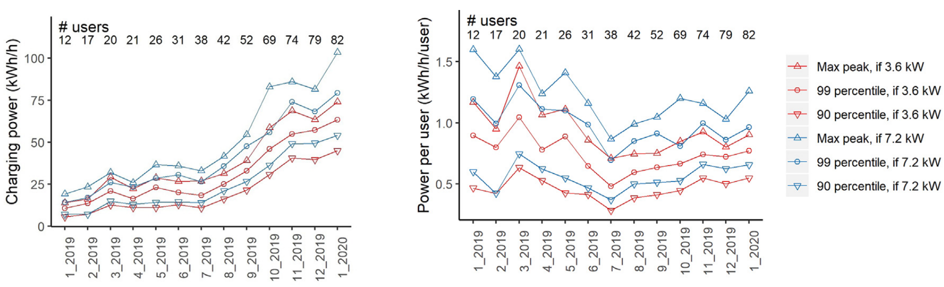

Fig. 12. Estimated hourly aggregated peak power (left) and power per user (right), with increasing number of users, assuming charging power 3.6 kW and 7.2 kW.

ing a charging session is the same, the idle capacity is higher with higher charging power. For the example session in Fig. 15, the idle capacity is a factor 2.3 higher when the charging power is 7.2 kW, than when it is 3.6 kW.

Fig. 16 shows an example of charging load and idle capacity for aggregated EV charging in a garage (Bl2) during a week, with assumed charging power 3.6 or 7.2 kW. During the week, there are 78 charging sessions in the garage, charged by 17 users. Energy charged is the same in both figures (around 930 kWh), while the idle capacity is 1200 kWh for the charging power of 3.6 kW and 3100 kWh for the charging power of 7.2 kW. Comparing the two charging levels during the week, the hourly aggregated charging peaks increase with a factor 1.2, going from 3.6 to 7.2 kW charging power, assuming immediate charging after plug-in. During the same week, the idle capacity for charging power 7.2 kW is a factor 2.6 higher than for charging power 3.6 kW. However, for idle capacity, the periods after the charging peaks are normally of most interest, since charging loads can be delayed in time. Also, idle capacity during other periods can be relevant, such as times with locally available RES. For the example week in Fig. 16, there is high idle capacity during night-time and a potential for moving afternoon- and evening charging loads to night-time, for both charging powers of 3.6 and 7.2 kW, respectively. If charging loads are moved to the daytime, for example to utilize photovoltaic (PV) solar energy, the idle capacity during the day is higher during the weekend than on weekdays. Comparing the two charging power levels in the selected week, the 7.2 charging power has a higher potential for daytime charging than does the 3.6 kW charging power.

Synthetic average daily charging load profiles and idle capacity profiles per user are shown in Fig. 17, for the aggregated EV charging during weekdays, assuming immediate charging after plug-in. The figures show the profiles with the 3.6 kW charging capacity (top) and the 7.2 kW charging capacity (bottom). The boxplot illustrates the distribution of hourly load values. As in Fig. 13, the average aggregated charging load is similar for the two charging capacities. The average daily idle capacity differs, with higher values when the charging capacity is 7.2 kW, than when it is 3.6 kW. For example, the daily idle capacity for private CPs during weekdays is 2.3 times higher with the 7.2 kW charging capacity than it is with the 3.6 kW charging capacity. Also in Fig. 17, the daily charging load profiles are based on the period with 30 to 82 users, with the number of users using private CPs is increasing from 18 to 58, and users using shared CPs are increasing from 12 to 24. In the Appendix, Figs. A4–A7 shows the same figures also for Saturdays and Sundays. The weekend data show that the charging demand is higher on Sundays than on Saturdays. This is as expected in Norway, since there is a culture for travelling during the weekends. For private CPs, the average idle capacity is nearly double from 09:00 to 16:00 during the weekends, compared to during the week, since more cars are parked then.

Average profiles give a quick overview of the flexibility potential, but since idle capacity is connected to the individual cars, the poten-

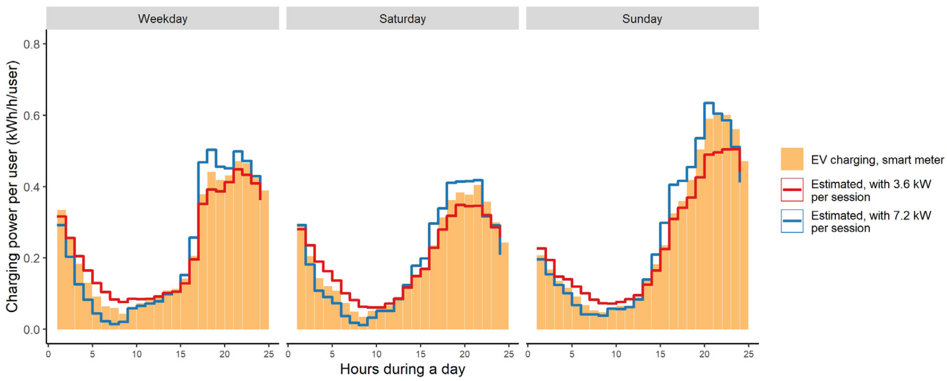

Fig. 13. Synthetic daily average charging load profiles per user, during weekdays and weekends. (Based on data with 57 users on average, using both private and shared CPs).

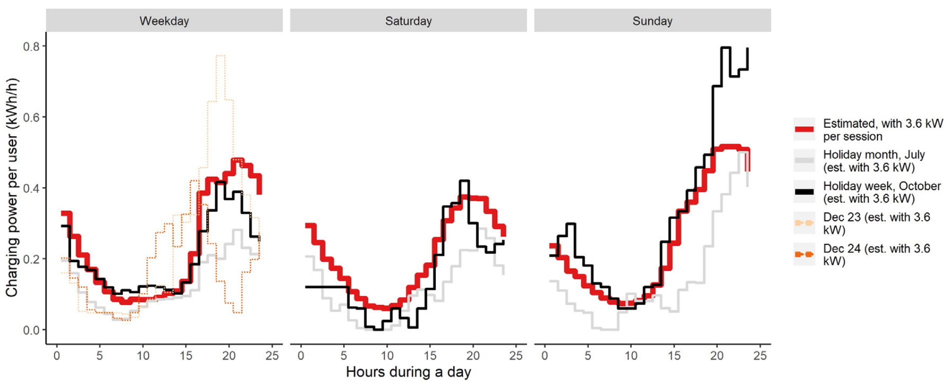

Fig. 14. Synthetic daily charging load profiles per user, for the aggregated EV charging during weekdays and weekends, showing annual average (red line) and holiday periods (black/grey/orange lines), assuming a charging power of 3.6 kW. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

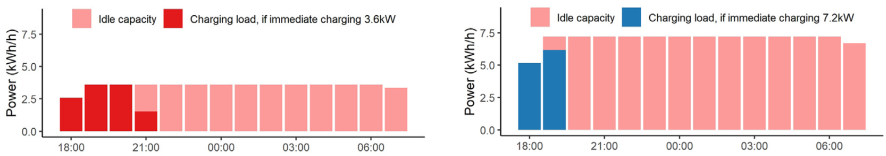

Fig. 15. Single charging session. Charging load and idle capacity, assuming charging power 3.6 (left) or 7.2 kW (right).

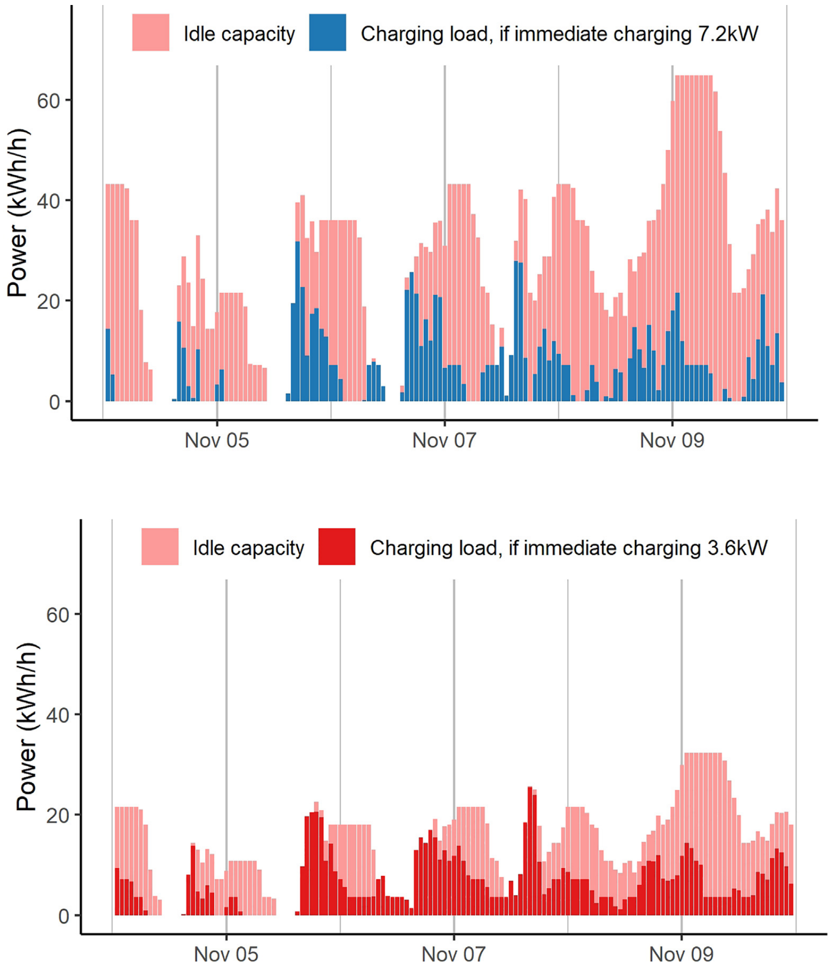

Fig. 16. EV charging in garage Bl2 during a week. Aggregated charging load and idle capacity, assuming charging power 3.6 (left) or 7.2 kW (right).

tial for moving charging loads in time depends on the length of the individual charging sessions. Average aggregated loads and idle capacity do not contain such information. Table A1 in the Appendix provides additional insights into the charging habits and non-charging idle times for private CPs during weekdays. The table is based on 3278 charging sessions during a data period with an average of 45 users (increase from 18 to 58 users). The orange column with hourly charging loads, is especially useful e.g. when estimating charging needs in building estates. The share with idle times can be read as following: e.g. during daily hour 03:00–04:00, all of the charging load can be charged (0.06 kWh/user), but none of charging has to happen immediately (50% can be delayed 1 to 2 h and 50% 7 to 8 h). If desired, also the charging load in the hour before can be delayed and charged during this hour (0.09 kWh/user), as well as other energy loads marked green from previous hours (total 3.9 kWh/user), limited by the maximum charging load during the hour in the blue column (2.65 kWh/user). The capacities and loads are presented per user, and should therefore be multiplied by the number of registered EV users in an apartment building or garage. Also in the Appendix, Table A2 provides a table with corresponding data for weekends, based on 1096 charging sessions and on average 44 users. Table A3 and Table A4 contain information from the shared CPs, based on 905 charging sessions during the weekdays, 407 charging sessions during the weekends, and

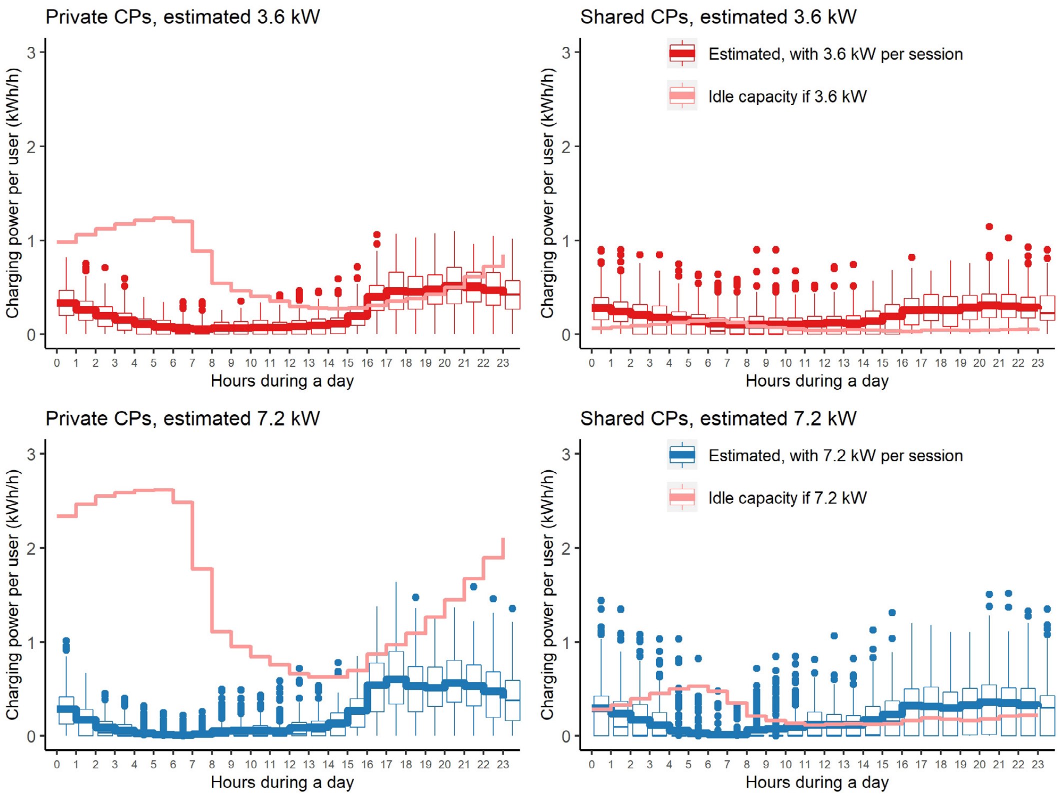

Fig. 17. Synthetic daily average charging load profiles and idle capacity profiles per user, showing private CPs (left) and shared CPs (right), with estimated charging power 3.6 kW (top) or 7.2 kW (bottom).

on average 18 users. In practice, to fully utilize the flexibility potential, it is necessary to know the expected connection times of the residents, as well as the required energy to be charged. This requires information from the users themselves (expected connection times) and energy or battery status information, preferably from the car to the charger.

5. Conclusions and future work

To prevent EV charging from having a negative impact on the power grid, it is essential to understand EV charging behaviour in different situations and premises. The literature review has identified a gap, with few studies analysing real data from residential EV charging in apartment buildings. This study proposes a methodology for using EV charging reports to describe charging habits, electricity load profiles, and flexibility potential of EV charging. The required input data are generally available for apartment buildings in Norway, which makes wide scale use of the methodology possible. Moreover, there is no need for new logging equipment or personal information about the residents. It is also possible to use the methodology for building categories other than apartment buildings. Data and hourly predictions from this study are available for other research groups.

The EV charging reports are used as a basis to describe EV charging habits for residents. Field data from a large housing cooperative in Norway are analysed in the case study, with 6878 EV charging sessions registered by 97 user IDs. The study finds a difference in residential charging habits when users have private CPs at their own parking space, compared to when they use a shared CP. For private CPs, the average connection time is 12.8 h, while it is 6.5 h for shared CPs. The average connection time for charged CPs is similar to the value for publicly accessible CPs found by [26], where the average was 7 h. The users with private CPs have on average 4.4 charging sessions per week, which is about 3.5 times more frequently than the users with shared CPs. There is a longer non-charging idle time for private charging sessions, which results in a higher potential for flexibility.

A correlation is found between plug-in/plug-out times and local hourly traffic data, thus providing possibilities for improved planning and simulation of residential charging. The authors aim to study this correlation more explicitly in future work, with EV charging reports and traffic data from more locations. The correlation can be part of a new model for EV charging loads and flexibility.

Information about energy and plug-in times from the EV charging reports are translated into hourly energy charging, assuming two different levels of charging power. The study compares the two charging power assumptions of 3.6 kW and 7.2 kW, respectively. In real life, EVs in a garage typically have a mix of charging power levels. By combining a lower and a higher charging power assumption when calculating the synthetic charging load, the true load can be expected to lie between the two synthetic levels.

Non-charging idle times are translated into energy flexibility potential, or *idle capacity*. While the daily average charging load profiles are similar for the two charging capacities, the average idle capacity differs, with higher values when the charging capacity is 7.2 kW, than when charging capacity is 3.6 kW. For example, the average idle capacity for private CPs during weekdays is 2.3 times higher with the 7.2 kW charging capacity than with the 3.6 kW charging capacity. The study provides tabulated values for additional insights into charging habits and non-charging idle times for private and shared CPs, for weekdays and weekends.

The study finds a significant potential for residential EV charging flexibility when private parking spaces have a CP. Also, the results support the theory that EV charging is a main source of flexible electricity use in apartment buildings. This is an important take-away for policy and decision makers, which can provide incentives for CPs at private parking spaces, as well as for charging energy management systems.

CRediT authorship contribution statement

A.L. Sørensen: Conceptualization, Methodology, Investigation, Data curation, Writing - original draft, Writing - review & editing. **K.B. Lindberg:** Conceptualization, Writing - review & editing, Supervision. **I. Sartori:** Conceptualization, Writing - review & editing, Supervision. **I. Andresen:** Conceptualization, Writing - review & editing, Supervision.

Declaration of Competing Interest

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

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Appendix

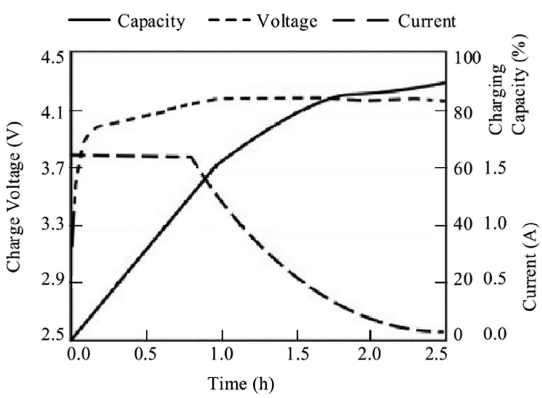

Fig. A1. Typical characteristics of the lithium-ion battery charging, from [42].

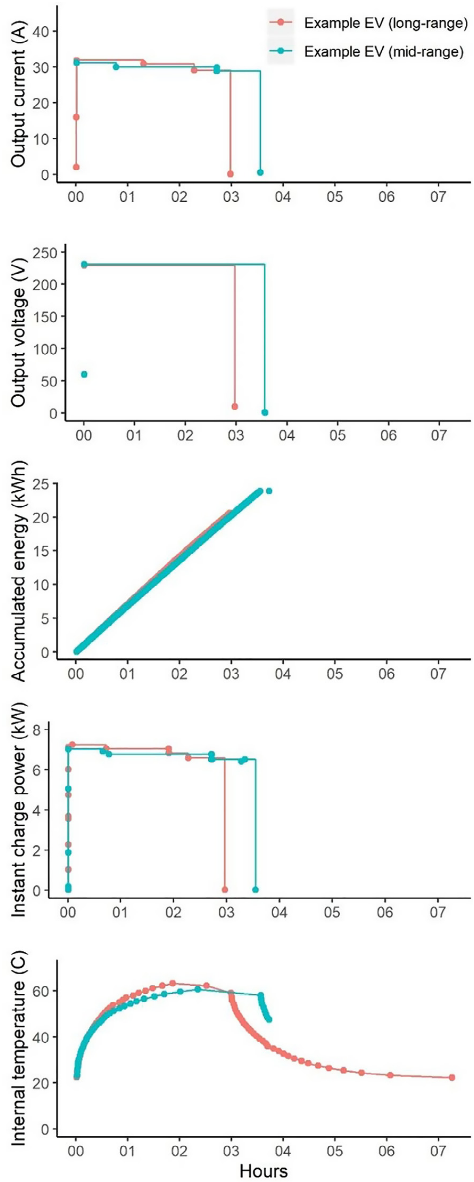

Fig. A2. Examples of charging characteristics of EV batteries from two charging sessions in the case study. Nominal charging power of the mid-range EV is 7.2 kW (session 943, user Bl2-4), while the long-range EV is limited by the available AC power of 7.4 kW (session 1158, user Bl2-3).

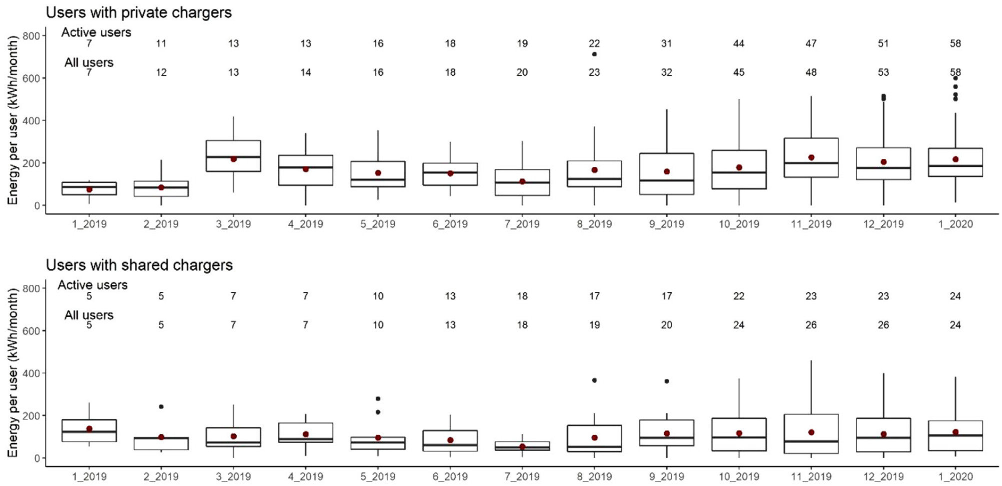

Fig. A3. Boxplots for monthly energy charged per user, divided according to users with private or shared CPs.

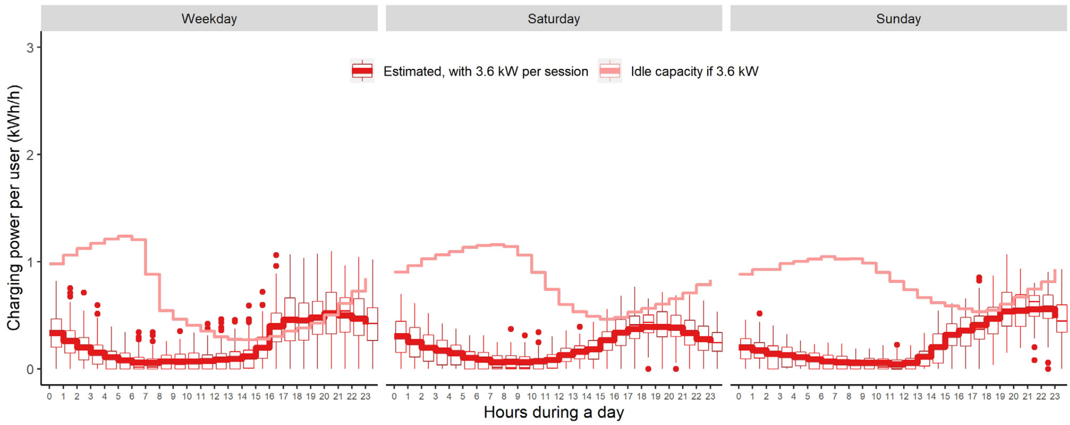

Fig. A4. Private CPs with estimated charging power 3.6 kW: Synthetic daily average charging load profiles and idle capacity profiles per user (data with 18 to 58 users).

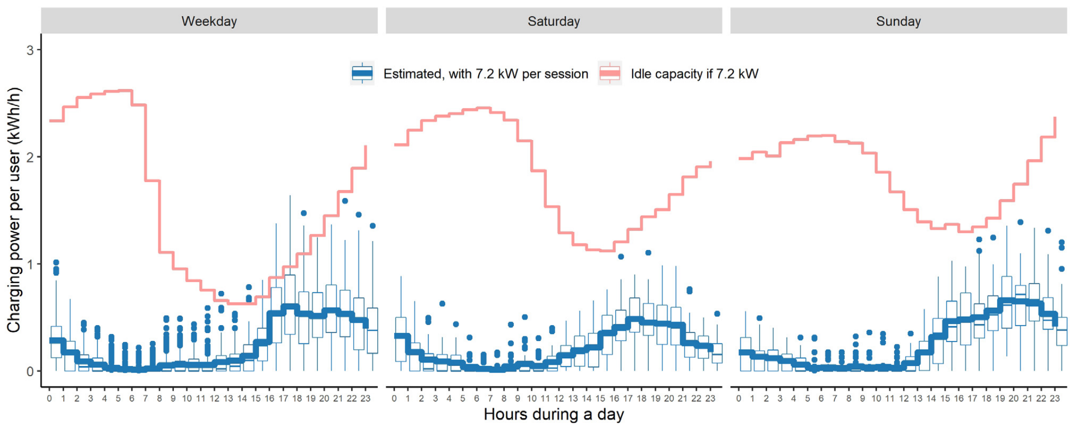

Fig. A5. Private CPs with estimated charging power 7.2 kW: Synthetic daily average charging load profiles and idle capacity profiles per user (data with 18 to 58 users).

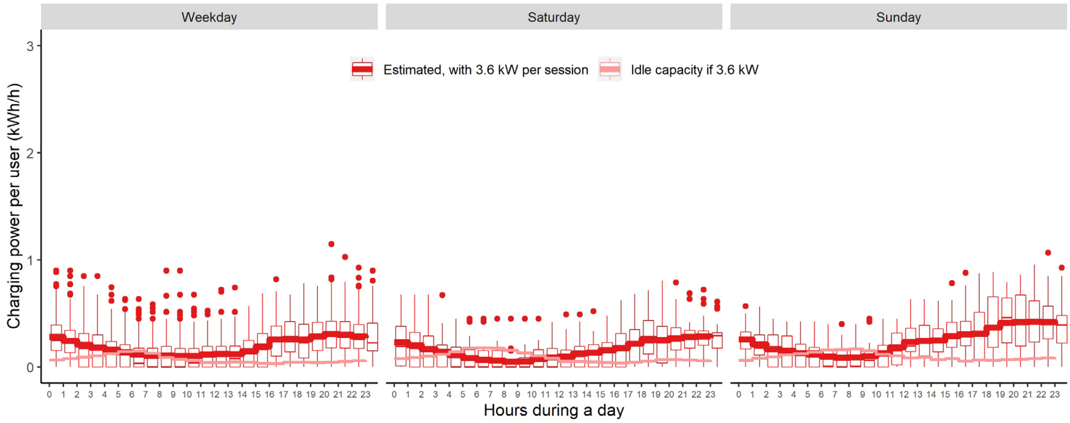

Fig. A6. Shared CPs with estimated charging power 3.6 kW: Synthetic daily average charging load profiles and idle capacity profiles per user (data with 12 to 24 users).

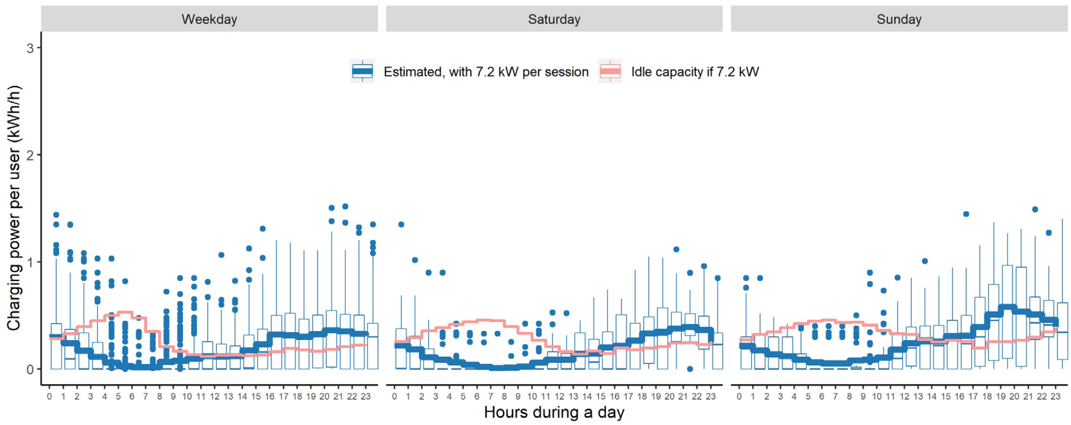

Fig. A7. Shared CPs with estimated charging power 7.2 kW: Synthetic daily average charging load profiles and idle capacity profiles per user (data with 12 to 24 users).

Table A1
Private CPs during weekdays: Average hourly charging load and idle capacity per user and share of plug-in, plug-out and non-charging idle times. Estimated charging power is 7.2 kW.

Daily hour	Share plug-in (% / h)	Share plug-out (% / h)	Available charging capacity *, if perfect foresight (kWh/h/user) * Sum of charging load and idle capacity	Charging load, if immediate charging (kWh/h/user)	Share with idle time of # hours														
					<1	1<2	2<3	3<4	4<5	5<6	6<7	7<8	8<9	9<10	10<11	11<12	12 < 18	18 ≤	
00 - 01	0.8 %	0.3 %	2.62	0.28	4 %	4 %	4 %	NA	8 %	27 %	19 %	8 %	8 %	8 %	8 %	4 %	NA	NA	100%
01 - 02	0.3 %	0.2 %	2.64	0.17	NA	NA	9 %	NA	9 %	NA	9 %	18 %	9 %	NA	NA	NA	27 %	18 %	100%
02 - 03	0.2 %	0.1 %	2.64	0.09	NA	NA	20 %	40 %	NA	NA	NA	NA	NA	NA	NA	NA	20 %	20 %	100%
03 - 04	0.1 %	0.2 %	2.65	0.06	NA	50 %	NA	NA	NA	NA	NA	50 %	NA	NA	NA	NA	NA	NA	100%
04 - 05	0.0 %	0.0 %	2.64	0.03	NA	NA	NA	NA	100 %	NA	NA	NA	NA	NA	NA	NA	NA	NA	100%
05 - 06	0.1 %	7.1 %	2.63	0.02	100 %	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	100%
06 - 07	0.3 %	22.5 %	2.49	0.01	11 %	22 %	NA	11 %	NA	22 %	NA	22 %	NA	NA	NA	NA	NA	11 %	100%
07 - 08	1.2 %	8.2 %	1.80	0.02	45 %	5 %	5 %	5 %	13 %	5 %	5 %	3 %	3 %	NA	3 %	NA	3 %	5 %	100%
08 - 09	1.2 %	4.8 %	1.18	0.05	33 %	15 %	13 %	3 %	10 %	5 %	10 %	NA	NA	3 %	3 %	NA	NA	8 %	100%
09 - 10	0.8 %	4.5 %	1.03	0.06	24 %	8 %	16 %	4 %	16 %	NA	NA	8 %	4 %	NA	NA	NA	NA	20 %	100%
10 - 11	1.3 %	5.8 %	0.93	0.06	42 %	14 %	12 %	NA	2 %	NA	2 %	2 %	NA	NA	NA	NA	NA	26 %	100%
11 - 12	1.6 %	4.3 %	0.85	0.06	30 %	23 %	4 %	11 %	4 %	4 %	2 %	2 %	NA	NA	NA	NA	6 %	15 %	100%
12 - 13	2.3 %	3.3 %	0.79	0.09	26 %	16 %	6 %	3 %	6 %	3 %	5 %	3 %	NA	NA	NA	NA	6 %	26 %	100%
13 - 14	2.9 %	3.6 %	0.76	0.10	31 %	11 %	7 %	7 %	6 %	1 %	1 %	NA	1 %	NA	NA	2 %	5 %	27 %	100%
14 - 15	4.7 %	3.6 %	0.81	0.15	29 %	10 %	13 %	3 %	2 %	1 %	NA	1 %	NA	1 %	NA	NA	16 %	24 %	100%
15 - 16	12.2 %	4.9 %	0.98	0.27	21 %	18 %	9 %	3 %	1 %	1 %	0 %	0 %	1 %	0 %	0 %	1 %	27 %	19 %	100%
16 - 17	18.3 %	8.4 %	1.41	0.54	30 %	10 %	4 %	2 %	2 %	0 %	1 %	0 %	1 %	1 %	0 %	3 %	34 %	12 %	100%
17 - 18	8.6 %	6.2 %	1.57	0.60	25 %	5 %	4 %	2 %	1 %	0 %	1 %	NA	1 %	1 %	4 %	7 %	33 %	17 %	100%
18 - 19	7.9 %	4.5 %	1.63	0.54	17 %	5 %	1 %	2 %	0 %	2 %	2 %	2 %	0 %	5 %	10 %	15 %	29 %	10 %	100%
19 - 20	10.6 %	3.3 %	1.78	0.51	16 %	5 %	2 %	1 %	2 %	2 %	1 %	2 %	3 %	9 %	19 %	13 %	17 %	8 %	100%
20 - 21	9.4 %	2.4 %	2.03	0.57	8 %	3 %	2 %	1 %	0 %	3 %	3 %	6 %	6 %	21 %	16 %	4 %	18 %	10 %	100%
21 - 22	6.9 %	1.3 %	2.22	0.54	3 %	0 %	NA	NA	1 %	3 %	6 %	11 %	22 %	19 %	8 %	7 %	12 %	8 %	100%
22 - 23	5.7 %	0.6 %	2.37	0.48	2 %	2 %	1 %	1 %	4 %	4 %	9 %	17 %	27 %	7 %	5 %	4 %	13 %	4 %	100%
23 - 24	2.6 %	0.3 %	2.50	0.40	3 %	1 %	NA	6 %	2 %	14 %	17 %	13 %	6 %	13 %	6 %	3 %	9 %	6 %	100%
Total	100 %	100 %	42.9	5.7															

Table A2
Private CPs during weekends: Average hourly charging load and idle capacity per user and share of plug-in, plug-out and non-charging idle times. Estimated charging power is 7.2 kW.

Daily hour	Shareplug-in (%/h)	Shareplug-out (%/h)	Available charging capacity *, if perfect foresight (kWh/h/user)* Sum of charging load and idle capacity	Charging load, if immediate charging (kWh/h/user)	Share with idle time of # hours														
					<1	1 < 2	2 < 3	3 < 4	4 < 5	5 < 6	6 < 7	7 < 8	8 < 9	9 < 10	10 < 11	11 < 12	12 < 18	18 ≤	
00–01	2.3%	0.6%	2.34	0.26	8%	NA	NA	NA	12%	4%	NA	4%	12%	16%	12%	4%	28%	NA	100%
01–02	1.4%	0.7%	2.34	0.16	7%	NA	NA	NA	NA	7%	7%	20%	7%	NA	7%	27%	20%	NA	100%
02–03	0.7%	0.2%	2.36	0.12	NA	NA	NA	NA	NA	25%	13%	25%	NA	NA	13%	NA	25%	NA	100%
03–04	0.7%	0.1%	2.38	0.09	13%	13%	NA	NA	13%	NA	NA	13%	38%	NA	NA	NA	13%	NA	100%
04–05	0.2%	0.3%	2.39	0.07	50%	NA	NA	NA	NA	50%	NA	NA	NA	NA	NA	NA	NA	NA	100%
05–06	0.4%	0.3%	2.39	0.03	25%	NA	25%	NA	NA	25%	NA	25%	NA	NA	NA	NA	NA	NA	100%
06–07	0.5%	6.7%	2.39	0.03	NA	NA	NA	20%	NA	NA	20%	20%	20%	NA	NA	NA	NA	20%	100%
07–08	0.5%	17.6%	2.33	0.02	17%	17%	33%	NA	17%	NA	17%	NA	NA	NA	NA	NA	NA	NA	100%
08–09	0.7%	5.3%	2.31	0.04	38%	13%	13%	38%	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	100%
09–10	0.8%	5.7%	2.18	0.05	44%	11%	NA	NA	NA	22%	NA	NA	NA	NA	NA	NA	NA	22%	100%
10–11	1.1%	6.1%	1.93	0.04	25%	25%	8%	NA	NA	8%	NA	8%	8%	NA	NA	NA	NA	17%	100%
11–12	2.3%	5.5%	1.69	0.06	40%	16%	8%	NA	NA	8%	NA	NA	8%	NA	NA	NA	4%	16%	100%
12–13	4.4%	5.1%	1.53	0.11	25%	13%	15%	NA	6%	NA	2%	NA	2%	NA	NA	4%	10%	23%	100%
13–14	7.5%	5.5%	1.47	0.18	18%	15%	10%	7%	2%	2%	NA	NA	NA	NA	1%	NA	10%	34%	100%
14–15	8.0%	4.9%	1.53	0.28	18%	13%	7%	6%	1%	3%	1%	NA	2%	1%	NA	NA	23%	25%	100%
15–16	11.8%	5.2%	1.65	0.41	16%	9%	4%	5%	4%	2%	NA	1%	1%	2%	2%	2%	22%	30%	100%
16–17	8.8%	5.7%	1.70	0.44	19%	9%	4%	2%	1%	NA	1%	1%	1%	2%	2%	2%	27%	28%	100%
17–18	10.4%	6.9%	1.86	0.50	17%	4%	4%	4%	2%	3%	1%	1%	NA	2%	4%	4%	36%	19%	100%
18–19	9.9%	5.7%	1.94	0.51	11%	6%	1%	2%	1%	2%	2%	3%	4%	6%	6%	6%	29%	21%	100%
19–20	8.9%	3.7%	2.10	0.55	8%	4%	1%	4%	2%	1%	NA	3%	2%	7%	11%	11%	26%	19%	100%
20–21	6.2%	2.5%	2.24	0.54	7%	3%	3%	3%	6%	3%	3%	NA	4%	12%	16%	4%	16%	19%	100%
21–22	4.7%	2.8%	2.37	0.45	6%	4%	2%	NA	2%	2%	8%	4%	10%	29%	8%	NA	16%	10%	100%
22–23	5.0%	1.8%	2.47	0.39	7%	2%	NA	NA	2%	5%	4%	16%	11%	15%	2%	13%	16%	7%	100%
23–24	2.9%	1.1%	2.50	0.30	6%	6%	NA	3%	NA	13%	3%	16%	9%	6%	13%	3%	22%	NA	100%
Total	100%	100%	50.4	5.6															

Table A3
Shared CPs during weekdays: Average hourly charging load and idle capacity per user and share of plug-in, plug-out and non-charging idle times. Estimated charging power is 7.2 kW.

Daily hour	Shareplug-in (%/h)	Shareplug-out (%/h)	Available charging capacity *, if perfect foresight (kWh/h/user)* Sum of charging load and idle capacity	Charging load, if immediate charging (kWh/h/user)	Share with idle time of # hours														
					<1	1 < 2	2 < 3	3 < 4	4 < 5	5 < 6	6 < 7	7 < 8	8 < 9	9 < 10	10 < 11	11 < 12	12 < 18	18 ≤	
00–01	1.3%	1.9%	0.44	0.21	8%	*NA*	*NA*	33%	8%	17%	17%	*NA*	8%	*NA*	8%	*NA*	*NA*	*NA*	100%
01–02	0.3%	1.0%	0.45	0.16	*NA*	*NA*	*NA*	33%	33%	33%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
02–03	0.2%	0.4%	0.46	0.12	*NA*	*NA*	*NA*	*NA*	50%	*NA*	*NA*	*NA*	*NA*	*NA*	50%	*NA*	*NA*	*NA*	100%
03–04	*NA*	0.1%	0.47	0.08	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
04–05	0.1%	0.1%	0.47	0.04	*NA*	*NA*	100%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
05–06	0.2%	0.6%	0.47	0.02	50%	50%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
06–07	0.1%	6.2%	0.43	0.01	100%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
07–08	2.0%	8.3%	0.31	0.01	72%	*NA*	17%	*NA*	*NA*	6%	*NA*	6%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
08–09	2.3%	5.2%	0.25	0.05	76%	*NA*	*NA*	5%	*NA*	10%	5%	5%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
09–10	1.5%	2.7%	0.24	0.07	71%	7%	*NA*	*NA*	14%	7%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
10–11	2.9%	4.1%	0.22	0.09	35%	23%	27%	12%	4%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	100%
11–12	4.0%	3.9%	0.22	0.11	39%	22%	11%	17%	3%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	8%	100%
12–13	3.4%	3.3%	0.25	0.13	45%	26%	16%	3%	6%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	3%	100%
13–14	4.5%	2.5%	0.25	0.13	44%	27%	17%	5%	*NA*	2%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	2%	2%	100%
14–15	8.2%	5.0%	0.27	0.16	36%	36%	14%	4%	3%	1%	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	4%	1%	100%
15–16	11.0%	5.9%	0.28	0.18	65%	16%	8%	4%	2%	*NA*	1%	*NA*	*NA*	1%	*NA*	*NA*	2%	1%	100%
16–17	10.4%	4.3%	0.37	0.27	60%	17%	3%	2%	2%	4%	2%	1%	*NA*	2%	*NA*	1%	4%	1%	100%
17–18	6.9%	8.8%	0.37	0.24	37%	19%	13%	6%	2%	*NA*	3%	*NA*	2%	*NA*	3%	3%	10%	2%	100%
18–19	8.0%	8.4%	0.36	0.22	50%	8%	8%	1%	4%	8%	*NA*	1%	4%	6%	*NA*	1%	6%	1%	100%
19–20	10.6%	6.2%	0.37	0.24	26%	10%	8%	5%	6%	8%	5%	4%	7%	2%	3%	3%	8%	2%	100%
20–21	8.3%	5.4%	0.42	0.28	20%	15%	11%	11%	4%	4%	7%	9%	4%	1%	5%	*NA*	8%	1%	100%
21–22	5.6%	6.0%	0.44	0.27	6%	16%	16%	12%	6%	2%	10%	8%	4%	8%	4%	2%	8%	*NA*	100%
22–23	5.2%	5.5%	0.43	0.26	6%	6%	4%	11%	9%	4%	9%	9%	17%	15%	6%	*NA*	4%	*NA*	100%
23–24	2.9%	4.3%	0.42	0.24	4%	*NA*	8%	12%	8%	8%	23%	8%	19%	4%	8%	*NA*	*NA*	*NA*	100%
Total	100%	100%	8.7	3.6															

Table A4
Shared CPs during weekends: Average hourly charging load and idle capacity per user and share of plug-in, plug-out and non-charging idle times. Estimated charging power is 7.2 kW.

Daily hour	Share plug-in (%/h)	Share plug-out (%/h)	Available charging capacity *, if perfect foresight (kWh/h/user) * Sum of charging load and idle capacity	Charging load, if immediate charging (kWh/h/user)	Share with idle time of # hours														
					<1	1 < 2	2 < 3	3 < 4	4 < 5	5 < 6	6 < 7	7 < 8	8 < 9	9 < 10	10 < 11	11 < 12	12 < 18	18 ≤	
00–01	3.4%	0.5%	0.38	0.20	NA	NA	36%	NA	7%	7%	7%	14%	7%	7%	NA	NA	14%	NA	100%
01–02	0.2%	0.5%	0.39	0.17	NA	NA	NA	NA	NA	NA	NA	100%	NA	NA	NA	NA	NA	NA	100%
02–03	NA	0.2%	0.39	0.12	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	100%
03–04	0.5%	0.2%	0.39	0.09	NA	NA	NA	50%	50%	NA	NA	NA	NA	NA	NA	NA	NA	NA	100%
04–05	NA	NA	0.41	0.07	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	100%
05–06	NA	0.7%	0.41	0.05	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	100%
06–07	NA	4.2%	0.41	0.03	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	100%
07–08	NA	5.2%	0.39	0.02	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	100%
08–09	1.5%	3.9%	0.38	0.03	67%	NA	NA	33%	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	100%
09–10	2.0%	4.9%	0.34	0.05	25%	50%	NA	NA	NA	13%	13%	NA	NA	NA	NA	NA	NA	NA	100%
10–11	4.4%	3.9%	0.30	0.06	22%	28%	22%	6%	NA	6%	6%	NA	NA	NA	NA	NA	NA	11%	100%
11–12	5.9%	5.4%	0.29	0.09	54%	17%	8%	8%	NA	NA	NA	NA	NA	NA	NA	NA	NA	13%	100%
12–13	6.9%	3.4%	0.29	0.11	46%	29%	4%	7%	NA	4%	NA	NA	NA	NA	NA	NA	7%	4%	100%
13–14	5.9%	7.4%	0.32	0.15	38%	25%	13%	NA	NA	4%	NA	NA	NA	4%	NA	NA	8%	8%	100%
14–15	9.1%	4.9%	0.33	0.14	46%	19%	11%	5%	3%	NA	NA	NA	NA	NA	NA	NA	16%	NA	100%
15–16	9.1%	7.9%	0.36	0.18	38%	32%	8%	NA	3%	NA	3%	3%	NA	NA	NA	3%	8%	3%	100%
16–17	6.6%	7.1%	0.38	0.18	52%	19%	NA	7%	NA	NA	NA	NA	4%	NA	4%	NA	15%	NA	100%
17–18	12.3%	6.1%	0.38	0.21	46%	6%	12%	2%	2%	NA	8%	4%	4%	NA	2%	4%	4%	6%	100%
18–19	9.3%	5.9%	0.46	0.26	47%	18%	3%	5%	NA	5%	3%	3%	NA	NA	3%	NA	13%	NA	100%
19–20	6.1%	5.9%	0.50	0.30	40%	12%	20%	4%	4%	NA	NA	8%	NA	4%	4%	4%	NA	NA	100%
20–21	5.4%	5.7%	0.48	0.27	36%	9%	NA	NA	NA	5%	NA	5%	NA	14%	5%	5%	23%	NA	100%
21–22	5.9%	5.7%	0.47	0.27	17%	8%	8%	NA	8%	13%	4%	13%	8%	4%	4%	NA	13%	NA	100%
22–23	3.4%	6.4%	0.45	0.25	7%	7%	NA	NA	NA	NA	14%	36%	14%	7%	NA	7%	7%	NA	100%
23–24	2.0%	3.9%	0.43	0.22	NA	NA	NA	NA	NA	NA	25%	25%	NA	NA	13%	25%	13%	NA	100%
Total	100%	100%	9.3	3.5															

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Main article II

A method for generating complete EV charging datasets and analysis of residential charging behaviour in a large Norwegian case study

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Table: The paper's context in the thesis.

	Supplementary articles	Main article I	Main article II	Main article III	Main article IV	Data articles *(D* describes planned articles)*
RQ1: What are the energy profiles for household energy use and PV generation for apartment buildings, and how are the energy profiles influenced by climate variables?	S I. Electricity S II. Heat-DHW S III. DHW S IV. PV				Main IV. Energy profiles	D* IV. Data Main IV
RQ2: How does the user habits influence the electricity load profiles of residential EV charging, and how is the el. load affected by EV cabin preheating?	S V. Stochastic EV charging	Main I. EV charging	Main II. EV charging	Main III. EV cabin preheating		D I. Data Main I D* II. Data Main II D* III. Data Main III
RQ3: What is the potential for electricity flexibility from EVs, in relation to non-flexible apartment building loads and PV generation, in the Norwegian context?					Main IV. Flexibility	

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A method for generating complete EV charging datasets and analysis of residential charging behaviour in a large Norwegian case study

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ABSTRACT

Electric vehicles (EVs) are part of the solution to achieve global carbon emissions reduction targets, and the number of EVs is increasing worldwide. Increased demand for EV charging can challenge the grid capacity of power distribution systems. Smart charging is therefore becoming an increasingly important topic, and availability of high-grade EV charging data is needed for analysing and modelling of EV charging and related energy flexibility. This study provides a set of methodologies for transforming real-world and commonly available EV charging data into easy-to-use EV charging datasets necessary for conducting a range of different EV studies. More than 35,000 residential charging sessions are analysed. The datasets include realistic predictions of battery capacities, charging power, and plug-in State-of-Charge (SoC) for each of the EVs, along with plug-in/plug-out times, and energy charged. Finally, we analyse how residential charging behaviour is affected by EV battery capacity and charging power. The results show a considerable potential for shifting residential EV charging in time, especially from afternoon/evenings to night-time. Such shifting of charging loads can reduce the grid burden resulting from residential EV charging. The potential for a single EV user to shift EV charging in time increases with higher EV charging power, more frequent connections, and longer connection times. The proposed methods provide the basis for assessing current and future EV charging behaviour, data-driven energy flexibility characterization, analysis, and modelling of EV charging loads and EV integration into power grids.

1. Introduction

1.1. Background

1.1.1. Electric Vehicles as important players to providing flexibility in the future energy market

Electric vehicles (EVs) are part of the solution to achieve carbon emissions reduction targets set under the Paris Climate Change Agreement [1]. This has led to policy support for EVs in several countries and substantial increase in EV sales in e.g., China, Europe, and the United States. In 2022, the number of different types of EV models available on the market had increased to around 500 [2]. On a global level, the market share of EVs was 14% in 2022, with Norway being the leading country with an 88% market share [2]. The EV market in Norway has passed the early adopter stage, and EVs are becoming the dominant car choice of the population. EV charging at home and at the workplace are dominating, with charge points (CPs) generally being below 22 kW [2]. Even though EVs are expected to account for a minor share of global electricity consumption also in the future, the EV fleet can challenge the grid capacity of power distribution systems [2,3]. Furthermore, EV charging is expected to have a high impact on residential and commercial energy load curves [3]. Smart charging is therefore becoming an increasingly important topic [4], and because EV charging loads can be shifted in time, smart charging can provide energy flexibility [5]. The energy flexibility of a building can be defined as "the ability to manage its demand and generation according to local climate conditions, user needs and grid requirements" [6]. Flexible energy use is becoming increasingly important in the energy system, since a growing share of the energy supply is variable and non-flexible renewable energy generation.

Fischer et al. [7] analysed electric load profiles for household appliances, electric heating systems, and EVs in the residential sector, and found that EVs have the highest flexibility potential among all the energy uses. For large scale utilization of energy flexibility in buildings, new solutions need to be developed, addressing technological, social,

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Nomenclature

BEV	Battery Electric Vehicle.
CP	Charge Point.
CPO	Charge Point Operator.
CPO reports	EV charging reports from CPOs.
DST	Daylight Saving Time.
EV	Electric Vehicle.
IT230V	230 Volt IT system (distribution grid).
LV	Low Voltage.
PHEV	Plug-in Hybrid Electric Vehicle.
SoC	State of Charge of the EV battery.
V2G	Vehicle to grid.
#	Number of.

Subscript

$E_{battery}$	Energy stored in the EV battery.
$E_{battery\text{-}size}$	EV battery capacity prediction per user ID.
$E_{charged}$	Energy charged per charging session.
$E_{connected(i)}$	Connected energy capacity in hour *i*.
$E_{idle(i)}$	Idle energy capacity in hour *i*.
$E_{load\ (i)}$	Energy charging load in hour *i*.
η	Charging efficiency.
$P_{charging}$	Average charging power.
$P_{preliminary}$	Preliminary EV charging power prediction per user ID.
P_{user}	Charging power prediction per user ID.
$SoC_{diff(i)}$	SoC difference for hour *i*.
SoC_{range}	Range from a minimum SoC-level to a maximum SoC-level.
$t_{charging}$	Charging time for an EV session.
$t_{connection}$	CP connection time for an EV session.
t_{idle}	Non-charging idle time for an EV session.
$t_{plug\text{-}in}$	CP plug-in time.
$t_{plug\text{-}out}$	CP plug-out time.

commercial, and regulatory aspects [8]. Li et al. [8] emphasized the advantages of utilizing flexibility sources from a cluster of buildings to increase the impact and role of energy flexibility. For EV charging, Charge Point Operators (CPOs) can have a role as aggregators of energy flexibility by facilitating the shifting of charging loads. In Norway, for example, several CPOs (such as the companies Tibber, Current, Kople, and ZapTec) provide CP management services for EV fleets, where e.g., aggregated charging loads in parking facilities are kept below the available distribution capacity, or charging loads are shifted to hours during the day when the energy spot prices are the lowest. In the future, such CP management systems may provide opportunities for residential and commercial users to engage in the flexibility market. However, more knowledge about charging habits is necessary to optimally utilize the EV charging flexibility, such as the number of cars that are connected to the CPs, daily charging demand, plug-in state of charge (SoC) of the EV batteries, and CP plug-out times.

The objective of this study is to provide realistic and high-grade EV charging data, and analyses of related EV charging behaviour, based on real-world data from more than 35,000 charging sessions in Norway. The results are useful as input for a range of energy studies, e.g., for load forecasting, for assessment of energy flexibility potentials in neighbourhoods, and for sizing of grid connection capacities.

1.1.2. The need and availability of high-quality datasets for optimizing the flexibility potential of EVs

For analysing energy flexibility in terms of load shifting and load shaving, data with hourly resolution is usually used [9]. If there is need for a faster response to flexibility requests, such as in frequency regulation, sub-hourly resolution is normally needed. Salim et al. [10] emphasized the importance of publicly available input data for modelling of occupant behaviour and energy in buildings at urban scale. Amayri et al. [11] concluded that there is a need for more publicly available datasets on EV charging in residential buildings to improve load forecasting and flexibility forecasting. Calearo et al. [12] stated that published EV data is limited, and describes how five parameters ideally should be available for EV studies in the smart grid context: 1) Battery capacity, 2) charging power, 3) plug-in SoC, 4) plug-in/plug-out time, and 5) charged energy. They refer to such data as *ideal*, "because it is the highest level of data availability one can have when conducting EV studies in the power system context". To sum up, there is a lack of complete datasets related to charging sessions and CPs.

Due to the fact that Norway has been a frontrunner in EV use, EV charging reports from CPOs are becoming commonly available, including CPs in private residential and commercial parking spaces. Such CPO reports include data for the parameters 4) and 5) mentioned above, i.e. plug-in/plug-out times and charged energy for the charging sessions [13,14]. However, the CPO reports do not include the parameters for 1), 2), and 3, i.e. battery capacity and charging power for each EV, or plug-in SoC for charging sessions. Our work provides a set of methodologies which complements the data in the CPO reports, providing a complete *ideal* dataset for EV charging based on an empirical residential case study in Norway.

1.2. State of the art: Prediction of EV charging power, battery capacity, and plug-in SoC, and their impact on residential charging behaviour

To complement the data in the CPO reports, values are needed for the parameters 1) charging power, 2) battery capacity, and 3) plug-in SoC. Sections 1.2.1 and 1.2.2 introduce these parameters, the availability of real-world data, and how the parameters typically are predicted in literature. Section 1.2.3 describes literature focussing on how EV charging behaviour is related to battery capacity and SoC values.

1.2.1. EV charging parameters

The energy demand during a charging session depends on the battery SoC at plug-in time, the final SoC, the battery capacity, and the charging efficiency. The time needed for charging depends on the charging power, which can be limited by the CP or the EV characteristics. The actual charging power is the lowest value of the AC power available at the location (Fig. 1, marked A) and the onboard charger capacity in the EV (Fig. 1, marked B).

When the connection time is longer than the charging time, there is a period of non-charging idle time which reflects the flexibility potential for the charging session. The energy which could potentially have been charged during the idle time, is called idle energy capacity. The idle energy capacity depends on the battery's SoC, the maximal charging power, and the availability of connected EVs [15]. When energy loads

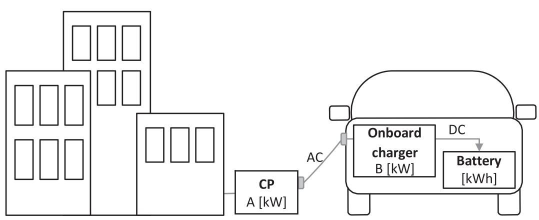


Fig. 1. Charging power is limited by available AC power in the CP (A) and EV onboard charger capacity (B).

for several EVs are aggregated, several studies have found that both the charging power peaks and the flexibility potential increases with higher charging power [13,15].

1.2.2. Prediction of EV charging power, battery capacity, and plug-in SoC

Fig. 2 shows an illustration of charging characteristics for EVs on the market, with onboard charger capacities on the horizontal axis and net battery capacities on the vertical axis, based on [13,16,17]. In a garage, different EVs typically have a mix of different charging power levels and battery capacities. Due to lack of data availability, EV characteristics such as charging power and battery capacity for each EV are often determined based on assumptions. Table 1 shows examples of AC charging power assumptions from literature. In references [13,15, 18–23] different scenarios with 'low' or 'high' charging powers were presented, where all the EVs have the same charging power level. In [24–26] a mix of charging power capacities were assumed for EV fleets in Germany, New Zealand and Norway, based on onboard charger capacities of typical EV models. As shown in Table 1, most studies either assume charging power levels based on typical power levels available at CPs (A in Fig. 1), or based on typical onboard charger capacities (B in Fig. 1). In [27], EV charging measurements from a shopping centre were analysed, and both the CP power and a mix of onboard charger capacities were addressed. The studied CPs had a power level of 22 kW, which means that most of the EVs were limited by their onboard charger capacities. The study found that most charging sessions had a peak charging power of around 4 kW, while some clusters had 7.5 kW and 11 kW. Simolin et al. [27] stated that there is a need for more studies taking into account the combination of the two CP power levels and the onboard charger capacity, including various power levels and charging sites, such as homes and workplaces. In our study, realistic databased charging power predictions are provided per EV user, taking both the CP power and the onboard charger capacity into account.

In general, real-world data that describe EV battery capacity and charging session SoC values are seldom available for AC charging, except in EV trials such as [29,30], where trial participants contribute with data. However EV trial data are often limited in size, geography and time, and, as stated by [20], usually represent a particular set of technologies and/or individuals. Accordingly, there is a need for more EV data from everyday users of CPs.

1.2.3. EV charging behaviour related to battery capacity and SoC values

Vermeulen et al. [31] acknowledged that there is limited research on the influence of battery capacity on EV charging behaviour. In [31], the research group predicted the battery capacities for EVs using public CPs in the Netherlands, based on information about energy charged from CPO reports. They assumed that all users would have at least one charging session where they charged their battery from 0% to 100%. Since several EVs could use the same user ID, for example if the user had a hired car or guests were using the chargers, the 98 percentile of the charging sessions was used. The EVs were split into plug-in hybrid EVs (PHEVs), and two groups of battery EVs (BEVs): low BEVs (up to 33 kWh battery capacity) and high BEVs (above 33 kWh). Due to the fact that only a few charging sessions involves charging the battery from 0% to 100%, the method underestimated the battery capacities, especially for BEVs with large batteries. Another research [32] also used CPO reports from public CPs in the Netherlands to predict battery capacities and start SoC of EVs. The researchers divided the users into 9 clusters and retrieved mean predicted battery capacities between 12.7 and 24.6 kWh. The study found a weak relationship between user types and battery capacities, and recommended further research to explore behavioural changes over time, with various EV types. Wolbertus et al. [33,34] presented charging data from a public dataset as well as private CPs in the Netherlands. The study predicted the users' battery sizes according to the maximum energy charged per user. The charging power was predicted to 3.7 kW (if single phase CP) or 11 kW (if three phase CP). In [33], the researchers found that users with battery sizes above 70 kWh charged 2.8 times a week, with about 25 kWh energy per charging session. Users with smaller battery capacities between 16 and 30 kWh charged 4 times a week, with about 10 kWh energy per charging session.

The optimal SoC range for operating EV batteries is commonly suggested to be 20–80% [35]. SoC values from AC charging are not usually available for CPOs, since most EVs do not yet support communication standards such as ISO15118 [36]. In a 6-month field trial with 40 EVs, [29,37] found that most EV users were comfortable with utilizing

Table 1
Examples of AC charging power assumptions found in literature.

Ref.	Charging power (kW)	Basis for power levels
Zade et al.[15]	3.7 / 11 / 22 (three scenarios)	CP
Sørensen et al. [13]	3.6 / 7.2 (two scenarios)	Onboard charger
Fischer et al. [18]	3.7 / 11 / 22 (three scenarios)	CP
Marra et al.[19]	3.7	CP
Dixon et al.[20]	3.7 / 7.4 (two scenarios)	CP
Shepero et al. [21]	3.7 / 6.9 / 22 kW (three scenarios)	CP
Calearo et al. [22]	3.7 / 11 (two scenarios)	CP
Bollerslev et al. [23]	3.7 / 11 / 22 kW (three scenarios + mix)	CP
Welzel et al. [24]	3.3 / 7.2 / 22 (mix of three levels)	Onboard charger
Su et al.[25]	6.6 / 11 (mix of two levels)	Onboard charger
Degefa et al. [26]	3.7 – 17 (mix of ten levels)	Onboard charger
Mobarak et al. [28]	6.6	Onboard charger
Simolin et al. [27]	3.7 / 7.4 / 11 / 22.1 (mix), CP 22 kW	Onboard charger or CP
Our study	Databased charging power predictions for all EV users individually	Onboard charger or CP

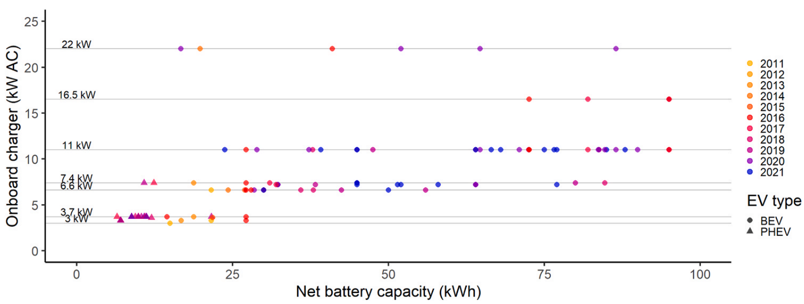


Fig. 2. *Onboard charger capacities and net battery capacities for EVs, based on market data from [16] and [17] (updated from [13]).*

approximately 80% of their available battery capacity. SoC values at plug-in and plug-out times were presented by [38], which analysed SoC data from trials with in total 29,262 charging sessions. Most of the EVs were part of company car fleets. Schäuble et al. [38] found that most of the charging sessions had a high start-SoC (median value of nearly 70%) and an end-SoC of more than 90%, which resulted in small SoC differences (less than 10% for 37% of the charging operations). Siddique et al. [39] calculated start SoC for 117,339 EV charging sessions in the US, based on information about energy charged per session and battery capacities. They found that the location category "single family residential" (about 17.7% of the sessions), which represented households with a dedicated CP, had a higher start SOC compared to other locations. This indicated that users with access to dedicated CPs typically will charge their EVs more regularly than users using public or shared CPs. Our findings in [13] supported this assumption, comparing charging behaviour of residential users with shared and private CPs. Residents with CPs on their private parking space had on average about 4.4 charging sessions per week, while residents using shared CPs charged about 1.2 times per week. The study also found that residents with a private CP had longer average connection times (12.8 h), than users with a shared CP (6.5 h).

1.3. Novelty and scientific contribution

The literature review showed that there is a general lack of EV charging data needed for data-driven analyses and modelling of EV charging and flexibility. Due to lack of data availability, EV characteristics are often based on rough assumptions. This paper presents a methodological framework that can be used to provide complete EV charging data. The methodological framework fulfils the requirements for an 'ideal' dataset for EV studies as specified by Calearo et al. [12]. The simple and practical set of methodologies that are proposed, were developed by combining and further developing existing methodologies from literature, and was based on a large empirical dataset obtained from a Norwegian case study with more than 35,000 charging sessions. Realistic predictions of battery capacities, charging power, and plug-in SoC for each EV and charging session were added to datasets with plug-in/plug-out times and energy charged, to provide complete EV datasets. Table 2 shows an overview of all the input and output data presented in this article. The needed input data are commonly available in CPO reports, which lays the ground for a wide-scale use of the methodology, covering different user groups, building categories, and geographic locations. The CPO reports represent data from everyday users of CPs.

Charging habits are related to EV characteristics such as battery capacity and charging power, which again will affect the load profiles and flexibility potential of EV charging. Table 3 includes a comparison of our study with the literature described in Section 1.2, focussing on EV charging behaviour related to EV charging power, battery capacity, and SoC values. The added value of our study is that the charging behaviour analyses were based on a large number of residential charging sessions

Table 2
Overview of input data and predicted output data in the article.

Input data from 35,000 CPO reports (residential)	Predicted output data		
	Per user	Per session	Hourly values
• User ID • Session ID • Plug-in time • Plug-out time • Connection time [h] • Energy charged [kWh]	• Charging power [kW] • Battery capacity [kWh]	• Charging time [h] • Idle time [h] • SoC difference • Idle energy capacity [kWh]	• Energy charged [kWh] • Idle energy capacity [kWh] • Connected energy capacity [kWh] • SoC difference • SoC from • SoC to

Table 3
Summary of literature describing EV charging behaviour related to battery capacity and SoC values.

Ref.	Description	CP ownership / Sector / Geographic location	EV share 2022 [40]
Vermeulen et al. [31]	Charging behaviour for users with different battery sizes. Battery capacity prediction was based on charging session data.	Public / Netherlands	Sales share: 35% Stoch share: 6%
Helmus et al. [32]	Charging behaviour for user clusters with daytime and overnight sessions. Battery capacity and start SoC predictions were based on charging session data.	Public / Netherlands	Sales share: 35% Stoch share: 6%
Wolbertus et al. [33]	Charging behaviour for users with different EV technologies, and the impact of access to home charging. Battery capacity and charging power predictions were based on charging session data.	Public and private / Netherlands	Sales share: 35% Stoch share: 6%
Schäuble et al. [38]	SoC analysis, based on trial data. Start SoC and end SoC values were either available from the trial, or SoC difference was calculated based on available EV battery size.	Company cars / Germany (trials)	Sales share: 31% Stoch share: 4%
Siddique et al. [39]	Charging behaviour for users with different charger type, EV type and location category. Start SoC predictions were based on energy charged per session and battery capacities. Dataset contained station-, session- and vehicle-characteristics.	CP network (home, workplace, public) / USA	Sales share: 8% Stoch share: 1%
Sørensen et al.[13]	Charging behaviour for residents using private or shared CPs. Analyses were based on charging session data.	Private / Residential / Norway	Sales share: 88% Stoch share: 27%
Our study	Charging behaviour and start SoC values for users with different battery sizes and charging power. Predictions were based on charging session data. Residential users (mainly with private CPs), in a mature EV market.	Private / Residential / Norway	Sales share: 88% Stoch share: 27%

in a mature EV market, where most of the EV users have private CPs. Charging behaviour was analysed for users with different battery sizes and charging power. Since the EV charging dataset was comprehensive, the analyses covered a wide range of EV charging behaviour, such as the energy charged, the idle times and related idle energy capacities, start SoC of the charging sessions, frequency and timing of EV charging sessions, etc. Such information can be employed as valuable inputs in various energy-related research studies, such as load forecasting, or when evaluating energy flexibility potentials within neighbourhoods.

The main contributions of our study are:

1. A set of methodologies for transforming readily available real-world EV charging data into high-quality and user-friendly EV charging datasets. These datasets are essential for conducting a range of different EV studies, including load forecasting and energy flexibility assessments. The methodologies are developed by combining and further developing existing approaches found in the literature, and

on data from a case study that includes more than 35,000 charging sessions from residential buildings in Norway.
2. A statistical analysis of the EV charging dataset that presents how residential charging behaviour and load shifting potential are affected by EV battery capacity and charging power. Behaviour data, such as energy charged, start SoC values, idle energy capacity, and frequency of charging, are presented for users with small and large EVs. The analysis is based on the large case study dataset from point 1, where CPs are mainly located on private residential parking spaces.

1.4. Structure of the article

The remainder of this paper is structured as follows: Section 2 introduces the input data used in the analysis, while Section 3 describes the methodology. Section 4 presents the results and a discussion of the findings including predictions of EV charging powers, battery capacities, hourly charging loads and SoC, and idle energy capacities. Section 4.3 provides an analysis of how EV battery and charging power capacities may affect charging habits. Finally, the conclusion of the paper is drawn in Section 5.

2. Input data for the analysis

The main data source for our analysis was CPO reports from apartment buildings in 12 locations in Norway. In total, 267 user IDs and more than 35,000 charging sessions were analysed (after cleaning). The CPO reports include information on plug-in time, plug-out time, and energy charged for each charging session, in addition to identifiers for user ID and location. Data availability for each location is listed in Table 4, including the number of user IDs and charging sessions before and after cleaning the data. Most of the CPs were located at private parking spaces for the residents and some locations also have shared CPs available for all residents. The CP ownership was not separated in this work, since it is not known for all the locations. The data and analysis for location TRO_R are further described in [13,14].

Most of the locations had an increasing number of user IDs during the period of data collection. The collection period for the locations varied, spanning from February 2018 to August 2021. During this period, Norway was affected by COVID-19, mainly from March 2020. COVID-19 rules and recommendations that were introduced from this time, might have affected the charging habits for the locations with data also from this period (BAR_2, KRO and OSL_T), e.g., due to increased use of home office and changes in travel activities. Consequently, only the period before March 2020 was included for prediction of hourly energy, idle energy capacity, and SoC (Sections 3.4 and 4.2), as well as for the comparison of charging habits (Sections 3.5 and 4.3). However, the whole data period was included for the prediction of EV charging power and net battery capacity (Sections 3.1, 3.2, and 4.1), since these are technical parameters related to the EV, i.e. not affected by user behaviour. Most of the input data were from before the COVID-19 period, and more than 80% of all the charging sessions were completed before March 2020.

The LV distribution system in most of the locations is of type 230 Volt IT system, which is typically the case for residential customers in Norway. For most EV users, the CP charging power (A in Fig. 1) is limited to a maximum of 7.4 kW (32 A). The users have the possibility to manually activate IT 3-phase charging on their CP, which provides up to 11 kW, but only some EV models support this. For the location OSL_T, a charging power of 7.4 kW is available at private parking spaces, while 22 kW is available at 16 shared CPs. Since 11 kW charging power is the limitation in most of our locations, this is the focus of the study.

Data cleaning removed 76 User IDs (22%) and about 3000 charging sessions (7.6%) from the original dataset, including the following:

- Sessions with no energy charged ($\leq$0.5 kWh) (n = 2289) (assumed faulty sessions).
- Sessions with too high energy charged (>150 kWh) (n = 2) (assumed faulty sessions, since the maximum battery capacity for EVs on the market is 100 kWh).

Table 4
Residential locations with EV data analysed.

Location		Data collection period	Months	Before cleaning		Used in analysis	
				# User IDs	# Charg. sessions	# User IDs	# Charg. sessions
ASK Asker	Sub-urban	2018–11–15 to 2020–02–03	14.5	23	6780	21	6372
BAR Bærum	Sub-urban	2018–09–07 to 2020–02–03	17	10	2108	8	1969
BAR_2 Bærum	Sub-urban	2020–02–04 to 2021–08–06	18	7	1116	6	1028
BER Bergen sør-vest	Urban	2019–10–31 to 2020–02–03	3	10	395	8	308
BOD Bodø	Urban	2018–10–24 to 2020–02–02	15	8	548	6	508
KRO Krokkleiva	Rural	2021–01–15 to 2021–05–06	3.5	18	598	9	492
OSL_1 Oslo	Urban	2019–10–08 to 2020–02–02	4	25	534	15	464
OSL_2 Oslo	Urban	2019–11–25 to 2020–02–02	2	8	167	4	127
OSL_S Oslo sør-øst	Urban	2018–02–06 to 2020–02–03	24	29	10,570	28	9757
OSL_T Oslo Tveita	Urban	2019–11–15 to 2021–03–29	16.5	80	6147	62	5478
TRO Trondheim	Urban	2019–03–08 to 2020–02–03	11	31	2379	23	2168
TRO_R Trondheim Risvollan	Urban	2018–12–21 to 2020–01–31	13	97	7245	77	6706
Total for the 12 locations		**2018–02–06 to 2021–08–06**		**346**	**38,587**	**267**	**35,377**
Total pre-COVID-19		**2018–02–06 to 2020–02–28**				**224**	**28,639**

- Sessions with connection time of less than 2 min (n = 131) (assumed faulty sessions).
- Sessions with connection time of more than 5 days (n = 155) (sessions affect average connection and idle time).
- A preliminary value for average power was calculated based on the energy charged divided by the connection time. For sessions with an average power higher than the available charging power (≥11.5 kW), plug-out times were removed (set to NA), since this indicated that the value was incorrect (n = 40). With removed plug-out times, the sessions were excluded for most of the analysis in this work.
- Plug-out times were also removed for OSL_T for average power ≥ 11.5 kW (n sessions= 22), even though 22 kW is available at their shared CPs. Two user IDs were removed (including all their 338 sessions), since they had more than one session (n = 12 + 6) with average power higher than 11.5 kW. It was therefore assumed that they normally used the shared CPs, charging with higher charging power, and that removing plug-out times for some sessions could provide misleading results.
- User IDs with less than 10 charging sessions were removed (n = 268 sessions, 72 user IDs).

Finally, corrections for time zones/daylight saving time (DST) were performed, before adding calendar data such as weekdays.

Fig. 3 shows plug-in times, plug-out times, connection times, and energy charged in the EV data locations. For all locations, the share of plug-in times increases in the evenings, with a peak in the afternoon (for most locations 16:00–17:00) when the working day typically ends in Norway. For the plug-out times, there is a peak in the morning (for most locations 7:00–8:00), corresponding to the start of a typical working day. OSL_1 stands out with an additional plug-in peak at 09:00 and plug-out peak at 14:00, but most of these charging sessions (plug-in: 91%, plug-out: 70%) are related to a single user. Both the morning and afternoon peaks are higher for some of the locations (BAR and KRO), which may be explained by a higher share of commuters in these areas. For the whole data period (n sessions = 35,377), the connection time is in average 12.7 h for the sessions, and 90% of the charging sessions last for less than 22.1 h. Average energy charged per charging session is 12.7 kWh. On average, each user starts 3.9 charging sessions per week.

3. Methodology

Based on the data available in the CPO reports, a set of simple-to-use methodologies are proposed for assessing complete and ideal EV datasets. The methodologies can be used for locations such as residential buildings and workplaces, where user IDs are unique. Flow charts for the methodologies are shown in Fig. 4, where values for EV charging power, EV battery capacity, and hourly battery SoC for charging sessions are assessed for each user ID individually. Firstly, charging power and battery capacity are predicted for each user ID, as described in Sections 3.1 and 3.2. The charging power and battery capacity predictions are then used to develop hourly SoC predictions, as described in Section 3.4. Section 3.5 describes a methodology for analysing how residential charging behaviour is affected by EV battery capacity and charging power. To do this, the 224 residential EV users were divided into four user groups, according to their battery capacity and charging power, and their charging habits were compared. All data analyses and predictions have been performed using the statistical computing environment R [41].

3.1. The EV charging power prediction method

The aim of the charging power prediction method is to provide predictions for the EV charging power per user ID. The EV charging power can be limited by the onboard charger in the EV or by the available AC power at the location. For each user ID, the predicted charging power value will be the lowest value of the two limitations.

When predicting the EV charging power, it is assumed that all user IDs have at least one charging session where they plug-out the charger while the battery is still charging. If this is the case, the available connection time ($t_{connection}$) equals the charging time ($t_{charging}$), and it is possible to calculate the average charging power ($P_{charging}$) using Eqs. 1

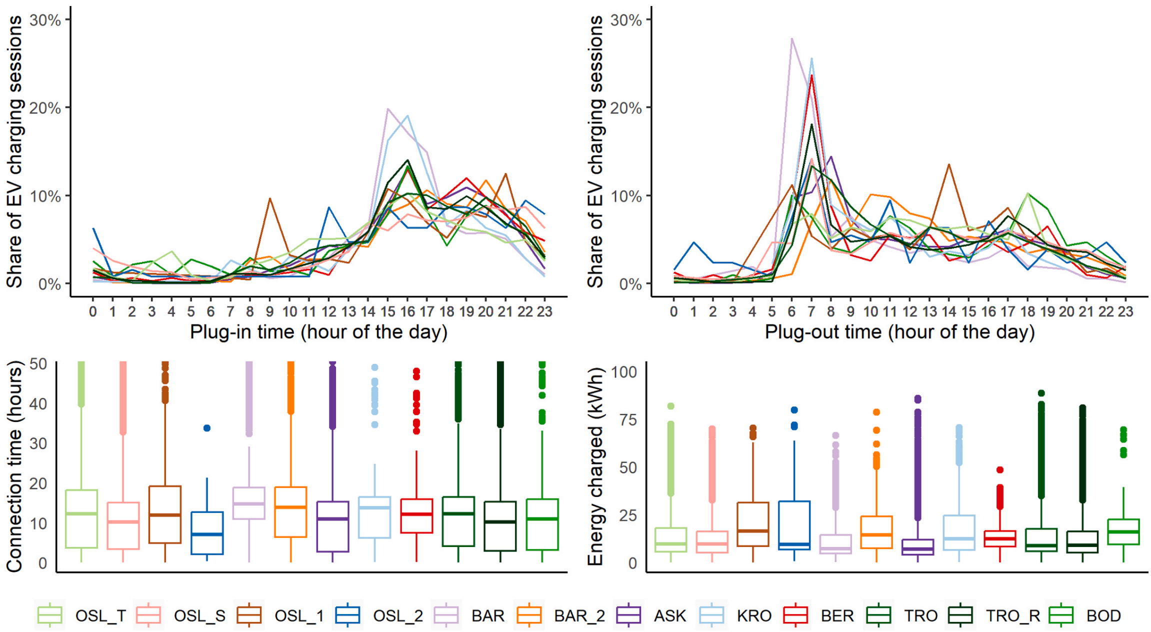


Fig. 3. Plug-in times, plug-out times, connection times, and energy charged in the EV data locations.

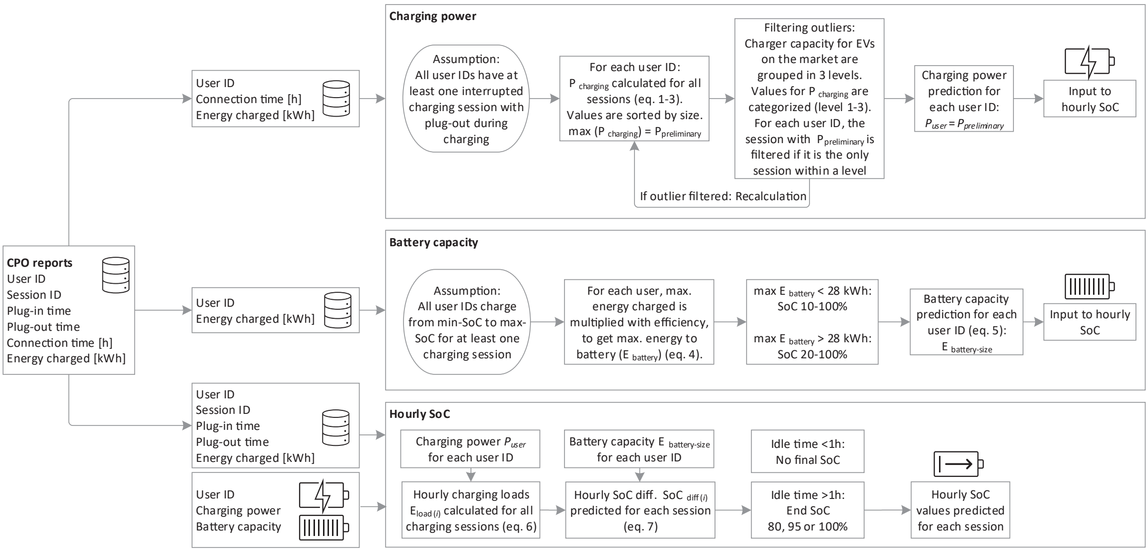


Fig. 4. Flow charts for predicting charging power, battery capacities, and hourly SoC, based on CPO reports.

to 3. The values for plug-out time ($t_{plug\text{-}out}$), plug-in time ($t_{plug\text{-}in}$), and energy charged ($E_{charged}$) are available from the CPO reports.

$$\text{CP connection time for an EV } session: \; t_{connection} = t_{plug-out} - t_{plug-in} \quad (1)$$

$$\text{When plugout during charging}: \; t_{charging} = t_{connection} \quad (2)$$

$$\text{Average EV charging } power: \; P_{charging} = E_{charged} \Big/ t_{charging} \quad (3)$$

To identify the interrupted charging sessions with plug-out during charging, the highest charging power values are of interest. For each user ID, the maximum value for $P_{charging}$ is therefore selected as the preliminary EV charging power prediction ($P_{preliminary}$). Our method is similar to the method proposed by [42], but while [42] used the predicted values to sort the users into two charging power levels, our method predicts all the charging power levels individually, reflecting the fact that actual charging power varies with the EV. When predicting realistic charging power values per user, also the results for hourly charging loads and idle energy capacities will become closer to reality. In addition, a second step is included to filter out errors and outliers, as explained in the following. Since charging power is predicted per user ID, the values are not necessarily connected to a specific EV. Some users may drive several EVs, or they may invite others/guests to use their user IDs. To improve the predictions, the $P_{preliminary}$ value for each user ID is therefore compared to typical levels for onboard charger capacities for EVs on the market (ref. Fig. 2). The charger capacities are grouped into three levels: Level 1 (mainly PHEVs and earlier models of BEVs): < 4 kW, Level 2 (mainly BEVs with onboard charger capacities around 7 kW): $4 < 8$ kW, Level 3 (mainly larger / newer BEVs with onboard charger capacity from 11 kW and above): 8–11.5 kW. For each user ID, the $P_{preliminary}$ value is categorised into one of the three charger capacity categories. If the same user has at least two charging sessions with $P_{charging}$ in the same charger capacity category, the $P_{preliminary}$ value is considered to be the final charging power prediction (P_{user}). Otherwise, the charging session with the preliminary prediction is filtered as an outlier, and a new $P_{preliminary}$ value is calculated. The recalculation is repeated, until all user IDs have a final charging power prediction. For the 267 user IDs that we analysed, P_{user} was predicted directly for 93% (249) of the user IDs ($P_{user} = P_{preliminary}$, no filtering needed). P_{user} was predicted for 6% (17) of the user IDs after filtering one outlier, and 1 user ID after filtering two outliers. Finally, user IDs with P_{user} values of less than 2 kW were removed (6 user IDs), since no EVs with less than 3 kW charging power were identified on the market, thus it was assumed that the predictions were too low. Due to the assumption that all user IDs have at least one interrupted charging session, P_{user} prediction for user IDs with no interrupted charging sessions will be too low. The assumptions and justifications applied in the method are summarized in Table 5.

Table 5
EV charging power prediction method: Assumptions and justifications.

Assumptions	Justifications
The average charging power for each EV user is constant	Actual charging power varies with EV, CP, SoC, temperatures etc. Charging power for single charging sessions is presented by e.g.[13,43–45]. For a large dataset it is necessary to apply a constant charging power, since the actual charging power is not known. The assumption of a constant charging power is generally used in literature (ref. examples in Table 1).
All user IDs have at least one interrupted charging session with plug-out during charging	The method provides charging power values per user, while studies in the literature generally assume the same charging power values for the complete EV fleet (ref. Table 1). The assumption may result in too low charging power values if no charging sessions are interrupted. To reduce this risk, user IDs with charging power values of less than 2 kW were removed (no such EVs on the market). The assumption may result in too high values if several EVs are connected to one user ID. The step of filtering outliers is therefore included, but with the risk of filtering real charging power values. Despite the risks, this is a transparent simplification, which is assumed to give satisfactory charging power levels when aggregated. The method is validated with EV data, as described in Sections 3.3 and 4.1.

3.2. The net EV battery capacity prediction method

The aim of the net EV battery capacity prediction method is to provide predictions for the net EV battery capacity per user ID. When doing this, it is assumed that all user IDs have at least one charging session where they charge their EV battery a certain SoC range; from a defined minimum SoC-level to a defined maximum SoC-level. Initially, the charging session with the highest value for energy charged for each user is selected. No large values or outliers are filtered in this process, since it is expected that some users seldom charge the full SoC range of their EV batteries [29,37]. A filtering process may therefore remove valuable data. The selected maximum values are multiplied by an efficiency for one-way AC/DC conversion to calculate the approximate amount of energy stored in the battery ($E_{battery}$), as shown in Eq. 4. For EV charging, [46] and [47] have found energy losses between 12% and 40%. Marra et al. [19] considered 88% charging efficiency, based on empirical studies. Thus, in our work, a charging efficiency (η) of 88% is assumed.

$$\text{Maximum energy stored in } battery: \ \max(E_{battery}) = \max(E_{charged}) \times \eta \quad (4)$$

$$\text{Battery capacity } prediction: \ E_{battery-size} = \max(E_{charged}) / SoC_{range} \quad (5)$$

The calculated values for maximum energy stored in the batteries (Eq. 4) are divided by an assumed SoC range for the charging session (Eq. 5) to get a prediction of the battery capacities. Two different SoC ranges are assumed for the EV users, dependent on the EV battery classification, i.e., small/medium (EV-SM) or large (EV-L). This is based on the hypothesis that users with large batteries are less likely to charge their EVs from nearly empty to completely full. As found by [29,37], most EV users prefer charging their EV batteries before reaching about 20% SoC. EV users with smaller batteries are expected to more frequently charge for a larger SoC range, based on the occasionally need for longer driving ranges. The findings by [31] support this theory, as they found few EVs with large batteries when assuming that all users charged their battery from 0% to 100%. Two different levels are therefore set for the minimum SoC-level: 10% for EV-SM and 20% for EV-L. The defined maximum SoC-level is set to 100% for all EV users. This gives a SoC range of 90% for EV-SM and 80% for EV-L.

The threshold value that is used to categorize the EVs into two battery capacity groups are based on Eq. 4, which represent the net battery capacity within the defined SoC-range only. When using different SoC ranges to predict the battery capacities (Eq. 5), a gap between the net battery capacity groups appears. The EV-SM group has battery capacities up to 31.1 kWh and the EV-SM group has battery capacities above 35 kWh. The threshold value is chosen based on the net battery capacity of typical EVs on the marked (ref. Fig. 2), and is comparable to the 33 kWh value used by [31]. There is no distinction between the BEV and the PHEV in our study, and PHEV is included in the EV-SM group. Table 6 shows a summary of the assumptions and justifications for prediction of EV battery capacity.

3.3. Method for validation of the EV charging power and battery capacity predictions

To validate the suggested methods, the EV charging power and battery capacity predictions in Section 4.1 were compared to information from 15 users in location TRO_R and BAR_2, including data on their nominal onboard charger capacities (kW AC) and net battery capacities (kWh). For the remaining locations, the CPO reports were anonymized, with no information about the users and their EVs. In addition, the results were compared to typical charging characteristic for models of EVs on the market [13,16,17], as shown in Fig. 2. The market data includes 102 models of BEVs and PHEVs described by [16] and [17]. Since some car manufacturers publish gross battery capacities only, the presented net battery capacity for these manufacturers is set equal to the capacity predicted by [16,17].

3.4. Hourly battery SoC prediction method

As a basis for predicting the hourly SoC values, energy charged during charging sessions were distributed hourly on the timeline, using the methodology presented in [13]. For calculating the hourly charging loads ($E_{load\ (i)}$), the EV charging power predictions per user ID (P_{user}) are multiplied with the hourly charging time (Eq. 6). It is assumed that the charging starts immediately after plug-in, and that the charging power is fixed over the whole charging time.

$$\text{Charging load for } hour\ i: \ E_{load(i)} = P_{user} \times t_{charging(i)} \text{ where } \sum E_{load(i)} = E_{charged} \quad (6)$$

For every charging session hour, the SoC difference for each EV is calculated as the hourly energy stored in the battery (energy load multiplied with efficiency) divided by the battery capacity prediction for each user ($E_{user\text{-}battery}$) (Eq. 7). Assuming a final SoC value, the SoC value every hour can be calculated, starting with the last hour of every session and then proceed reverse in time, hour-by-hour until the first session hour. We assumed that all uninterrupted charging sessions continued charging until the battery was nearly full, i.e., with final SoCs of 80%, 95% or 100%. This assumption is justified by [38], which found median values above 95% for final SoCs. No final SoC values were assumed for charging sessions where the predicted non-charging idle time was less than an hour, since these charging sessions may have been stopped by the user.

$$\text{SoC difference for } hour\ i: \ SoC_{diff(i)} = E_{load(i)} \times \eta / E_{user-battery} \quad (7)$$

Table 6
EV battery capacity prediction method: Assumptions and justifications.

Assumptions			Justifications
All user IDs have at least one charging session where they charge their EV battery at a certain SoC range			For a large dataset it is necessary to apply this simplification, since the actual battery capacity is not known. A similar assumption is made by [31]. The assumption may result in too low or too high EV battery capacity predictions if the maximum SoC range is smaller or larger than assumed. The method is validated with EV data, as described in Sections 3.3 and 4.1
Some users seldom charge the full SoC range of their EV batteries			Based on findings in [28,33]. No large values or outliers are therefore filtered in this process. The method may result in too high values if several EVs are connected to one user ID.
	EV-SM	EV-L	
η	0.88	0.88	Based on [19], supported by [46,47].
SoC_{range}	0.9 (10–100%)	0.8 (20–100%)	Most EV users prefer charging their EV batteries before reaching about 20% SoC [29,37]. EV users with smaller batteries are expected to more frequently charge a larger SoC range. This is strengthened by the findings of [31]. To improve the results, two different SoC-ranges are therefore assumed for EV-SM and EV-L.
max ($E_{battery}$)	< 28 kWh	> 28 kWh	Calculated using Eq. 4.
$E_{battery\text{-}size}$	< 31.1 kWh	> 35 kWh	Calculated using Eq. 5. The threshold value for EV-SM and EV-L is chosen based on the net battery capacity of typical EVs on the marked (ref. Fig. 2), and is in the range of the value used by [31] of 33 kWh.

3.5. Comparing charging habits for EV users with different battery and charging power capacities

In this work, we investigate how residential charging behaviour is affected by the EV battery capacity and charging power. To do this, energy charged, SoC-values, idle energy capacities, and time related data are compared for EV users with different battery and charging power capacities. Hourly values for idle energy capacities are predicted by using the methodology presented in [13], where hourly idle times for a session are multiplied by the assumed charging power for the user ID. The session idle time is calculated according to Eq. 8. The sum of the charging loads and idle energy capacities is referred to as the connected energy capacity (Eq. 9). The hourly time series include all hours, also hours with no connected EVs.

$$\text{Idle time per session}: t_{idle} = t_{connection} - t_{charging} \tag{8}$$

$$\text{Connected energy capacity for hour} i: E_{connected(i)} = E_{load(i)} + E_{idle(i)} \tag{9}$$

The hourly energy loads and idle energy capacities in Section 4.3 are presented normalized per user. Each user ID is classified as 'active' after their first charging session and 'inactive' after their last charging session. For the first and last 30 days in the measurement period of a given location, users are classified as 'active' if having at least one charging session during the 30-days period. This is done to prevent faulty classification of active users that are not charging frequently.

The hypothesis that EV battery and charging power capacity influence the charging behaviour is tested by organising the user IDs into four user groups according to their predicted net battery capacity (below/above 33 kWh) and AC charging power (below/above 4 kW). Then, charging habits for the four user groups are presented and compared, with particular focus on the two main user groups SM_Low and L_High, which represent the largest differences in EV technology. For example, we want to compare if energy charged per session for SM_Low is significantly different than for L_High. The comparison is done by using a two-sample Mann-Whitney U Test [48,49], performed with the wilcox. test function in R [50]. The Mann-Whitney test is rank-based, and does not rely on distribution assumptions, such as the two-sample t-test does. It tests the null hypothesis (H_0): That the two independent groups have the same distribution, against the alternative hypothesis (H_1): That the distribution of the first group differs from the second group. The result is evaluated as significant if the calculated p-value is less or equal to 0.05. This suggests that the values for the two groups are different, and it is likely that an observation in one group is greater (or smaller) than the observation in the other group. Mean charging habit values are calculated for the two groups, such as average load profiles, charging energy and frequencies, charging duration, and start SoC values. Distributions are shown in graphs, with data for SM_Low, L_High, and all users. The case study values are compared with values from relevant studies in the literature.

4. Results and discussion

4.1. EV charging power and net battery capacity prediction

Fig. 5 shows the EV charging powers predicted for all the EV users. The grey lines in the figure represent onboard charging capacity levels for EVs on the market (ref Fig. 2). Black stars represent charging power for 15 of the EVs for which information was received about the onboard charger capacities (manufacturer data from [16,17]) as well as the available AC power at the location. For these 15 EVs, the predicted charging power values are close to the real values (difference of up to 0.5 kW).

The user IDs are grouped into three charging power levels, where 46% of the user IDs are predicted to be within charging power level 1 (<4 kW), 38% are within level 2 (4 <8 kW), and 16% are within level 3 (8–11.5 kW). The charging power levels per location are further described in Table 7. For most locations there are users within all the three charging power levels. As stated above, the charging power is limited by the onboard charging capacity of the EV or the power available from the CP (typically 7.4 or 11.0 kW in Norway). For users with onboard charging capacities below 7.4 kW, the power is most likely limited by the onboard charging capacity of the EV. For two of the locations (BER, and OSL_S), all the user IDs were predicted to be within power level 1. This is most probably due to local power limitations for the charging power, which for example can be caused by limited grid connection power capacity of the building. For users with onboard charging capacities above 7.4 kW, the charging power is mostly limited by the CP. The exception is EVs that have activated three-phase charging, where the charging power may be up to 11.0 kW for some EV models.

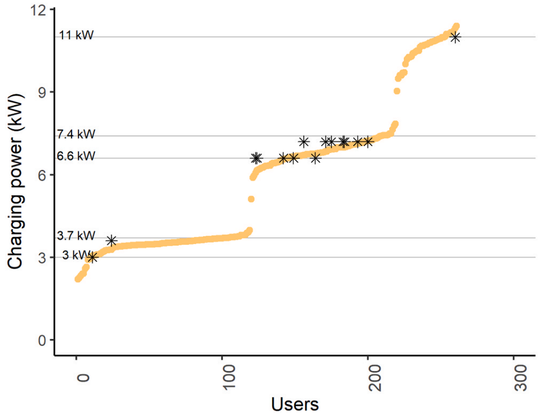


Fig. 5. EV charging power predictions for all EV users. Grey lines: Nominal onboard charger capacity for EVs on the market. Black stars: Validation of charging power for 15 EVs.

Fig. 6 shows net EV battery capacity predictions for all the EV users. 55% of the user IDs are predicted with EV-SM (below 33 kWh) and 45% with EV-L (above 33 kWh). Comparing the predicted battery capacities with known net battery capacities for the 15 EVs, it was found that the predicted values are close to the real values for the five users with EV-SM. The differences are up to 3.5 kWh, and all the predictions are lower than the real values. For the ten users with EV-L, the differences between the predictions and the real values are larger. One user was found to have charged 78.6 kWh, even though the net battery capacity was 52 kWh. Assuming that the values are correct, the charging losses must be larger than predicted (the EV in question used an external transformer during charging). For the remaining nine EVs, the differences were up to 15 kWh, some higher and some lower than the real values. These differences may be explained by a variance between the real values and the assumptions for charging efficiencies or SoC ranges in Table 6. However, even though there are some differences between the predictions and the real data, the methods provide a fairly accurate indication of the net battery capacities.

All the predictions of EV charging power and EV battery capacities are combined in Fig. 7, together with charging characteristics for EVs on the market (ref. Fig. 2). Four user groups are marked in the figure (SM_Low, SM_High, L_Low, L_High), forming a basis for the analysis in Section 4.3. Fig. 7 shows that the predictions provided by the methods in this paper are in the range of typical EVs on the market. Since the charging power method also takes the local power capacity into account, and not only the onboard charger capacity, EVs with onboard charger capacities above 11.0 kW are not represented in the results.

32 users are grouped as L_Low, even though there are no such EVs identified on the market. This may be explained by local power

Table 7
Charging power levels in the 12 case locations: Share of users within each level.

Location (n) Level	ASK (21)	BAR (8)	BAR_2 (6)	BER (8)	BOD (6)	KRO (8)	OSL_1 (14)	OSL_2 (4)	OSL_S (27)	OSL_T (60)	TRO (23)	TRO_R (76)	All (261)
1 (<4 kW)	0.52	0.88	0.17	1.00	0.17	0.13	0.36	0.25	1.00	0.23	0.33	0.47	0.46
2 (4 <8 kW)	0.29	0.12	0.66		0.33	0.50	0.07			0.54	0.42	0.53	0.38
3 (8–11.5 kW)	0.19		0.17		0.50	0.37	0.57	0.75		0.23	0.25		0.16

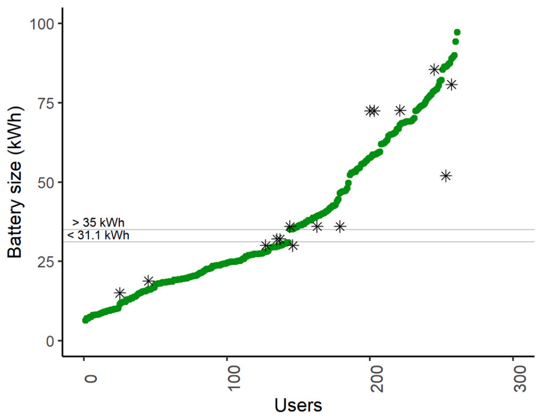


Fig. 6. Net EV battery capacity predictions for all EV users. Grey lines: Max/min battery capacities for EV-SM and EV-L. Black stars: Validation of net battery capacity for 15 EVs.

limitations. Such possible power limitations were discussed earlier in Section 4.1 for two of the locations (BER, OSL_S). The possible power limitation is supported by Fig. 7, where 23 user predictions for the two locations are grouped as L_Low (red tringles in the figure). Local power limitations may also be the case for the remaining 9 users, or these users may not have disconnected their EVs during charging. There are also EV models which does not charge optimally on the IT grid (e.g. the Zoe transformer provides 3.6 kW [51]), which may explain some differences between the predicted low charging power and the actual onboard charging power of the EVs.

4.2. Hourly battery SoC predictions

Hourly battery SoC values are predicted for all the charging sessions. Table 8 shows an example of input data and predictions for one of the charging sessions (TRO_20989). In the example, an end SoC of 95% is assumed.

The distribution of start SoC values are shown in Fig. 8. The figure illustrates situations with assumed end SoCs of 80%, 95% and 100%. In our study, 59% of the residential EVs are plugged-in when SoC is above 50%, assuming an end-SoC of 95%. The values are in the range of the findings by [52], which discovered that a high share (65%) of the EV drivers plug in their company cars when the SoC is above 50%. The distribution of start SoC values can also be compared with results presented by [39], which analysed SoC values for EV drivers with a dedicated home charger available. They found that the start SoC values for these drivers were distributed between approximately 20% and 90%, and with a rise towards the higher start SoC values. A high start SoC provides opportunities for Vehicle to grid (V2G) in the future, since the EVs can deliver energy to the building or grid during peak periods.

Fig. 9 shows median values for the predicted start SoCs and how the SoC values differ in the course of a day. Assuming an end SoC of 80–100%, the median start SoC values of the dataset are 42–62%, close to the mean values of 40–60%. The predictions can be compared to hourly median values from [38], where start SoC values were available from 9566 charging sessions. Due to the low number of observed sessions at night in [38], the values were aggregated from 11 pm to 6 am (n = 321). The study also found that the start SoC values differed over the day. This can also be found from the data in our study, but to a smaller degree than in [38]. This may have several explanations; The users may behave differently (private EVs in our study compared to mainly company EVs in [38]), or the predicted values may not be fully accurate. Still, the predicted start SoC values are in the same range as the measured values found in [38].

Daily average SoC values for connected EVs are shown in Fig. 10, along with the number of connected EVs and new connections each hour. The figure shows how the average SoC-values for all the connected EVs are at the lowest in the afternoon, when most new EVs are being connected. During the night-time, the average SoC-values are getting close to the end SoC-values since most of the EVs have finished charging and there are few new connections.

4.3. Comparing charging habits for EV users with different battery and charging power capacities

This section analyses how residential charging behaviour is affected by EV battery capacity and charging power. For the aggregated EV

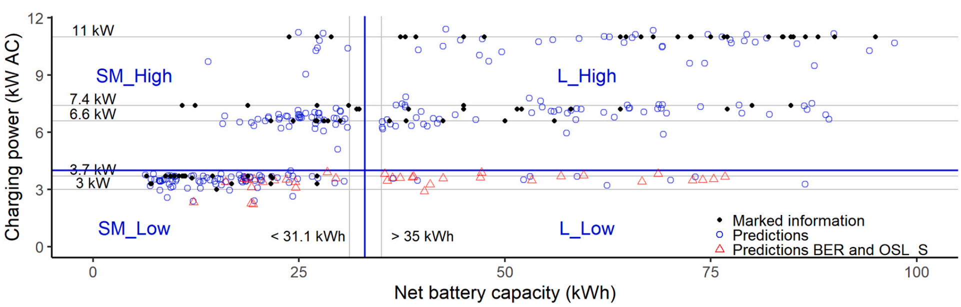


Fig. 7. User predictions: EV charging power and battery capacities (n users = 261). EV market information: Nominal onboard charger capacity and net battery capacity. Four user groups are defined: SM_Low, SM_High, L_Low, and L_High.

Table 8
Data for example session (TRO_20989).

User and session data										
CPO report data					Predicted user data		Predicted session data			
Session ID	$t_{plug\text{-}in}$	$t_{plug\text{-}out}$	$t_{connection}$ [h]	$E_{charged}$ [kWh]	$P_{charging}$ [kW]	$E_{battery\text{-}size}$ [kWh]	$t_{charging}$ [h]	t_{idle} [h]	SoC_{diff}	E_{idle} [kWh]
TRO_ 20989	2020–01–16 19:12:00	2020–01–17 08:08:00	12.9	12.5	7.1	55.6	1.8	11.2	19.8%	79.4

Hourly data						
Date from	E_{load} [kWh]	E_{idle} [kWh]	$E_{connected}$ [kWh]	SoC_{diff}	SoC from	SoC to
2020–01–16 19:00	5.7	0	5.7	9.0%	75.2%	84.2%
2020–01–16 20:00	6.8	0.3	7.1	10.8%	84.2%	95.0%
2020–01–16 21:00	0	7.1	7.1	0	95.0%	95.0%
2020–01–16 22:00	0	7.1	7.1	0	95.0%	95.0%
2020–01–16 23:00	0	7.1	7.1	0	95.0%	95.0%
2020–01–17 00:00	0	7.1	7.1	0	95.0%	95.0%
2020–01–17 01:00	0	7.1	7.1	0	95.0%	95.0%
2020–01–17 02:00	0	7.1	7.1	0	95.0%	95.0%
2020–01–17 03:00	0	7.1	7.1	0	95.0%	95.0%
2020–01–17 04:00	0	7.1	7.1	0	95.0%	95.0%
2020–01–17 05:00	0	7.1	7.1	0	95.0%	95.0%
2020–01–17 06:00	0	7.1	7.1	0	95.0%	95.0%
2020–01–17 07:00	0	7.1	7.1	0	95.0%	95.0%
2020–01–17 08:00	0	0.9	0.9	0	95.0%	95.0%

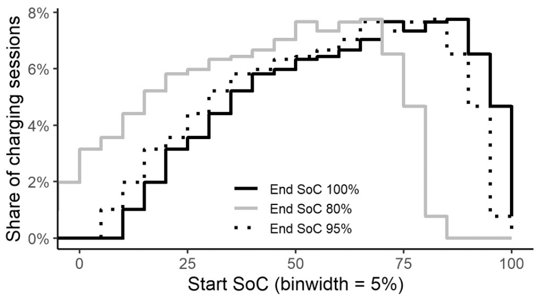


Fig. 8. Distribution of start SoC for the charging sessions, with assumed end SoCs of 80%, 95% og 100%.

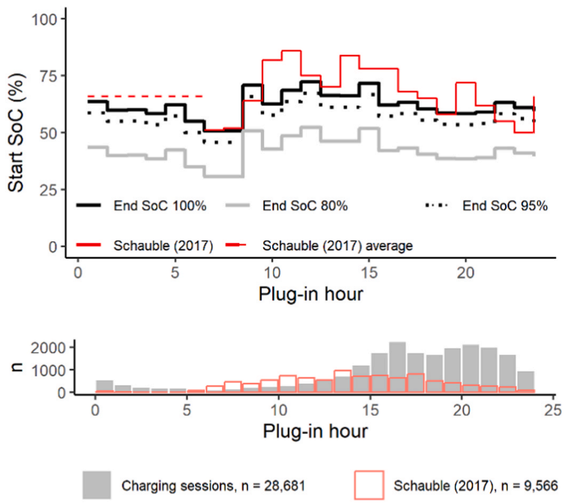


Fig. 9. Hourly distribution of predicted start SoC (median line) (n = 28,681). Median predictions are compared with measured values in [38]. Lower fig.: Number of charging sessions starting each hour.

charging, Fig. 11 shows how the average load profiles have an increased energy use in the afternoons and evenings, with the highest load occurring between 16:00 and midnight. The average load is at the lowest during night/early morning and during daytime. The average load profiles for the 12 locations in our study are similar to the profiles found in a previous analysis of the location TRO_R in [13], which were verified with hourly smart meter data. For charging sessions with idle times less than 1 h, the charging loads are marked as non-flexible. Most of this non-flexible charging occurs during the afternoon/evening. Fig. 11 also shows average connected energy capacities, where the difference between energy charged and connected energy capacity is the average idle energy capacity. The connected energy capacities illustrate how the EVs typically stay plugged-in during night-time. During workdays, the daily connected energy capacity is on average more than four times as high as the energy charged during the day. Even though this is based on average values, it reflects a considerable potential for shifting the EV charging in time, especially from afternoon/evenings to night-time. Other data-based EV studies confirm this flexibility potential in the residential sector, e.g. [13,53–56].

When analysing grid-capacity, the maximum load profile may be more important than the average load profile. Load profiles per user is shown in Fig. 12, including the maximum energy charged, the 99th percentile, the 90th percentile, and the average and 25th percentiles of hourly energy charged. The maximum load profiles have two afternoon/evening peaks during workdays, around 17:00 and 21:00, and one afternoon peak on Saturdays. In Fig. 12, only periods with 30 or more users are included, since the aggregated peak power per user is reduced with increasing number of users [13].

In the future, charging habits may change due to increasing battery capacities and available charging power, which again will affect the load profiles and flexibility potential of EV charging. In Fig. 13, daily average load profiles are shown for four user groups (SM_Low, SM_High, L_Low, L_High), based on net battery capacity (below/above 33 kWh) and charging power capacity (below/above 4 kW). In Table 9, the charging habits of the two user groups SM_Low and L_High are further described and compared. Mann-Whitney p-values are included in the table, to test if SM_Low and L_High are significantly different. SM_Low and L_High were chosen, since these are main user groups which also represent the

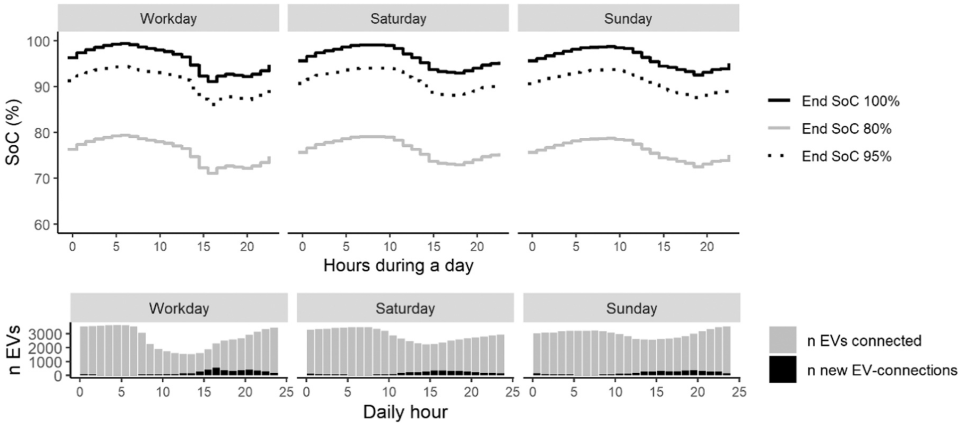


Fig. 10. Upper figure: Daily average SoC values for connected EVs. Lower figure: Number of connected EVs (n connected hours = 373,989) and new connections each hour (n sessions = 28,681).

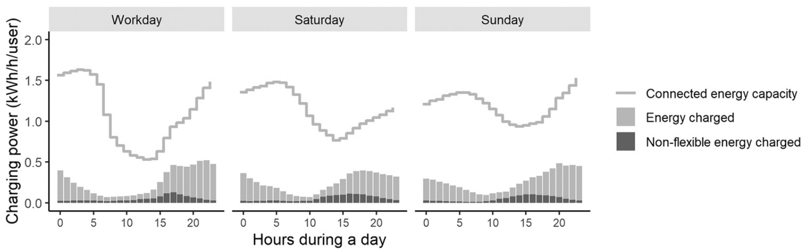


Fig. 11. Daily load profiles per user: Energy charged, non-flexible energy charged (idle time < 1 h), and connected energy capacity. (n users = 224, n sessions = 28,682).

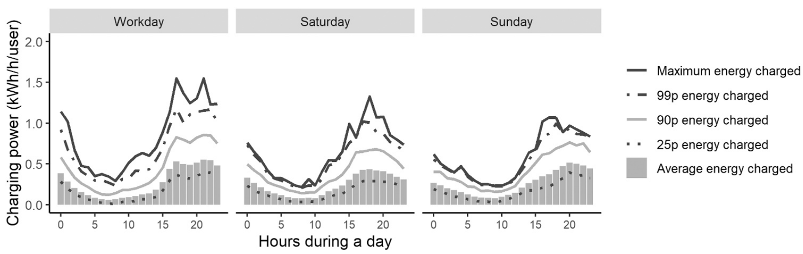


Fig. 12. Daily load profiles per user: Maximum, 99th percentile, 90th percentile, average, and 25th percentile energy charged (n users = 30 < 224).

largest differences in EV technology. The market data found in [16] and [17], including technical data from 102 models of EVs, show that 78% of the EVs have net battery capacities and onboard charger capacities within the SM_Low (25 EVs) or L_High (55 EVs) groups, while the remaining models are SM_High (22 EVs).

Fig. 13 shows that the average energy charged every day is about 1.5 times higher for the users with EV-L than for the users with EV-SM. The energy consumption of an EV is influenced by vehicle-, environment-, and driver-related factors [57], and in general, EVs with large batteries are heavier than EVs with small/ medium sized batteries. Still, the results indicate that users with larger battery capacities also drive more than the users with smaller batteries. This corresponds to interview results found by [58], where drivers with a battery capacity of more than 55 kWh used their car more frequently for long trips, compared to drivers with smaller battery capacities. It is also in line with a questionnaire amongst Dutch EV drivers [59], where only 23% of the Tesla Model S drivers (L_High) answered that they regularly or often used other transportation than the EV due to long distances, while 95% of Nissan Leaf drivers (SM_Low) indicated the same. Another reason for the difference may be due to the charging location, since [39] found that owners of EVs with large battery capacities were more likely to charge at home. Fig. 13 shows that it is especially in the afternoons/evenings that the users with EV-L have a higher hourly energy demand than the users with EV-SM, while the day-time charging is low and more similar for all the four user groups. For the two user groups with low charging power, SM_Low is finished charging around midnight, while L_Low requires more night-hours to finalize the charging.

A histogram of energy charged per charging session is included in

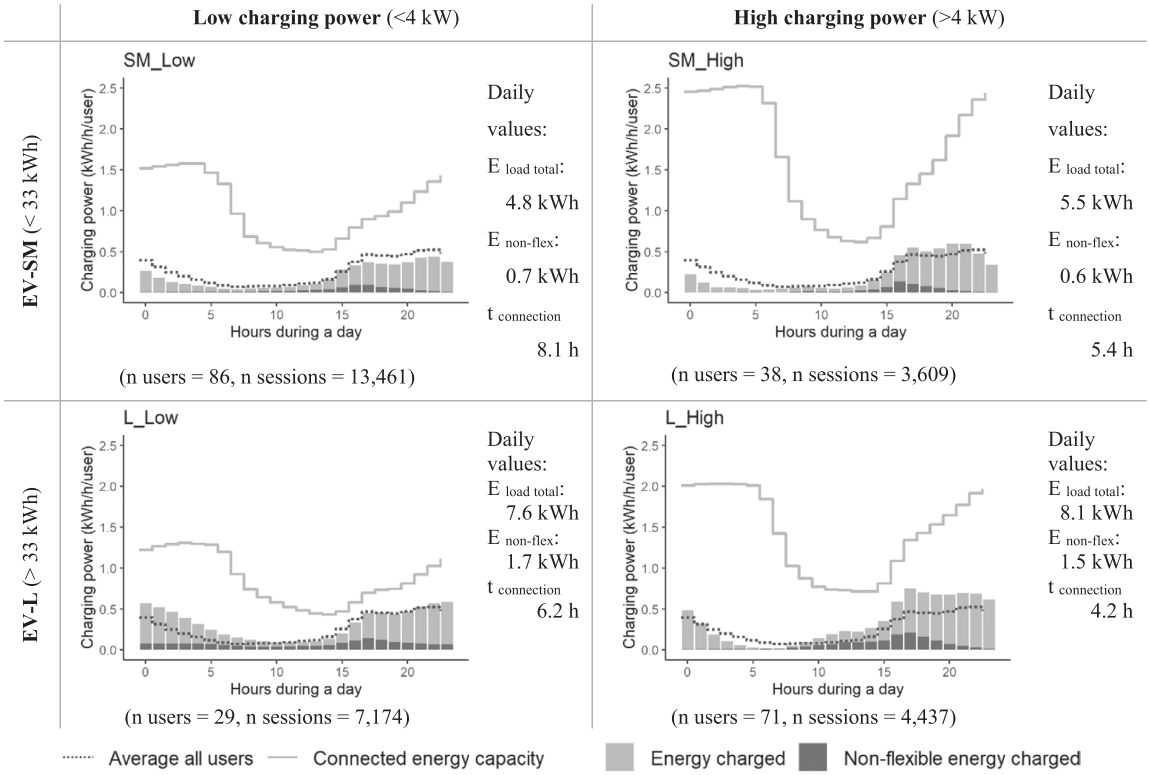


Fig. 13. Daily load profiles per user during workdays, for four different EV categories. The figure shows energy charged, non-flexible energy charged (idle time < 1 h), and connected energy capacity.

Table 9-C, where the vertical line represents the max/min battery capacity for EV-SM and EV-L. The mean value for all charging sessions is 12.4 kWh (SD 11.2 kWh), where L_High charges nearly three times as much energy during each session compared to SM_Low. The results are in line with results from the Netherlands reported in [33], where session energy was 25 kWh for EVs with battery capacities > 70 kWh, and 10 kWh for EVs with battery capacities of 16–30 kWh. The results indicate that most EV users with larger batteries seldom utilize the full battery capacity. Only 16% of all EV-L sessions (n = 2291) charge more than 33 kWh. This is confirmed by the histogram of predicted SoC values per charging session, illustrated in Table 9-D. Looking at all users together, charged energy is less than half of the net battery capacity for 65% of the charging sessions. For SM_Low, the average SoC difference is 42% while it is 34% for L_High. It should be noted that these average SoC difference values are affected by the choice of using different SoC ranges when predicting battery capacities for SM_Low and L_High. If battery capacities for L_High were predicted with the same SoC range as for SM_Low (90%), the average SoC difference becomes more similar: 41% for SM_Low and 37% for L_High. However, also [39] found a relationship between battery capacity and start SoC, where EVs with larger batteries are charged at higher start SoC.

Idle energy capacities represent the flexibility potential of EV charging, since the EV charging can be shifted in time. Comparing idle energy capacities for SM_Low and L_High in Table 9-E, the average daily idle energy capacity is 1.3 times higher for L_High. As shown in Fig. 13, the idle energy capacity is higher for SM_Low than for L_Low, which can be explained by the fact that the L_Low group has less idle time due to less average connection time (SM_Low: 8.1 h, L_Low: 6.2 h), and that the L-Low need more time for charging a larger energy amount. A similar relationship can be found between SM_High and L_High.

Users with small and large weekly charging demands are compared, corresponding to 25th and 75th percentiles of the demands. For users with lower weekly charging demand (25th percentile), the average values are 25 kWh of energy charged per week and 24 kWh of idle energy capacity per week. For users with higher weekly charging demand (75th percentile), the average values are 61 kWh of energy charged per week and 42 kWh of idle energy capacity per week. The data indicates that users with lower weekly charging demand have a longer idle time per charging session (average 14.3 h of idle time per session) compared to users with a higher weekly charging demand (average 7.9 h of idle time per session).

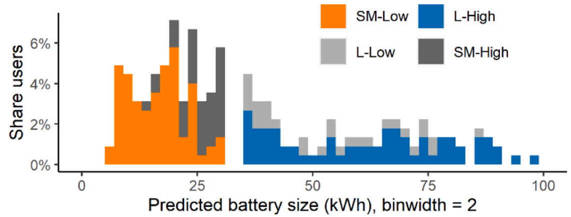
The charging sessions are distributed fairly evenly throughout the week, as shown in Table 9-K. Users with larger batteries charge less frequently than users with smaller batteries: 2.6 times per week for L_High, compared to 4.7 times per week for SM_Low. The results are supported by [58], where about 40% of the interviewed Norwegian Tesla drivers (L_High) charged their EVs less than 3 times per week, while 30% of other EV drivers stated the same. Similar results were found amongst Dutch EV drivers [59], where 62% of the Tesla Model S drivers (L_High) stated that they charged their EVs 3 times a week or less, while 80% of Nissan Leaf drivers (SM_Low) stated that they charged their EVs more than 3 times per week. Also the charging frequencies reported in [33] were similar, where EV drivers with large battery capacities (>70 kWh) in the Netherlands charged their EVs 2.8 times per week, and small battery capacities owners (16–30 kWh) charged 4 times per week.

Table 9
Charging data for all users, SM_Low and L_High. N users = 224 (SM_Low 86, L_High 71), n sessions = 28,681 (SM_Low 13,461, L_High 4437).

Mean values (standard deviation) | Distribution

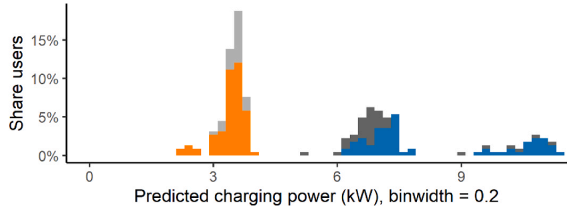
A. Battery capacity (calculated according to the net EV battery capacity prediction method, described inSection 3.2)

	All users	SM_Low	L_High
[kWh per user]	37.2 (24.0)	16.4 (6.2)	61.7 (18.2)



B. Charging power (calculated according to the EV charging power prediction method, described in Section 3.1)

	All users	SM_Low	L_High
[kW per user]	5.6 (2.6)	3.4 (0.4)	8.3 (1.8)



C. Energy charged (from CPO reports)

	All users	SM_Low	L_High
[kWh per user/day]	6.2	4.8	7.8
[kWh per session]	12.4 (11.2)	7.9 (4.9)	23.4 (16.9)

Mann-Whitney p-value: Significant (< 2.2e-16)

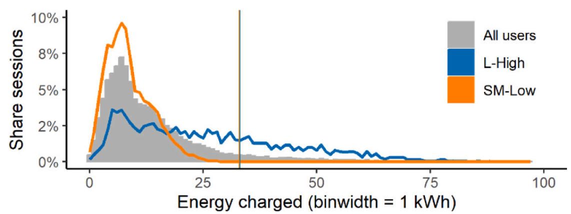


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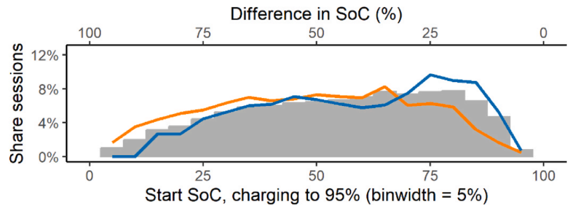
Table 9 (*continued*)

Mean values (standard deviation) — Distribution

D. SoC (calculated according to the hourly battery SoC prediction method, described in Section 3.4)

SoC-diff per session	36% (23%)	42% (23%)	34% (21%)
Mann-Whitney p-value: Significant (< 2.2e-16)			
	59% (23%)	53% (23%)	61% (21%)

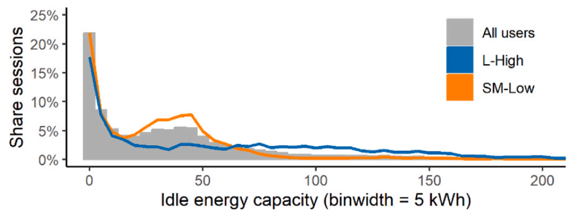
Start SoC per session, given 95% end SoC — Mann-Whitney p-value: Significant (< 2.2e-16)



E. Idle energy capacity (predicted according to methodology presented in [13], as described in Section 3.5)

	All users	SM_Low	L_High
[kWh per user/day]	20.5	20.6	27.1
[kWh per session]	44.8 (66.8)	34.7 (43.0)	82.5 (112.2)

Mann-Whitney p-value: Significant (< 2.2e-16)



F. Weekly charging sessions (from CPO reports)

	All users	SM_Low	L_High
[# per user]	3.7 (2.6)	4.7 (2.9)	2.6 (1.9)

Mann-Whitney p-value: Significant (1.47e-06)

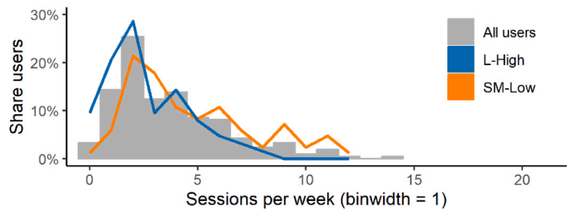


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Table 9 (*continued*)

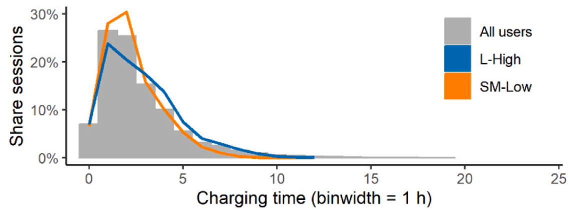
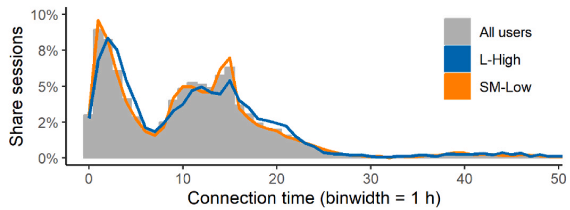
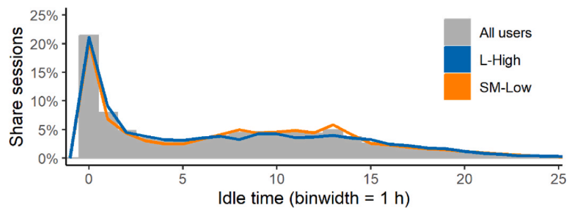
Mean values (standard deviation)	Distribution
G. Charging time (predicted, based on Eq. 3 in Section 3.1: $t_{charging} = E_{charged} / P_{charging}$) All users / SM_Low / L_High [hours per session] 2.7 (2.3) / 2.3 (1.5) / 2.8 (2.0) Mann-Whitney p-value: Significant (< 2.2e-16)	
H. Connection time (from CPO reports) All users / SM_Low / L_High [hours per session] 12.0 (12.2) / 12.5 (13.3) / 12.4 (12.9) Mann-Whitney p-value: Not significant (0.070)	
I. Idle time (predicted, based on Eq. 8 in Section 3.5) All users / SM_Low / L_High [hours per session] 9.3 (12.0) / 10.2 (13.1) / 9.6 (12.7) Mann-Whitney p-value: Significant (0.00030)	

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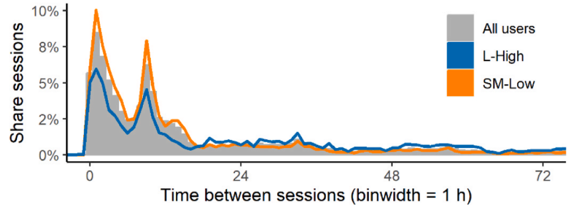
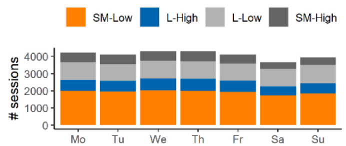
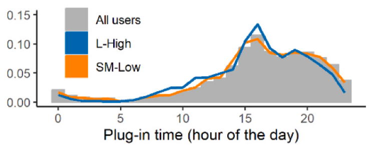
Table 9 (*continued*)

Mean values (standard deviation)				Distribution
J. Time between charging sessions (from CPO reports)				
	All users	SM_Low	L_High	
[hours]	31.0 (58.9)	23.4 (47.7)	50.9 (81.0)	
Mann-Whitney p-value: Significant (< 2.2e-16)				

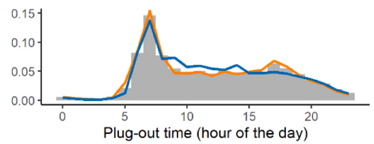
K. Sessions per day of the week
(from CPO reports)



L. Distribution of plug-in times
(from CPO reports)



M. Distribution of plug-out times
(from CPO reports)



The connection times are not significantly different for the user groups SM_High and L_High, and there is a twin peak in the density distribution, where users either charge for a few hours during daytime or for a longer overnight period. Similar charging durations were found by [34], for EV drivers in the Netherlands. For both groups in our dataset, about 23% of the sessions last for less than 3 h, while about 45% of the sessions last for more than 12 h. This confirms that the main rationale behind the connection times is the daily habits of people and not their type of EV. The predicted charging times and idle times are quite similar for the two user groups. Even though energy charged per charging session is higher for L_High, this is compensated by the higher charging power. The average time between charging sessions is about 23 h for SM_Low and 51 h for L_High (after removing situations with more than 1 month between charging sessions).

The magnitude of the available charging power has impacts for the car users, and for the electricity loads and flexibility potential. For the users, a higher charging power provides the possibility of charging the EV faster. However, this may come with a cost, e.g., related to higher power tariffs or a need to upgrade the electricity distribution and fuse sizes for the building. For many users, however, the charging time is normally not an issue even with lower charging powers, since their daily driving distances are limited. In this study, the energy charged was below 19 kWh for 80% of the EV sessions, which can be charged in about 5.5 h even with a low charging power of 3.6 kW. When the charging power is high, there is a risk that also the peak power will be higher, i.e. if the EV charging coincides with the peak domestic demand [20]. When comparing two charging power levels for apartment buildings in [13], the hourly aggregated charging peaks increased with a factor of 1.2, going from 3.6 to 7.2 kW charging power, assuming immediate charging after plug-in. Bollerslev et al. [23] found that the peak power demand was reduced by about 40% and 60%, respectively, when going from a charging power of 3.7 kW to 11 or 22 kW. However, a high charging power also provides a better opportunity for smart charging. In [13], the average idle energy capacity during weekdays was 2.3 times higher with a charging power of 7.2 kW compared to a charging power of 3.6 kW. Such smart charging strategies can save costs for the users and provide benefits for the electricity grid.

5. Conclusions

With an increasing number of EVs worldwide, there is a need for more data and research on EV characteristics and related EV charging behaviour. This paper proposes a set of methodologies for generating complete EV charging datasets, from data commonly available in CPO reports. The case study includes more than 35,000 charging sessions from 267 users in 12 residential locations in Norway. Residential charging behaviour is analysed, and it is described how these are affected by EV battery capacity and charging power.

- A set of simple methods are proposed for more accurate predictions of battery capacities, charging power, and plug-in SoC for all EVs and charging sessions. In our study, 46% of the users were found to have a charging power below 4 kW, while the remainder had a charging power between 4 and 11 kW. Also, we found that 55% of the users could be assumed to have battery capacities below 33 kWh, while 45% of the users had battery capacities between 33 and 100 kWh.
- Our work presents a statistical analysis on how residential charging behaviour is affected by EV battery capacity and charging power. On average, users in the residential case study charged around 6.2 kWh per day, having an average of 3.7 weekly charging sessions. The average energy charged every day was found to be 1.6 times higher for users with large batteries and high charging power (L_High) compared to users with small/medium batteries and low charging power (SM_Low).
- The results indicate that most EV users seldom utilize their full battery capacity, and especially EV users with larger batteries. For 65% of the charging sessions, the charged energy was found to be less than half of the predicted net battery capacity.
- The daily load profiles suggest that there is a considerable potential for shifting residential EV charging in time, especially from afternoon/evenings to night-time. Such utilization of energy flexibility can reduce the grid burden of residential EV charging. While the average charging time was less than 3 h, the EVs were in average connected to the CPs for 12 h. Comparing SM_Low and L_High, the average daily idle energy capacity was 1.3 times higher for L_High.

For high idle energy capacities, it is advantageous with high charging power, frequent connections, and long connection times. If users start charging less frequently in the future, this will affect the idle times and most likely reduce the flexibility potential. Other publicly available charging infrastructure and end-user costs may also impact the residential charging behaviour. For example, the use of public fast charging or EV charging in workplaces may reduce the need for home charging. In a future perspective, the use of V2G may increase the flexibility potential of EV charging, since the EV batteries can deliver electricity to the building or grid during the idle periods.

To generate the EV charging dataset in this work, it was necessary to make some assumptions, e.g., for charging efficiency and for maximum SoC range charged per EV user. However, the results were compared to results from the literature, which reinforced the validity of our findings. Further studies could be extended with larger datasets, and include also commercial buildings. In 2022, there were about 600.000 million EVs in Norway (8 million in Europe), and CPO reports are often available for energy management and invoice purposes. Having more such studies will make it possible to analyse how EV charging behaviour differs depending on building categories and user groups. EV charging related to office buildings will, for example, have different load profiles and flexibility potential compared to EV charging for company fleets such as healthcare services. If more real-world values for charging power, battery capacity, and session start SoC are made available, the validity of our results may be further increased.

The proposed set of methodologies aims to provide a complete EV dataset with EVs and charging sessions, where realistic predictions for battery capacities, charging power, and plug-in SoC are added to datasets with plug-in/plug-out times, and energy charged. Such datasets provide the basis for assessing current and future EV charging behaviour, data-driven energy flexibility characterization, and modelling of EV charging loads and EV integration with power grids.

CRediT authorship contribution statement

Åse Lekang Sørensen: Conceptualization, Methodology, Investigation, Data curation, Writing – original draft preparation, Writing – review & editing **Igor Sartori**: Conceptualization, Writing – review & editing, Supervision. **Karen Byskov Lindberg**: Conceptualization, Writing – review & editing, Supervision. **Inger Andresen**: Conceptualization, Writing – review & editing, Supervision.

Declaration of Competing Interest

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

Data Availability

Data will be made available on request.

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Main article III

Grid-connected cabin preheating of Electric Vehicles in cold climates – A non-flexible share of the EV energy use

Åse Lekang Sørensen, Bjørn Ludvigsen, Inger Andresen

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Table: The paper's context in the thesis.

	Supplementary articles	Main article I	Main article II	Main article III	Main article IV	Data articles *(D* describes planned articles)*
RQ1: What are the energy profiles for household energy use and PV generation for apartment buildings, and how are the energy profiles influenced by climate variables?	S I. Electricity S II. Heat-DHW S III. DHW S IV. PV				Main IV. Energy profiles	D* IV. Data Main IV
RQ2: How does the user habits influence the electricity load profiles of residential EV charging, and how is the el. load affected by EV cabin preheating?	S V. Stochastic EV charging	Main I. EV charging	Main II. EV charging	Main III. EV cabin preheating		D I. Data Main I D* II. Data Main II D* III. Data Main III
RQ3: What is the potential for electricity flexibility from EVs, in relation to non-flexible apartment building loads and PV generation, in the Norwegian context?					Main IV. Flexibility	

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Grid-connected cabin preheating of Electric Vehicles in cold climates – A non-flexible share of the EV energy use

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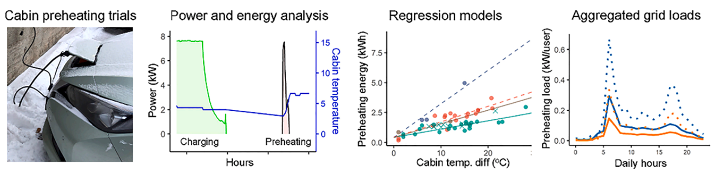
HIGHLIGHTS

- Grid-connected EV cabin preheating is used to extend driving ranges in cold climate.
- Experimental study with 51 preheating sessions of five typical EV models.
- Multiple linear regression models for energy use for EV cabin preheating.
- EV preheating energy loads are analysed with apartments loads during the winter.
- EV cabin preheating data are available for load simulations and forecasting.

GRAPHICAL ABSTRACT



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ABSTRACT

The number of EVs is increasing globally. In cold climates, it is generally recommended to use electricity from the grid to preheat the EV cabin before using the car, to extend driving ranges, to ensure comfort, and for safety. A majority of such preheating sessions are happening in the morning hours during the winter, when there is also a high demand for other energy use. It is thus important to understand the power loads for grid-connected preheating of EV cabins. This work presents an experimental study, with 51 preheating sessions of five typical EV models during different outdoor temperatures. The results of the study showed that during the preheating sessions, most of the EVs had a power use of between 3 and 8 kW initially, which was reduced to about 2 to 4 kW after a 10 to 20 min initial period. For most of the sessions, the preheating lasted between 15 and 45 min. The preheating energy use was found to be up to 2 kWh for most EVs, with a maximum of 5 kWh. Multiple linear regression models were developed, to investigate the relationship between various variables and the energy use for preheating. Finally, hourly energy loads for EV cabin preheating were compared to other energy loads in apartment buildings. The power and energy loads for preheating EV cabins are affected by a number of parameters, such as the specific EV, charge point, preheating duration, temperature levels, and user habits.

1. Introduction

1.1. Background and context

Greenhouse gas (GHG) emissions from the transportation sector contributed to 23 % of the energy-related GHG emissions worldwide in 2019, of which 70 % came from road vehicles [1]. Electric vehicles (EV) are part of the solution to reduce GHG emissions from land-based transport. The number of EVs is increasing globally, and reached 1 % stock share in 2020 [2]. As the density of EVs is increasing, it is important to understand the electricity use of the EVs. EV charging loads

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Nomenclature

AC	Alternating current
AMS	Advanced metering system, smart meters
BEV	Battery electric vehicle
COP	Coefficient of performance
CP	Charge point
CPO	Charge point operator
DC	Direct current
DHW	Domestic hot water
EV	Electric vehicle
GHG	Greenhouse gas
HP	Heat pump
HVAC	Heating, ventilation, and air conditioning
ICE	Internal Combustion Engine
Li-ion	Lithium-ion
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MLR	Multiple linear regression
MSE	Mean square error
MY	Model year
NA	Not available
PHEV	Plug-in hybrid electric vehicle
PTC	Positive temperature coefficient resistance
RH	Relative humidity
RTR	Rate of temperature rise
SoC	State of charge of the EV battery
V2G	Vehicle-to-grid
RMSE	Root mean square deviation

have an impact on the power grid, and [3] found that in 28 European countries, uncontrolled EV charging would increase peak demand in the range of 35–51 %. The situation can be improved using smart charging solutions and smart grid technology [4,5], e.g. by shifting EV charging loads to hours with capacity in the grid. However, not all of the EV charging loads are flexible in time. The flexibility potential of EV charging is related both to charging habits of the users, and to characteristics of the EV and the charge point (CP) [6].

The driving ranges of EVs are significantly reduced when the ambient temperature decreases, as documented in laboratory and field tests by [7–11]. The reduction is largely related to the energy use of the heating, ventilation, and air conditioning (HVAC) systems of EVs. The HVAC or climate systems in the cars aim to ensure comfort for the driver and passengers, and provide safety functions such as defogging of windows [12]. Conventional Internal Combustion Engines (ICE) use waste heat (>5 kW) from their gasoline engines for cabin heating and window de-icing [13]. However, there is little waste heat available in EVs due to their high efficiency, and the EVs therefore use energy from the battery for heating. The heating equipment can be driven by a positive temperature coefficient resistance heater (PTC heater), from an air source heat pump (HP), or from a combination of the two solutions [14]. PTC materials have a self-regulating characteristics, since PTC materials change their resistivity with the material temperature [15]. With higher temperatures, the resistivity rise, and the heat power decreases. Maximum capacity of PTC heaters studied in literature is usually in the range of 5 to 6 kW [16]. It has been found that the use of PTC heating equipment may decrease the driving range of EVs>50 % in cold climates [17]. Systems with HPs are more efficient than PTC heaters, and can provide both cooling and heating [13]. Several researchers found that the efficiency of a HP is reduced during cold weather conditions [13,14,17,18]. PTC heaters therefore often supplement HPs when the temperature is low, as for example in the VW eGolf, where the HP is not operated below −10 °C [19]. The thermal management system in the EV determines the preheating method.

Norway is a frontrunner market for EVs, with 16 % battery EVs (BEVs) and 6 % plug-in hybrid EVs (PHEVs) of the total car stock in 2021 [20]. Most EV owners charge their EVs at home (88 %) or at work (6 %) [21], usually connected to a 230 V IT distribution grid. About 70 % of home-CPs [21,22] are of the type "level 2" [23], with typically 3.6 to 7.4 kW charging power (16–32 A) [24]. The climate in Norway is cold during winter, with average temperatures of −5 to −7 °C from December to February [25], and with local differences e.g. between coastal and inland areas. To extend the driving range of EVs during cold winter days, EV owners are generally recommended to use electricity from the grid to preheat the EV cabin and battery before using the car, by e.g. drivers' associations [26,27], and car manufacturers [28,29].

Preconditioning includes both precooling and preheating of the EV cabin, but this work focuses on preheating. Cabin preheating is becoming common practice for BEV and PHEV owners in cold climate [12]. This share of the EV energy demand is typically not flexible in time, since the energy is often delivered from the grid directly, and not taken from the battery. Normally during cabin preconditioning, AC electricity from the grid is converted to DC electricity in the EV, using the onboard charger of the car [30]. The HVAC system is then powered by DC in the EV, to cool or heat the EV cabin.

In addition to cabin preheating, many EVs can also preheat the battery of the car, either before charging or during the preheating period. Li-ion batteries have a poor performance during sub-zero temperatures, which reduces the driving range of the EVs and even creates potential safety hazards [31,32]. The batteries can therefore be preheated, typically by either applying an external heat source, or by generating internal heat in the battery. Air preheating is often adopted in EVs due to simple structures and low costs, and has a rate of temperature rise (RTR) of about 0.5–3 °C/min [32]. Liquid preheating systems are more efficient but are more complex, with RTR of about 0.67 ℃/min, which is e.g. used by Tesla [32]. PTC preheating has been used in early model EVs, such as the Nissan Leaf, and requires a longer preheating period [32].

Preheating of EVs usually occurs shortly before departure, during days with low outdoor temperature. Charging habits of residential EV users are described in [33], showing how a majority of the cabin preheating sessions during workdays will happen in the morning hours, corresponding to the start of a typical workday. During such hours there is also a high demand for other energy use in the building sector, and some locations experience grid capacity challenges. In Norway, morning hours during cold winter days are the time of the year with the highest peak loads [34]. The cost of electricity is therefore usually higher in the early morning hours [35].

1.2. Literature review: Power loads for EV preheating and their impact on the grid

A number of articles presents possible solutions for more efficient EV HVAC systems in cold climates [13,14,17,18,36–40]. [41] studied how HVAC loads during driving increases the frequency of EV charging, and concluded that regional electric utilities must include also the HVAC loads of EVs in their load growth scenarios. The improvement in EV driving range due to cabin preconditioning has been studied by e.g. [30,42–45]. Our literature review has identified only a few studies that describes the power and energy demand of EV preheating, and how this may impact the grid. The main findings of the literature review are summarized in the following, and listed in Table 1.

Experimental studies with power data for EV HVAC loads are presented by [37,39,40,46,47]. [37] did lab tests in an environmental

Table 1
Literature review: Comparison between related research and own study.

Topic	Authors	Reviews	Experiments	Simulations
HVAC loads during driving	Qi et al. [13], Zhang et al. [14], Zhang et al. [36]	✓		
	Zhang et al. [17], Seo et al. [18], Wang et al. [37], Meyer et al. [38], Mimuro et al. [39], Yu et al. [46], Kim et al. [47]		✓	
	Zhang et al. [40], Kambly et al. [41]			✓
Increased EV driving range due to preheating	Kambly et al. [30], Barnitt et al. [42], Neubauer et al. [43], Nerling et al. [44], Ramsey et al. [45]			✓
Preheating power/energy. Grid impact	Antoun et al. [48], Antoun et al. [49], Lindgren et al. [50]			✓
	Own study		✓	

chamber on a PTC heater and a HP system for a compact EV. The nominal power of the PTC heater was 1.5 kW, while the actual power reached a maximum of 2.3 kW initially, before stabilizing on about 1.7 kW. For the HP systems, the power was in the range of 1 kW to 1.3 kW, affected by ambient temperatures (-10 °C and −15 °C) and system solutions. [39] tested a 4 kW PTC heater, a HP and a fuel-operated heater in a model year (MY) 2013 Nissan Leaf. They found that the PTC heater consumed 1.41 kWh electricity over 30 min, while the HP consumed 65 % of this. During the tests, the outside temperature was 3 to 4 °C, the initial cabin temperature was approx. 6 °C and the requested cabin temperature was 26 °C. [40] analysed the performance of a MY2017 Nissan Leaf with HP, and proposed a heating system which reduced the amount of needed incoming fresh air. They simulated interior-air and fresh-air modes for HP operation with different fresh-air ratios, and found that the cabin heat load varied from 1.2 kW with interior-air mode to 4.0 kW with fresh air mode. [46] tested a BEV with PTC heater in a climatic wind tunnel in a laboratory. Their results show how the PTC heater has a high input power initially, to quickly achieve the required thermal comfort level in the EV cabin. After a couple of minutes, the heating loads were found to stabilize on a lower power load. Comparing the heating load for air supplies of 100 % fresh air, 20 % recirculation air, and 30 % recirculation air, the stable heating loads were 4.32 kW, 3.63 kW and 3.29 kW, respectively, for a start-up cabin temperature of −10 °C. The energy used by the PTC was 2.52 kWh, 1.80 kWh and 1.60 kWh for the three air modes. With 100 % fresh air, it took 25 min to rise the temperature to 24 °C. The heating load was temperature dependent, and with 100 % fresh air the heating load varied from 2.96 W with 0 °C ambient temperature to 5.77 kW with −20 °C. [47] did experimental studies on the heating performance of a 5 kW PTC and a HP. The researchers demonstrated how the PTC heater was required to supplement the HP, to provide sufficient cabin heat during a cold start. This was found to be due to slow warm up speeds of the HP. While it took 13 min for the PTC alone to reach a target temperature of 25 °C from 0 °C, it took the HP 40 min, and a combined system reached the target value in 8 min. The heating power for the solutions were 4.5 kW for the PTC, 1.1 kW for the HP and 5.3 kW for the combined system.

Only a few works in literature investigate EV preheating loads and their grid impact. In [48,49], the impact of large-scale EV preheating on the residential distribution grid has been simulated. In the model presented in these articles, each preheating session was assigned a certain hour in the morning (from 05:00 to 10:00), a time duration (normal distribution, on average 20 to 30 min), and a power rate. The assigned power rates in the study match the level 2 charger rates (7.2 kW in [49]), and the power was assumed to be constant during the duration. The studies conclude that EV preheating can have a negative impact on the voltage level and power losses in the residential grids, and that the added load can be handled by combining network reconfigurations with vehicle-to-grid (V2G) energy transmissions.

Another relevant work is [50], which simulated how outdoor temperatures affect battery charging and performance of EVs. Their model included 212 EVs with maximum 3.6 kW charging power, maximum 4.0 kW cabin heater power (COP 2.5), and 0.3 kW battery heater power (COP 1). The vehicle data and the thermal model used in the simulation were based on [43] (Nissan Leaf, 4 kW PTC, modelled HP). EV driving behaviour was based on travel diaries available from the Finnish national travel survey. Preheating of the EV cabins started 10 min prior to the trip, while battery heating was constant during parking. The study found that at − 10 °C, preheating and battery heating during parking introduced a constant grid load of around 30 kW over the whole day, or 140 W per EV. The authors state that most of this energy is used for constant battery heating, not for preheating the cabin. They also conclude that cabin preheating seems more helpful than standby battery heating in lowering the energy consumption during driving.

1.3. Research gap and our contribution

As the number of EVs are increasing, it is important to understand how cabin preheating of EVs may impact the power loads and energy use in buildings, and how the aggregated loads will have an impact on the electricity grid. Our literature review identified a need for more experimental knowledge within this topic. There exist some experimental studies with power data for EV heating sessions [37,39,40,46,47], but these studies focused on improving the HVAC systems in EVs and were not seen in relation with energy loads in buildings or the grid. The few studies analysing how EV preheating loads may impact the distribution grid [48–50], were based on simulations. To validate and improve models and simulations, access to real-world data is a significant factor [51]. This article presents data from an experimental study with 51 preheating sessions of five typical EV models, during different outdoor temperatures conditions. Multiple linear regression models are developed, to investigate the relationship between the cabin preheating energy use and various variables, such as outdoor air temperature, cabin temperature difference, preheating duration, EV size, and heating system. The performance of the models was evaluated, using a dataset for validation with 17 additional preheating sessions. Further, the preheating loads are compared with typical electricity and heating loads in Norwegian apartment buildings during winter. Finally, aggregated grid loads for preheating EVs are assessed, by combining the trial results with datasets describing residential EV charging behaviour. Our main research questions are: What are the power load and energy consumption for grid-connected preheating of EV cabins in cold climates? And how will the preheating loads impact the daily energy loads for apartment buildings during the winter, for individual apartments and on an aggregated level? The new insight will be useful when e.g. simulating and forecasting EV energy loads on the grid in cold climates. It can also prepare the ground for development of new cabin preheating solutions, where the grid burdens are reduced while still maintaining the demand for extended driving ranges, comfort, and safety.

The paper is organized as follows: Section 2 describes the methods used in the work. Section 3 presents the results and a discussion of the findings. In section 4, the conclusions from the work are drawn.

2. Methods

Sections 2.1 and 2.2 describe the CPs and logging equipment used in the experimental study, and section 2.3 describes the EVs which are tested. Section 2.4 describes the linear regression analysis which was applied on the trial data. Section 2.5 and 2.6 describe the methods used when comparing the preheating loads with other energy loads in apartment buildings, and when assessing the aggregated grid loads for preheating EVs.

The preheating of the EVs happened during two trials, both located outside. At site 1 in Oslo (lat 59.94455, long 10.71369) the tests were performed during the winter 2021/2022. The EVs in the test included the models BMW i3, Jaguar I-PACE, Nissan Leaf, Tesla Model 3, and VW eGolf, with logging of power (second/minute resolution) and cabin temperatures. The five EV models tested are typical in the Norwegian market, and the models cover 38 % of the EVs in the national EV stock (ref. Table 3 [52]). At site 2 in Bærum (lat 59.94292, long 10.61269) the tests happened during winter periods in 2020–2022. At this site, three different Nissan Leaf cars were tested, including one of the cars tested at site 1. At site 2, the power was logged through the CP monitoring system (15-minute resolution), and there were no logging of the cabin temperatures.

2.1. *Preheating of EVs at site 1*

2.1.1. *CP specifications*

The EVs were connected to a level 2 CP with 7.4 kW power available (EVlink [53], AC 230 V power supply, 32 A, Type 2 charging cable). The CP monitoring system provided information about plug-in and plug-out times, and energy use for each session [54].

2.1.2. *Energy metering and energy losses*

Power consumption was logged every second with a power and energy analyser (ELIT PQ5 [55]). For the analyses, the power data was averaged per minute. The primary power meter was installed inside the electricity distribution board located in the nearest building (about 45 m from the CP). The measurement data included the energy losses from the primary power meter to the EV. To analyse the energy losses, the primary power meter data was compared with two other data sources: 1) A second power meter installed on the EV-side of the CP, 2) Energy use for each session, available from the CP monitoring system. The average difference between the primary power meter and the two meters by the CP was in the range of 7 %, as described in Table 2. This difference is due to both energy losses (such as in the 45 m cable, where power losses are calculated to be 1.4%) and measurement uncertainty (the power meter accuracy was IEC62053-22 class 0.5, with > 1% error in current and 0.2% error in voltage measurements). The results presented in section 3 are based on the primary power meter (not adjusted), since the building distribution board was considered to be the most natural boundary for the building and grid analysis. Fig. 2 illustrates one example session (ID 73) with EV charging and preheating of Nissan Leaf (MY2018) at site 1, metered at two locations. For the example session, the EV is fully charged (100%) at about 12:40 and the cabin preheating starts at 13:00. The three pulses in the charging power (~1 kW) towards the end of the charging, are part of the battery control system for the Nissan Leaf MY2018.

2.1.3. *Temperature logging*

A trial temperature logger was placed in the EVs during charging sessions, measuring the cabin temperature every minute with a 0.5 °C resolution (EasyLog RH/temp data logger [56], accuracy 0.55 °C). The temperature logger was typically placed in the cup holder between the seats in the cabin. Hourly outdoor air temperatures were downloaded

Table 2
Calculated differences between the power meters.

Site	*Meter 1*	*Meter 2*	*Description*	*Differences*
Site 1	Primary power meter	Secondary power meter	For 6 charging sessions, a second power meter was installed on the EV-side of the CP. The difference between the primary and secondary power meter was calculated for all minute-values. When calculating average energy differences, periods were chosen where both meters measure *steady* power rates (in total 13 h selected among the 24 measured hours). This was done to avoid periods with measurement errors or time differences between the meters. Fig. 2 shows one example session (ID 73) with power data from the two power meters. For the example session, the period from 09:18 to 10:33 was included in the power loss calculation.	7.3 %
Site 1	Primary power meter	CP monitoring	The energy differences were calculated as the difference between the session energy use metered in the CP monitoring system and the session energy use metered by the primary meter. 38 sessions were included in the calculation.	6.7 %
Site 2	AMS-meter	CP monitoring	The differences between the AMS-meter and CP monitoring system were calculated for 8 preheating sessions (hourly values).	<1 %

for the weather station Blindern (SN18700) located nearby (500 m) [57].

2.2. *Preheating of EVs at site 2*

2.2.1. *CP specifications*

The EVs were connected to a level 2 CP, with 7.4 kW power available (Zaptec pro [58], AC 230 V power supply, outdoor parking solution where 10 CPs share 63 A, Type 2 charging cable). For the trial sessions, the power available for the trial EVs was not limited by other ongoing EV sessions in the CP infrastructure.

2.2.2. *Energy metering and energy losses*

Power consumption was logged every 15 min by the CP monitoring system [59]. The electricity distribution board with AMS meter was located beside the CP (1 m). The energy losses between the CP monitoring and AMS meter are minimal (up to 1 %, as described in Table 2). The energy losses are not included in the results.

2.2.3. *Temperature logging*

Hourly outdoor air temperatures were downloaded for the weather station Blindern (SN18700) located about 6 km away [57].

2.3. *EVs tested in the trials*

EV owners were invited to take part in the trials, charging and preheating their private EVs on the CPs. Seven EVs were selected from the

Table 3
EV characteristics for EVs in the trial.

Location	*EV-model*	*Share EV stock* [a]	*Model year*	*Onboard charger capacity (kW)* [b]	*Net battery capacity (kWh)* [b]	*Heating system*
Site 1	BMW i3	5.8 %	2016	7.4	27.2	5.5 kW PTC and 3 kW HP [60]. The HP operates between −10 °C and 22 °C [60].
	Jaguar I-PACE	1.4 %	2019	7.4	84.7	7.0 kW PTC and HP [d].
	Nissan Leaf [c]	14.1 %	2018	6.6	36	PTC and HP. 5.35 kW heating power, according to [61]. Seat heater and steering heater also activates under preheating [62].
	Tesla Model 3	7.2 %	2019	11 [e]	72.5	8 kW heating power [63], whereof 6 kW PTC (no HP for MY2019, but this is standard from 2020).
	VW eGolf	9.3 %	2017	7.2[f]	31.5	5 kW PTC [g] (no HP).
Site 2	Nissan Leaf	14.1 %	2013	6.6	21.6	PTC (no HP).
	Nissan Leaf	14.1 %	2015	3.3	27.2	PTC and HP.
	Nissan Leaf [c]	14.1 %	2018	6.6	36	PTC and HP.

a. Share of the national EV stock in Norway per March 2022 [52].
b. EV manufacturer data from [64] and [65].
c. Nissan Leaf MY2018 is the same for both locations.
d. Customer service Jaguar Land Rover Limited, personal communication May 2022.
e. Maximum charger capacity is limited by CP (7.4 kW).
f. Actual measured charger capacity for the EV is approximately 5 kW.
g. Customer service Harald A. Møller AS, personal communication May 2022.

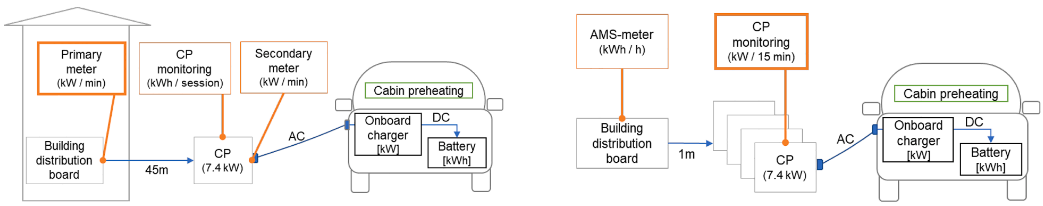

Fig. 1. System overview of test site 1 (left) and test site 2 (right), with metering locations.

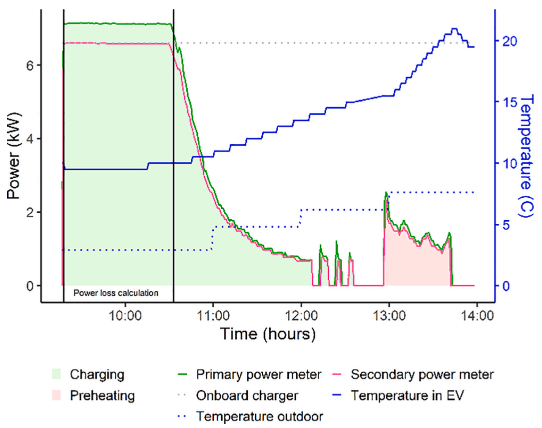

Fig. 2. Example session (ID 73) with EV charging and preheating of Nissan Leaf (MY2018) at site 1, metered at two locations.

volunteers, representing five EV models, as listed in Table 3. The EV owners at site 1 filled in a form for every charging session, noting the timing of the preheating, requested preheating temperature, and battery state of charge (SoC)-values. The EV owners decided themselves to either start the preheating from the dashboard in the EV, or externally from an EV app. For the users starting the preheating from the dashboard (Nissan Leaf), a time for the finished preheating was set. The starting time is then calculated by the EV, based on expected duration necessary for reaching the requested temperature. For the users starting the preheating externally from an EV app (BMW i3, Jaguar I-PACE, Tesla Model 3, VW eGolf), a time for the starting point of the preheating was set. For some sessions, preheating started close to the plug-out time, being interrupted by the EV departure. This was accepted, since it was assumed that this is how the preheating function is often used in real life. The requested preheating temperatures varied in the EVs, and were either preselected by the EV or set by the users. At site 1, 46 sessions were metered. 24 of the sessions were selected for further analysis, since their preheating time was clearly separated from their charging time. At site 2, 27 preheating sessions were analysed. All the EVs were preheated from the CP, not from their battery. For some EV models, the users can choose to use the energy from the battery to preheat the EV, but this function was not activated during the trials.

2.4. *Multiple linear regression models for cabin preheating energy use*

A linear regression analysis was applied on the trial data, to investigate the relationships between the cabin preheating energy use, and multiple well-known and independent variables. The analysis was performed using the statistical computing environment R [66]. The equation for a multiple linear regression (MLR) model is described with Eq. (1), where y_i is the outcome for unit no. i, α is the constant intercept term, $x_{1i}, x_{2i}, \cdots, x_{mi}$ are the explanatory variables for unit no. i, $\beta_1, \beta_2, \cdots, \beta_m$ are the fixed regression coefficients, and ε_i are the random errors. The variables can be numerical or categorical, where the categorical variables are used to compare groups.

$$y_i = \alpha + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_m x_{mi} + \varepsilon_i \tag{1}$$

If the effect of x_1 depends on the level of x_2 there is an *interaction*

[67]. When there is an interaction between x_1 and x_2, the model is described with Eq. (2).

$$y_i = \alpha + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{1i} x_{2i} + \varepsilon_i \tag{2}$$

When selecting the explanatory variables for the regression model, the aim was to create a simple model with good empirical fit, and with generally available input data. A forward selection approach was used for selecting variables; Single linear regression models were first analysed, with one variable only, and the most significant variables (lowest P-values) were selected. A number of MLR models were created, adding one extra variable for each step, before comparing the adjusted R^2 values for the models. The adjusted R^2 is a modified version of R^2, which is adjusted for the number of variables. Variables and interactions were tested and added to the selected model until there was no improvement in the adjusted R^2 value. Before including variables in the models, also practical aspects were taken into account, for expected data availability and other practical considerations. The dependency between the variables was analysed by calculating the Pearson correlation (r_{12}) between the variables, to prevent that dependent variables were used in the same model. Pearson correlation has values $-1 < r_{12} < 1$, and the correlation increases with higher negative or positive values. Two models were finally selected and presented along with related statistical parameters for R^2, adjusted R^2, mean absolute error (MAE), mean square error (MSE), root mean square deviation (RMSE), and mean absolute percentage error (MAPE) [68]. The high value for the adjusted R^2 and the low values for MAE and RMSE are considered to be favourable, and show that the models can be used for describing the cabin preheating energy use.

The regression models were created with data from the 51 preheating sessions in the trial. To validate the models, an additional independent dataset was used to assess how the models performed. The dataset used for validation consisted of 17 preheating sessions, which were not earlier included when training the models. Compared to the trial dataset that was originally used for creating the models, the additional dataset used for validation included some differences in the EVs and CPs used. The aim of introducing these differences was to evaluate if the developed models were well generalized, or if they fitted too closely to the trial dataset. Three EVs were used in the preheating sessions in the dataset for validation: Nissan Leaf MY2018 (same EV as used in the trial, 10 sessions), Kia Soul MY2015 (not used in the trial, 1 session), and Tesla Model S MY2019 (not used in the trial, 6 sessions). Three 7.4 kW CPs were used for the validation: One in site 1 (new CP, not used in the trial), and 2 in site 2 (1 used in the trial, one new). To evaluate the performance of the models, statistical parameters for R^2, MAE and RMSE were presented, and compared with the parameters for the trial dataset.

2.5. Comparing energy loads for EV cabin preheating with other energy loads in an apartment

Based on the cabin preheating trials and modelling results, two levels of cabin preheating were selected for comparison with other residential energy loads. Hourly resolution was used in the comparison, since this is the current resolution for AMS metering of electricity use in Norway [69]. It was assumed that the preheating happened within one clock hour during the morning, between 07:00 to 08:00. Hourly energy use was recorded and presented for an apartment during an example day, with real energy measurements for electricity use, space heating and domestic hot water (DHW). The electricity use for a range of Norwegian apartments were obtained from measurements of hourly data, available from 505 apartments located at Risvollan in the city of Trondheim [70]. The example apartment was randomly selected (apartment ID 10), and its daily electricity use during the example day corresponds to the average electricity use for all the apartments during the same date. The electricity use did not include space heating and domestic hot water, since this was provided by district heating. Thus, the data for space heating and DHW were obtained from another apartment building located in Bærum close to Oslo, including 24 apartments heated by an electric boiler and with electric DHW tanks. The hourly energy profiles shown for the example day is the total heat load divided on the 24 apartments. The average heated apartment area for the case in Bærum/Oslo (86 m^2) is similar to the average area in Trondheim (88 m^2). The example date was selected due to its low outdoor temperature in both locations (January 9th 2018, with in average −9 °C in Risvollan and −7 °C in Oslo [57]). For the EV charging load, two alternative load profiles are shown (3.6 kW or 7.4 kW charging power), both started charging at midnight, and with a session energy use of 15 kWh, which is typical for home charging [33].

2.6. Aggregated grid loads for EV cabin preheating

To assess expected aggregated power demand for cabin preheating, four preheating scenarios were combined with an EV charging dataset from a range of apartment buildings. The EV charging dataset is described in [6], and contains information on plug-out times for 34,499 charging sessions from 261 EV users in apartment buildings in 12 locations in Norway. To preheat the EV cabin with electricity from the grid, the EV must be connected to a CP. It is assumed that the EV user habits for preheating the EVs are in line with the user habits for EV charging, which is normally the main reason for CP connections. [33] found a correlation between plug-out times and local hourly traffic data, which indicates that most residential EV users travel after disconnecting their EVs. In the preheating scenarios it was assumed that all the EVs are preheated before plug-out times. The results are therefore relevant for cold days only. Estimated energy use for preheating was 2 kWh in scenario 1 and 2, or 4 kWh in scenario 3 and 4, as shown in Table 4. Scenarios 1 and 3 were based on plug-out distribution data from all the 261 EV users, with in average 0.5 CP connected sessions per day (named CP sessions). Scenarios 2 and 4 were based on plug-out distribution data from the 25 % EV users with most frequent charging, with in average 1 CP session per day. Hourly data is illustrated in a daily profile. If the plug-out time for a certain CP session was in the beginning of the hour (first 30 min), then the preheating time was set to the preceding hour. If the plug-out time was in the end of the hour (last 30 min), then the preheating time was set to the same hour as the plug-out time. The average daily profiles are presented per EV user.

Finally, the aggregated daily profiles for EV cabin preheating were compared to daily load profiles for other energy loads in the apartment buildings. For this analysis, it was assumed that every apartment has 0.7 EVs and that 50 % of the EVs use cabin preheating. The current density of personal cars in Norway was 1.4 car per households in 2020 [71] (including cars using fossil fuels), but apartments typically have lower access to parking spaces than freestanding houses. Parking requirements vary with the location /municipality, and is e.g. min. 0.4 to 1.2 car per apartment [72]. The chosen EV density of 0.7 car per apartment corresponds to the available parking spaces for the apartments located at Risvollan. Scenario 1 was used as a basis for the aggregated profiles, with 2 kWh preheating 0.5 times per day. Preheating was added to the daily profile of other residential energy loads during the winter (December, January, February): apartment electricity use, apartment space heating and DHW, and residential EV charging. The average daily profiles for apartment energy use were based on the same data sources as described in section 2.4. The profiles for residential EV charging were

Table 4
Cabin preheating scenarios for aggregated loads.

Scenario	*Preheating energy (kWh/preheating session)*	*Average connection frequency (CP sessions/day)*
1	2	0.5
2	2	1.0
3	4	0.5
4	4	1.0

based on the EV charging dataset in [6], assuming immediate charging after plug-in.

3. Results and discussion

3.1. Power and energy for cabin preheating

In this section, the experimental results for EV cabin preheating are presented and discussed. In total 51 preheating sessions are analysed, whereof 24 sessions at site 1 (5 EVs, BMW i3, Jaguar I-PACE, Nissan Leaf, Tesla Model 3, and VW eGolf), and 27 sessions at site 2 (3 EVs, all Nissan Leaf). Sessions where the charging and the preheating happened simultaneously were not included, since in these sessions the preheating power and energy could not be separated from the charging.

3.1.1. Experimental data and analysis for each EV model

Table 5 lists details for the preheating sessions at site 1, such as initial temperature in the EV cabin before preheating, outdoor temperature, preheating duration, preheating energy, and SoC-values. Before starting the preheating of the EV cabins, the EV batteries were charged to about 100 % SoC (for Tesla 80–95 % SoC). This was done to prevent simultaneous charging and preheating. After the preheating session it was controlled that the SoC was still 100%, to make sure that the preheating energy was not supplied by the battery. Fig. 3 shows the relationship between preheating energy and outdoor temperatures for the sessions at site 1, marking if the sessions were ended by the EV thermal management system or stopped by disconnecting the EV from the CP. Fig. 4 shows the relationship between preheating energy and cabin temperatures for the sessions. Fig. 5 shows a charging and preheating example for each of the five EV models at site 1, while Fig. 6 shows all the preheating sessions for the EV models at the same site.

For BMW i3, the charging power was close to the onboard charger capacity of 7.4 kW. The cabin preheating power was initially on the same level as the onboard charger capacity, being reduced to between 2 and 5 kW after approx. 10 min. The preheating duration and power were found to be related to the outdoor temperature, where the coldest session (ID 4, −6.6 °C) used 2.1 kWh energy during a 30-minute preheating period, before being automatically stopped by the EV thermal

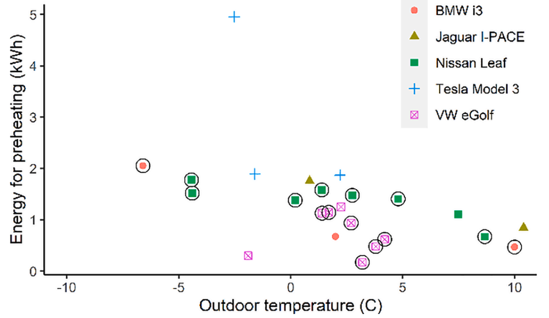

Fig. 3. Energy-Temperature diagram for preheating sessions at site 1. The circled sessions are ended by the EV thermal management system, while det remaining sessions were stopped by disconnecting the EV from the CP.

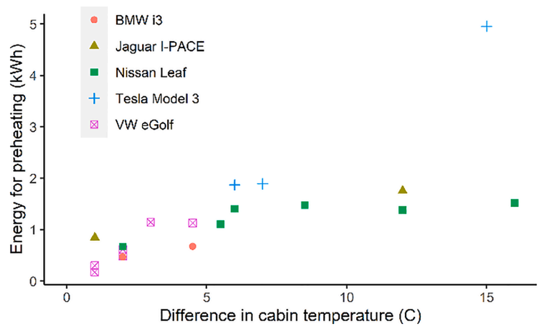

Fig. 4. Energy-Temperature diagram for preheating sessions with difference in cabin temperatures (site 1).

Table 5
Preheating energy and temperatures for sessions at site 1.

ID	EV model	Management system used	Preheating request (°C)	Temp outdoor (°C)	EV temp, initial (°C)	EV temp, end (°C)	Duration (min)	Ended by	Energy (kWh)	SoC initial (%)	SoC end (%)
4	BMW i3	App	NA	−6.6	NA	NA	31	EV	2.1	100	100
70 *	BMW i3	App	NA	2.0	4.5	9.0	9	Plug-out	0.7	100	100
76	BMW i3	App	NA	10.0	22.0	24.0	14	EV	0.5	100	100
29 *	Jaguar I-PACE	App	21	0.8	0.5	12.5	23	Plug-out	1.8	100	100
71	Jaguar I-PACE	App	21	10.4	18.0	19.0	18	Plug-out	0.8	100	100
3	Nissan Leaf	EV dashboard	26	−4.4	NA	NA	46	EV	1.8	98	96
1	Nissan Leaf	EV dashboard	26	1.4	NA	NA	36	EV	1.6	100	100
7	Nissan Leaf	EV dashboard	26	−4.4	−1.5	14.5	46	EV	1.5	100	100
27	Nissan Leaf	EV dashboard	26	2.7	5.0	13.5	36	EV	1.5	100	100
50 *	Nissan Leaf	EV dashboard	22	0.2	6.5	18.5	36	EV	1.4	100	100
28	Nissan Leaf	EV dashboard	26	4.8	9.5	15.5	31	EV	1.4	100	100
73	Nissan Leaf	App	22	7.5	15.5	21.0	46	Stopped	1.1	100	100
74	Nissan Leaf	EV dashboard	22	8.7	19.5	21.5	30	EV	0.7	100	100
15	Tesla Model 3	App	21–22	−2.5	2.5	17.5	67	Plug-out	5.0	NA	NA
16 *	Tesla Model 3	App	21.5	−1.6	1.5	8.5	16	Plug-out	1.9	95	94
24	Tesla Model 3	App	21	2.2	3.0	9.0	20	Plug-out	1.9	80	79
62	VW eGolf	App	24	2.2	NA	NA	20	Plug-out	1.3	100	100
30A *	VW eGolf	App	22	1.4	5.0	9.5	16	EV	1.1	100	100
30B	VW eGolf	App	22	1.7	8.5	11.5	16	EV	1.1	100	100
61	VW eGolf	App	22	2.7	NA	NA	15	EV	0.9	100	100
25A	VW eGolf	App	24	4.2	5.5	7.5	16	EV	0.6	100	100
25B	VW eGolf	App	24	3.8	8.0	10.0	16	EV	0.5	100	100
26	VW eGolf	App	24	−1.9	6.5	7.5	6	Plug-out	0.3	100	100
77	VW eGolf	App	22	3.2	13.0	14.0	15	EV	0.2	100	100

* Example session IDs in Fig. 5.

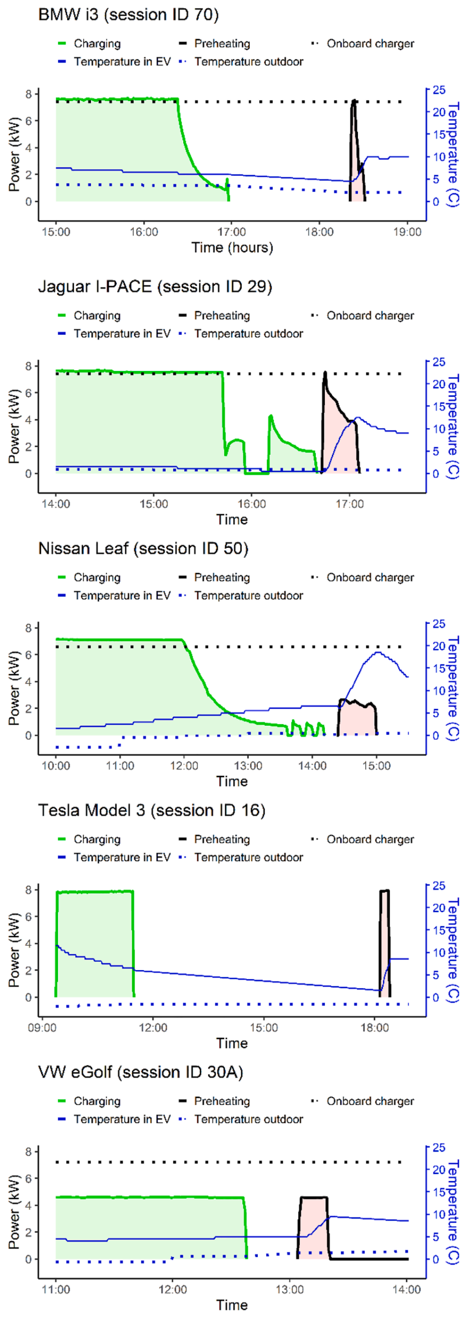

Fig. 5. Site 1 example trial sessions for each EV model, showing charging and preheating power for the EVs.

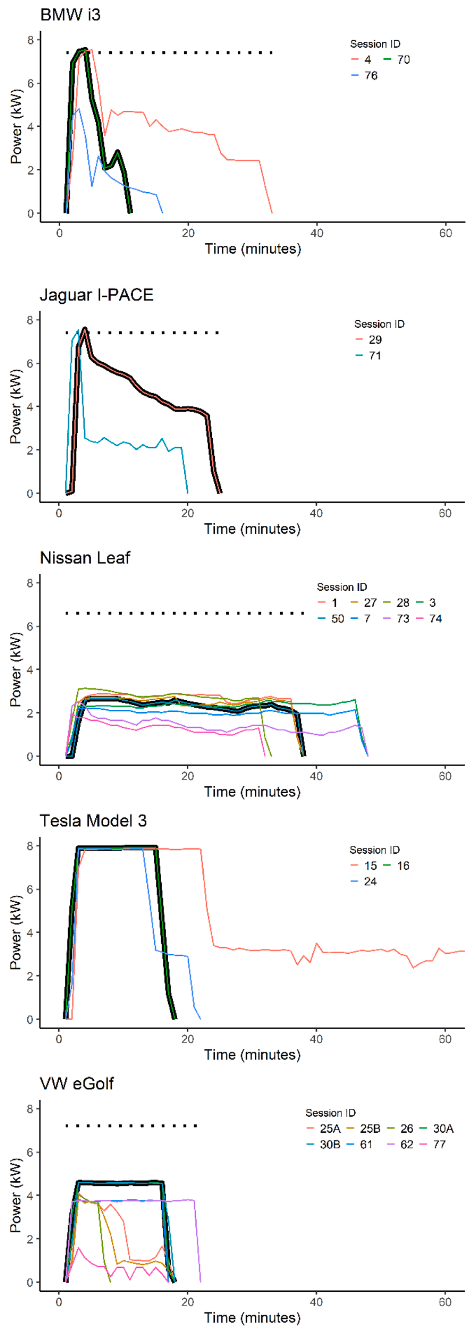

Fig. 6. Site 1 sessions for each EV model, showing preheating power. Example sessions from Fig. 5 are emphasized in black. Dotted lines: onboard charger capacity for the EVs.

management system.

For Jaguar I-PACE, the charging power was close to the onboard charger capacity of 7.4 kW. Also for this EV, the initial cabin preheating power was close to the onboard charger capacity, but the power was reduced after approx. 5 min. The initial power demand was most likely related to initial PTC-use, which is often necessary before the HP can start (Customer service Jaguar Land Rover Limited, personal communication May 2022). For the coldest session (ID 29, 0.8 °C), the energy use was 1.8 kWh during a 25-minute session, increasing the cabin temperature by about 12 °C (from 0.5 to 12.5 °C). The preheating power during this session decreased from about 7.5 to 4 kW, and the session ended when the EV was plugged out from the CP.

For Nissan Leaf, three cars were tested with different model years: MY2018 was tested at site 1 and site 2, while MY2013 and MY2015 were tested at site 2 only. The charging power of MY2018 was close to the onboard charger capacity of 6.6 kW, as shown in Fig. 5 and Fig. 6. The cabin preheating power was lower, between 2 and 3 kW, and was found to be fairly stable during the preheating session. Fig. 7 describes preheating power for all the three cars. MY2013 has the highest preheating power, of about 4 to 5 kW, and is also the only Nissan Leaf EV in the trial without HP. The preheating duration and resulting energy use is related to the outdoor temperature, as shown in Fig. 8. For the Nissan Leaf-sessions, preheating was requested for a certain departure time. According to [62], the necessary operation time for preheating is calculated two hours before the set preheating time, dependent on the ambient temperature. When the ambient temperature is low, the preheating duration is longer, with a maximum of 2 h. The longest preheating session at site 2 lasted for nearly 2 h, with an outdoor temperature of −10 °C. The needed preheating energy during this session was about 3 kWh. At site 1, the two coldest sessions (ID 3 and 7, −4.4 °C) used about 1.5–1.8 kWh energy and lasted for 45 min. For one of these sessions (ID 7), the cabin temperature increased about 16 °C during the preheating (from −1.5 to 14.5 °C).

For Tesla Model 3, the charging power was limited by the CP capacity of 7.4 kW. The cabin preheating power was initially on the same level as this maximum, before being reduced to about 3 kW after approx. 20 min. Preheating during the coldest trial session (ID 15, −2.5 °C) lasted for 67 min, before being ended by plugging out the EV from the CP. The cabin temperature increased about 15 °C during the preheating session (from −1.5 to 14.5 °C), with an energy use of about 5 kWh. For comparison, [73] found that the preheating energy consumption for Tesla Model S was in the range of 7.5 kWh at –22 °C. The energy use for the other two Tesla sessions was about 1.9 kWh, and both of these sessions were ended by plug-out of the EV after about 20 min. Tesla recommends activating preheating at least 30–45 min before departure [28]. Tesla owner's manual [74] states that the preheating automatically turns off after four hours, or if the charge level drops to 20 %, if using the mobile app to turn on the climate control system.

For the VW eGolf used in the trial, the charging power was about 4 kW, which is lower than the listed onboard charger capacity of 7.2 kW. For most sessions, the preheating power was initially on the same level as the charging power. The reason for the higher initial power level is that also the battery is preheated in the beginning (Customer service Harald A. Møller AS, personal communication May 2022), and it takes a

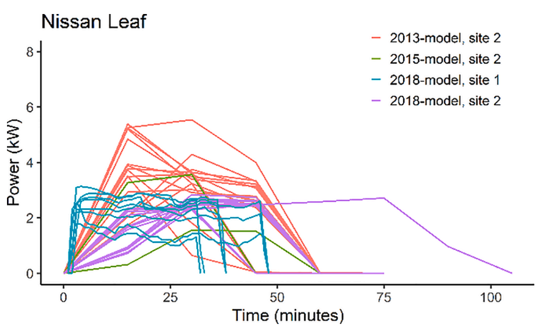

Fig. 7. Preheating power for Nissan Leaf models in the trial.

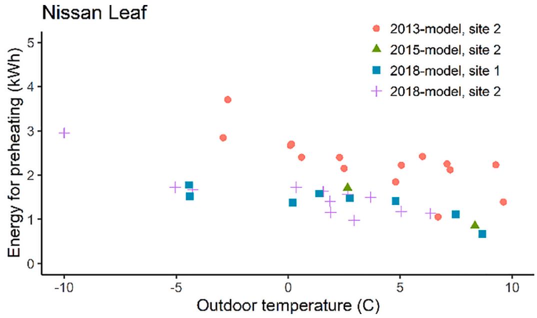

Fig. 8. Energy-Temperature diagram for Nissan Leaf models in the trial.

few (>5) minutes before the cabin temperature starts to increase. After about 10 min battery preheating the power was reduced, with preheating of the cabin only. The preheating sessions lasted for about 20 min in total, before being ended by the EV thermal management system. Both the energy use (0.2–1.3kWh) and the cabin temperature differences (1–4.5 °C) were quite small for the VW eGolf used in the trial. There seemed to be a temperature dependence between the energy use and outdoor temperature, as shown in Fig. 3 (session 26 at −1.9 °C can be excluded, since it is plugged out during preheating).

3.1.2. Summary of the cabin preheating trial: Power, cabin temperatures, and duration

In summary, the EV cabin preheating power and energy loads were found to be affected by a number of parameters, such as the specific EV (EV model, HVAC system, fresh air rates), CP (available charging power), user (preheating duration, EV settings), initial cabin and battery temperatures, and weather conditions (ambient temperature, solar radiation). In this trial, preheating sessions for five EV models were explored, with 24 sessions at site 1 and 27 sessions at site 2. Most of the EVs had a power use between 3 and 8 kW initially. After a 10 to 20 min initial period, the cabin preheating power was reduced to about 2 to 4 kW. The explanation for the higher power use initially is dependent on the characteristics of the cars. A main reason is that the PTC power use is higher in the beginning, to quickly achieve a thermal comfort level [46,47], and that the PTC provides start-up heat before a HP takes over (Customer service Jaguar Land Rover Limited, personal communication May 2022). In addition, the PTC-elements themselves have a higher power requirement in the beginning, due to their characteristic with a higher heat power when the material temperature is lower [15]. [47] shows how a 5 kW PTC has a heating capacity of approx. 4.8 kW at 0 °C, decreasing to 4.2 kW with 25 °C. Another explanation for the higher initial power use is that, for some EV models such as VW eGolf (Customer service Harald A. Møller AS, personal communication May 2022) and Tesla [75], also the battery is preheated in the start of the preheating session.

The increase in cabin temperatures ranged from 1 to 16 °C, as shown in Fig. 4. Some sessions had a high start temperature in the EV cabin. There is an uncertainty in the recorded cabin temperatures, since the temperatures were logged in only one location in the cabin (normally in the cup holder between the seats). Still, there seems to be a difference between the EV models in how fast the cabins are heated, and if the temperature levels requested for the preheating sessions can be reached. The small temperature differences for the tested VW eGolf may indicate that the energy was mainly used for preheating of the battery, and not the EV cabin. New experimental studies on this topic should consider measuring temperatures both in the EV cabin (preferable at a number of places), and by the battery. Since only one EV is tested for most of the models, the results may not be general for the EV models but depend on the specific EV and its settings. An extended number of EV models need to be investigated in future experimental work, with more vehicles of the same brands.

In the trial, most of the preheating sessions lasted for 20 to 40 min, before they were either stopped by the user /plug-out of EV, or automatically stopped by the EV thermal management system. During the trial, the outdoor temperatures varied between −10 °C and + 10 °C. The presented results have an emphasis on the lower ambient temperatures, since the winters in Norway are cold, especially during the morning hours. For the lower temperatures, the preheating energy use was around 2 kWh for the EVs in the trial, with the exception of Tesla Model 3, where about 5 kWh of energy use were observed. The maximum preheating duration was found to be dependent on the type of EV model, and can last for up to two hours for Nissan Leaf (temperature dependent) [62] or up to 4 h for Tesla Model S (user dependent) [74]. For some of the EV models, a longer preheating duration would more than double the cabin preheating energy observed in this trial.

3.1.3. Cabin preheating using energy from the battery

The focus of this work has been on energy use for preheating, using energy from the grid. However, it should be noted that several EV models alternatively can preheat the EV using energy from the battery. This could fulfil comfort and safety goals of the driver, but to a less degree the goal of extending the driving range of the EV, since the battery SoC will be reduced. For EVs with large battery capacities, a limited reduction in SoC may be acceptable in many cases, since it is found that a high share of EV sessions has a start SoC above 50% [6,76]. When preheating the EV cabin, the energy use may differ when using energy from the battery, compared to using energy from the grid. The reason for this is that some EV models reduce the maximum preheating duration or the preheating power when the EV is not connected to a CP. This means that the comfort goals are not necessarily achieved. When comparing energy use, it should be noted that energy measurements of grid-connected preheating include energy losses in the charging process, when AC electricity from the grid is converted to DC electricity in the battery. Such energy losses are not necessarily included when analysing SoC reductions related to cabin preheating using energy from the battery.

In this work, cabin preheating using energy from the battery was tested in a limited “battery trial”. The battery trial consisted of 11 preheating sessions, using the Nissan Leaf MY2018. The EV was not connected to the CP during the battery trial, and the option “Battery Operation OK” was turned on. The outdoor temperatures during the sessions varied from 2 to −11 °C. During the battery trial, the battery SoC was reduced by about 3 % in the sessions with outdoor temperatures from −8 to −11 °C (3 sessions 3 %, 1 session 4 %). For the sessions with outdoor temperatures from 2 to 9 °C, the battery SoC was reduced by about 2 % (2 sessions 1 %, 4 sessions 2 %, 1 session 3 %). A reduction of 3 % corresponds to about 1 kWh energy, given a net battery capacity of 36 kWh, not including energy losses in the charging process. The temperature difference in the EV cabin was in average about 4 °C, and the requested cabin temperature (22 °C) was not reached. This can be explained by the preheating duration, which is maximum 15 min for Nissan Leaf when using energy from the battery [77]. For the grid-connected preheating sessions for the same EV, the preheating durations were longer and the EV cabin temperature differences larger (ref. Table 5).

When preheating the EV using energy from the battery, the grid energy use for preheating may become flexible in time, similar to other EV charging loads. Preheating of EVs using energy from the battery should be investigated further, to increase the knowledge of advantages and disadvantages with this solution. This includes for example experimental analyses of different EVs, achievement of comfort, safety, and driving range goals, SoC and energy analysis, and analyses of user habits related to preheating and charging.

3.2. Multiple linear regression models for cabin preheating energy use

To investigate the relationship between the cabin preheating energy use (E) and various variables, a MLR analysis was applied. As a first step towards the MLR models, the relationship between E and each of the identified explanatory variables were analysed. The explanatory variables are listed in Table 6, showing their p-values, description of data availability, and an evaluation of practical considerations. The variables used in a MLR model should be independent to each other. To evaluate this independence, Table 7 shows the correlation between the numerical variables. The table shows that some variables are dependent on each other, for example cabin temperature difference and preheating duration, and should not be used in the same model.

The variables with the lowest p-values are considered to be the most significant. Still, this is not the only evaluation criterion to be considered, since also some practical considerations need to be taken into account. The practical considerations were:

Numerical variables:

- T, Tc and D are the numerical variables with the lowest p-values. Among these, T is easily available from public weather stations. Tc and D are generally not available, but model input assumptions can be made. D is a valuable variable, since it can be used to calculate the average preheating power P ($P = E / D \cdot 60$). D was therefore included in further testing together with T, even though there was a correlation between T and D ($r_{12} = -0.42$).
- Sun was evaluated to be a non-reliable variable, since solar conditions are depending on the local context such as shading from surroundings.
- Cc and Cb are not necessarily related to the preheating system in the EV, and were excluded due to their medium/high p-values.

Categorical variables:

- It is an advantage that the models are dependent on EV specifications such as S and H instead of the specific M, since this makes the models more general.
- For B, there was a small dataset, with only two EVs, and limited data for drawing general conclusions. The parameter was excluded due to the high p-value.
- End and L are related to local conditions such as user habits and EV fleet, and were not evaluated to be relevant for the model.

Combinations of the variables were tested in the MLR models, and Table 9 shows the MLR models with the highest adjusted R^2 values. The model formula first:second specifies the interaction between the two variables [78]. mod_TDSH* and mod_CSH* were selected for further analysis, as they are general models (not dependent on M), and with high values for adjusted R^2 (0.83–0.84). Coefficients and model error statistics for the two selected models are shown in Table 10.

The models were evaluated using an additional dataset for validation, consisting of 17 preheating sessions, as listed in Table 8. Three different EVs and three different CPs are represented in the dataset. It can be noted that both for the trial dataset (Table 5) and validation dataset (Table 8), there are uncertainties related to the measured cabin temperatures, as described in section 3.1.2. All the 17 sessions were used for validating mod_TDSH*, with EV info, outdoor temperatures, preheating durations, and energy charged. Ten of the sessions included cabin temperatures, and were used to validate mod_CSH*, with EV info, cabin temperature differences, and energy charged. Model error statistics for the validation data is shown in Table 10. The mod_TDSH* and mod_CSH* predict energy charged from the validation data with R^2 0.895 and R^2 0.752, respectively. The MAE and RMSE error values for the validation data are slightly higher than for the trial data, which indicates that the models have a high generalization performance.

To evaluate how the location and the CP affect the results, all the

Table 6
Explanatory variables tested for MLR models for cabin preheating energy use (kWh).

	Variables	*Abb.*	*Unit*	*p-value*	*Description data availability*	*Practical evaluation*
Numerical	Outdoor air temperature	T	°C	0.00283	Public weather station.	+++
	Cabin temperature diff.	Tc	°C	1.43e-05	Site 1: Measured (19 of 24 sessions). Site 2: Difference between T and 18 °C.	++
	Preheating duration	D	min	2.84e-07	Preheating duration. Site 1: 1 min time resolution. Site 2: 15 min time resolution. For site 2, duration time for the initial 15 min (D_i) was estimated for sessions when average power during the first 15 min (P_i) is below the average power during the next 15 min (P_{i+1}), using the following equation: $D_i = P_i/P_{i+1} \times 15$. D_i was rounded up to next integer.	+++
	Sunminutes	Sun	min	0.667	Public weather station.	–
	Onboard charger capacity	Cc	kW	0.0692 (* 0.825)	EV characteristics, ref. Table 3. * Max. 7.4 kW as available in CP.	–
	Net battery capacity	Cb	kWh	0.924	EV characteristics, ref. Table 3.	–
Categorical	EV model	$M_{BMW\text{-}MY16}$ [...] $M_{Leaf\text{-}MY18}$		8.02e-05	EV characteristics, ref. Table 3.	+
	EV size	S_{SM} S_L		0.125	Classification related to Cc and Cb. Small/Medium: Nissan Leaf eGolf, BMW i3. Large: Jaguar I-PACE, Tesla model 3.	+++
	Heat pump or PTC only	H_{HP} H_{PTC}		0.00475	EV characteristics, ref. Table 3.	+++
	Battery preheating	B_{TRUE} B_{FALSE}		0.792	TRUE for eGolf and Tesla.	–
	Ended by	End_{User} End_{EV}		0.768	Classification of sessions ended by users.	–
	Location	L_{Site1} L_{Site2}		0.0394	Trial location.	–

Table 7
Correlation between the numerical variables (Pearson method).

	T	Tc	D	Sun	Cc	Cb
T	1.00	-0.59	-0.42	0.55	-0.26	-0.30
Tc	-0.59	1.00	0.78	-0.23	-0.22	-0.16
D	-0.42	0.78	1.00	-0.03	-0.13	-0.13
Sun	0.55	-0.23	-0.03	1.00	-0.23	-0.28
Cc	-0.26	-0.22	-0.13	-0.23	1.00	0.68
Cb	-0.30	-0.16	-0.13	-0.28	0.68	1.00

preheating sessions for Nissan Leaf MY2018 are presented in Fig. 9. The charging power is 7.4 kW for all the three CPs used, and the CP is therefore not a limiting factor for the EV (onboard charger capacity is 6.6 kW). Thus, the differences in CPs does not affect the results for the sessions. In further studies, we would recommend to investigate how the charging power of CPs affect the results for EVs with different onboard charger capacities.

The two selected models can be used in parallel, since they have different input values, and therefore different advantages when applying them in analysis. Model TDSH* uses outdoor temperature data as input, combined with assumptions for duration and the EV fleet (Small/medium or large EVs heated by HP og PTC only). Fig. 10 and Fig. 11 show how predictions for E changes with T and D for four different EV fleets. The figures are based on predictions for the T-values [-10, 0, 10 °C] and the D-values [15, 30, 45, 60, 75, 90 min]. Calculated values for average preheating power P were 2.3 kW for $S_{SM}H_{HP}$ (2.3 kW in trial), increasing to 3.7 kW for $S_{SM}H_{PTC}$ (3.3 kW in trial), 3.9 kW for S_LH_{HP} (3.7 kW in trial), and 4.8 kW for S_LH_{PTC} (5.7 kW in trial). The second model,

Table 8
Dataset with preheating sessions used for validation.

	Site	EV model	EV info	Temp outdoor T (°C)	EV temp, Initial (°C)	EV temp, end (°C)	Temp diff Tc (°C)	Duration, D (min)	Energy (kWh)
1	Site 1 CP*	Nissan Leaf (2018)	S_{SM} H_{HP}	−1.5	10.0	20.0	10.0	38	1.3
2	Site 1 CP*	Nissan Leaf (2018)	S_{SM} H_{HP}	−0.9	8.0	19.5	11.5	40	1.4
3	Site 1 CP*	Nissan Leaf (2018)	S_{SM} H_{HP}	−1.8	2.5	17.0	14.5	41	1.6
4	Site 2	Nissan Leaf (2018)	S_{SM} H_{HP}	−0.4	4.0	11.5	7.5	35	1.3
5	Site 2	Nissan Leaf (2018)	S_{SM} H_{HP}	3.3	3.0	11.5	8.5	35	1.3
6	Site 2	Nissan Leaf (2018)	S_{SM} H_{HP}	8.2	3.0	11.5	8.5	35	1.3
7	Site 2	Nissan Leaf (2018)	S_{SM} H_{HP}	0.2	2.0	16.5	14.5	35	1.4
8	Site 2	Nissan Leaf (2018)	S_{SM} H_{HP}	−2.5	−1.5	9.0	10.5	50	1.5
9	Site 2	Nissan Leaf (2018)	S_{SM} H_{HP}	0.4	2.0	11.5	9.5	40	1.5
10	Site 2	Nissan Leaf (2018)	S_{SM} H_{HP}	−10.0	−10.5	11.0	21.5	75	2.6
11	Site 2	Kia Soul (2015)	S_{SM} H_{HP}	2.1	NA	NA	NA	30	1.8
12	Site 2 CP*	Tesla Model S (2019)	S_L H_{PTC}	0.8	NA	NA	NA	18	1.8
13	Site 2 CP*	Tesla Model S (2019)	S_L H_{PTC}	−0.3	NA	NA	NA	30	2.3
14	Site 2 CP*	Tesla Model S (2019)	S_L H_{PTC}	−1.0	NA	NA	NA	24	2.5
15	Site 2 CP*	Tesla Model S (2019)	S_L H_{PTC}	−5.7	NA	NA	NA	29	2.8
16	Site 2 CP*	Tesla Model S (2019)	S_L H_{PTC}	−1.0	NA	NA	NA	25	3.0
17	Site 2 CP*	Tesla Model S (2019)	S_L H_{PTC}	3.7	NA	NA	NA	69	5.7

CP*: Other CPs at the sites were used during the validation.

Table 9
MLR models and respectively adjusted R^2 values.

MLR model		*adjusted R^2*
mod_TM	$E = \alpha + \beta_1 \cdot T + \beta_2 \cdot M$	0.6553
mod_TDM*	$E = \alpha + \beta_1 \cdot T + \beta_2 \cdot (D : M)$	0.838
mod_CM*	$E = \alpha + \beta_1 \cdot (C : M)$	0.8423
mod_DSH*	$E = \alpha + \beta_1 \cdot (D : S : M)$	0.7755
mod_TDSH*	$E = \alpha + \beta_1 \cdot T + \beta_2 \cdot (D : S : H)$	0.8303
mod_CSH*	$E = \alpha + \beta_1 \cdot (C : S : H)$	0.8453

mod_CSH*, used assumptions for T_C and the EV fleet as an input. Fig. 12 shows how the energy use for the four EV fleets increases with an increasing T_C. For the same temperature difference, the predicted E for EVs with PTC is 2 times higher than for EVs with HP. Comparing predicted E for EVs with different sizes, E for S_L is 1.9 times higher than for S_{SM}. A larger dataset would improve the models, since there are few sessions especially for $S_L H_{HP}$ and $S_L H_{PTC}$. Still, the models show interesting relations between the parameters, as described above.

3.3. Comparing energy loads for EV cabin preheating with other energy loads in an apartment

Cabin preheating of EVs typically happens during cold winter days, for example during morning hours. During such periods, the Norwegian electricity grid is already experiencing high peak loads [34]. It is therefore relevant to compare the energy loads for EV cabin preheating with other energy loads in buildings, and to analyse scenarios for aggregated power loads for cabin preheating of residential EVs. Apartment buildings have been chosen as the focus of this work, since this is a building type with an expected high density of EV charging and cabin preheating use.

For the comparison with other residential energy loads, two levels of cabin preheating were selected: 2 kWh or 4 kWh. The selected levels represent typical values, based on the cabin preheating trials and modelling results. Fig. 13 illustrates the cabin preheating together with other residential energy loads during an example day with low outdoor temperature (in average −9 °C for Fig. 13 a, and −7 °C for Fig. 13 b). The figures have an hourly resolution, and it is assumed that all the preheating happens between 07:00 to 08:00 in the morning. Apartment electricity use, space heating and DHW, and EV charging are shown in the figures. For the example day, energy for EV cabin heating increases the hourly energy peak in the morning from 4.2 kWh/h to 6.2 kWh (48 %), or from 4.2 kWh/h to 8.2 kWh (95 %), including all the energy loads (Fig. 13 d). Two alternative charging power levels are shown in Fig. 13 c) and 9 d), where the energy distribution depends on the EV charging strategy. The EV charging happens during the night, with a constant charging load. The daily peak load of the apartment is caused by either the EV charging or the EV cabin preheating. While the EV charging is often recognized as flexible, this is normally not the case for the cabin preheating. For apartment buildings with flexible EV charging, the energy loads from EV cabin heating can become the largest daily energy peak.

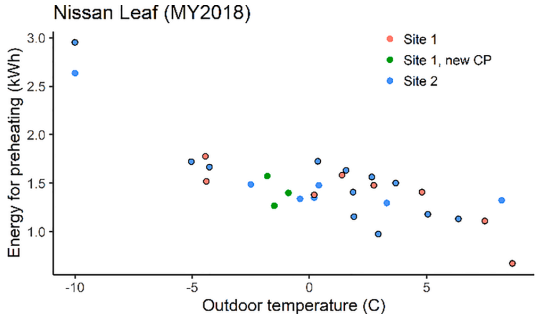

Fig. 9. Energy-Temperature diagram for preheating sessions with Nissan Leaf MY2018, using three different CPs. The figure includes trial sessions used for model training (black circles) and validation sessions.

3.4. Aggregated grid loads for EV cabin preheating

The aggregated power demand for EV cabin preheating depends on the habits of the EV owners. Not all EV owners are connected to an EV charger at the same time, nor are they plugging out their cars simultaneously. To assess expected aggregated power demand for preheating, the trial results are therefore combined with an EV charging dataset from a series of residential buildings in Norway. It is assumed that the preheating habits during cold days are in accordance with the average charging habits of today, without adding any extra CP connections for preheating of the EVs. Fig. 14 illustrates average daily profiles for the four EV cabin preheating scenarios described in Section 2.6. During workdays there is a morning peak in the preheating loads, closely before the morning peak in CP plug-outs, corresponding to the start of a typical workday. For the four scenarios, the workday morning peak varies between 0.15 kW and 0.67 kW per user. During the rest of the day, and during the weekends, the preheating load is more evenly distributed, and the average daily load varies from 0.04 kW in Scenario 1 to 0.2 kW per user in Scenario 4. There is a difference in user habits in scenarios 1 and 3 (with all users) compared with 2 and 4 (with most frequent users). The reason for this is most likely that the most frequent users have smaller battery capacities than the average users, and that they therefore more frequently charge their EVs during the day, before disconnecting from the CP in the afternoon.

The average daily profiles in Fig. 14 show the preheating load per EV user. When comparing the profiles with energy use in buildings, the share of EVs per apartment is relevant, as well as the share of EV owners actually using cabin preheating. Cabin preheating is probably most relevant for EV owners parking outside or in cold garages. In Fig. 15, the aggregated cabin preheating loads are compared to other residential energy loads, assuming that every apartment has 0.7 EVs and that 50 %

Table 10
MLR correlations in selected models and model error statistics for trial data and validation data.

		Trial data used for training the model						*Validation data*		
	Coefficient	*R^2*	*adjusted R^2*	*MAE*	*MSE*	*RMSE*	*MAPE*	*R^2*	*MAE*	*RMSE*
mod_TDSH*	$E = 0.550588 – 0.045338 \cdot T$ $+ 0.049860 \cdot (D{:}\ S_L{:}\ H_{HP})$ $+ 0.023514 \cdot (D{:}\ S_{SM}{:}\ H_{HP})$ $+ 0.065395 \cdot (D{:}\ S_L{:}\ H_{PTC})$ $+ 0.046261 \cdot (D{:}\ S_{SM}{:}\ H_{PTC})$	0.848	0.830	0.25	0.11	0.33	28%	0.895	0.29	0.37
mod_CSH*	$E = 0.41914$ $+ 0.11391 \cdot (C{:}\ S_L{:}\ H_{HP})$ $+ 0.06961 \cdot (C{:}\ S_{SM}{:}\ H_{HP})$ $+ 0.28108 \cdot (C{:}\ S_L{:}\ H_{PTC})$ $+ 0.12975 \cdot (C{:}\ S_{SM}{:}\ H_{PTC})$	0.860	0.845	0.27	0.11	0.33	23%	0.752	0.30	0.35

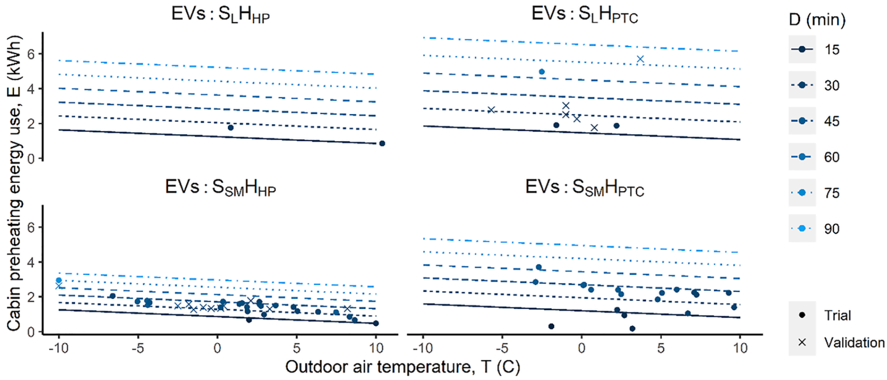

Fig. 10. The relationship between E and T, with different Ds, EV sizes (SM or L) and heating systems (HP or PTC only). Model TDSH* predictions (lines), trial data (dots), and validation data (crosses).

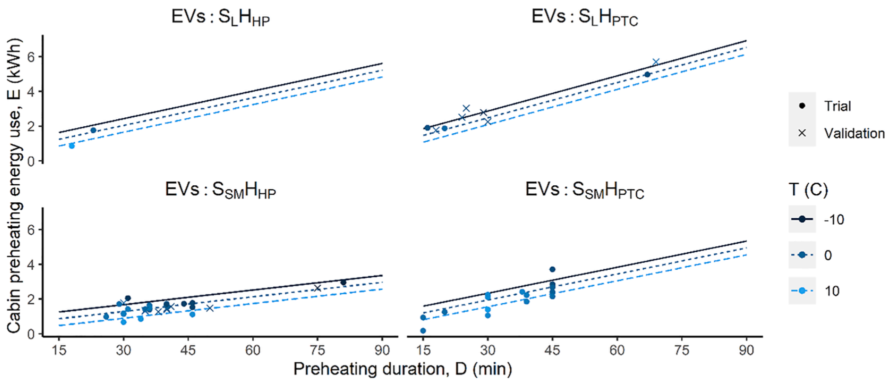

Fig. 11. The relationship between E and D, with different Ts, EV sizes (SM or L) and heating systems (HP or PTC only). Model TDSH* predictions (lines), trial data (dots), and validation data (crosses).

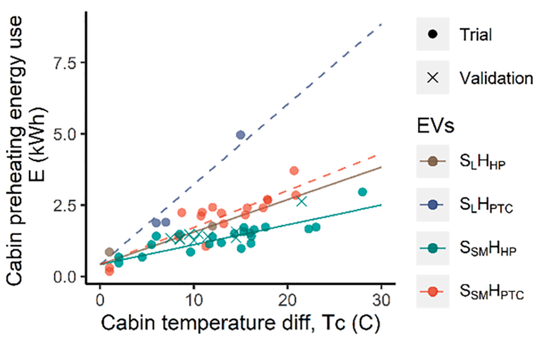

Fig. 12. Model CSH* predictions (lines), trial data (dots), and validation data (crosses) for E as a function of T_C. The EVs have different sizes (SM and L) and heating systems (HP or PTC only).

of the EVs uses cabin preheating according to scenario 1, with 2 kWh preheating 0.5 times per day. The daily profiles illustrate the seasonal difference between aggregated hourly loads during summer (June, July, August) and winter (December, January, February). For this study, winter loads during workdays are most relevant, since this is the dimensioning period for the grid. The average apartment electricity load during winter is between 0.5 and 0.8 kW/apartment, with the highest energy loads in the afternoons/evenings. For space heating and DHW, the apartments have an average daily heat load between 1.5 and 2.5 kW/apartment during the winter, with a morning and evening peak. The EV charging load during winter is in the range of 0.1 kWh per EV user during morning/daytime, and 0.5 kW per EV user during evenings/early night hours.

Fig. 15 illustrates that EV cabin preheating has a rather small effect on an aggregated level, given the assumptions in this study. During workdays, the preheating scenarios increase the average morning load during the winter with 0.5–2 %, including all the apartment energy loads and EV charging. Compared to apartment electricity only, the average morning peak increases with about 10 % on workdays. The actual aggregated load will depend on a number of parameters, such as the EV density, the number of preheating sessions per day, the preheating power and duration, outdoor temperatures, and user habits.

4. Conclusion

The number of EVs is increasing globally, and in Norway the share of BEVs and PHEVs was 22 % of the total car stock in 2021 [20]. In cold climates, it is generally recommended to use electricity from the grid to

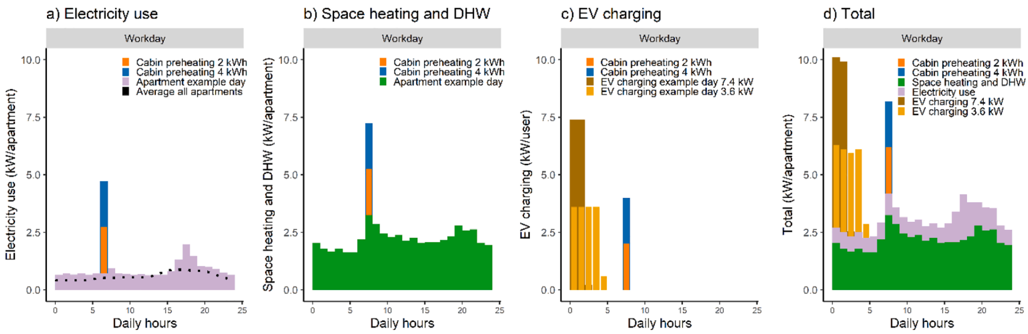

Fig. 13. Example day January 9th 2018, for an apartment with one EV, showing energy for space heating and DHW, energy for EV charging (3.6 og 7.4 kW) and cabin preheating (2 or 4 kWh), and other electricity use in the apartment.

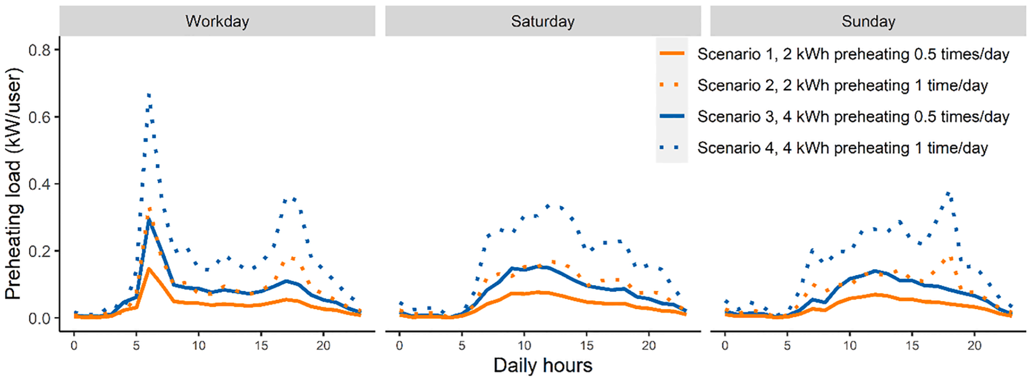

Fig. 14. Average daily profiles for cold days: Aggregated EV cabin preheating loads per EV user.

preheat the EV cabin before using the car. During workdays, a majority of EV cabin preheating sessions happen in the morning hours, when there is also a high demand for other energy use. Morning hours during cold winter days are the time of the year with the highest peak loads in Norway. It is thus important to understand the power load and energy consumption for grid-connected preheating of EV cabins. Our literature review identified a need for more experimental knowledge within this topic. This work presented data from preheating sessions of various EVs, during different outdoor temperatures. The models BMW i3, Jaguar I-PACE, Nissan Leaf, Tesla Model 3, and VW eGolf were tested, representing 38 % of the EVs in the Norwegian EV stock. Based on the trial data, linear regression models were developed. Further, preheating loads were compared to typical electricity and heating loads in apartment buildings, and aggregated grid loads for preheating EVs were assessed.

The preheating of EVs happened at two sites, both with a 7.4 kW CP. The outdoor temperatures varied between −10 °C and + 10 °C. During the preheating, most of the EVs had a power use between 3 and 8 kW initially. After a 10 to 20 min initial period, the cabin preheating power was reduced to about 2 to 4 kW. Maximum duration for preheating is car dependent, and for example Nissan starts the preheating up do 2 h before departure, depending on the outdoor temperature, while Tesla

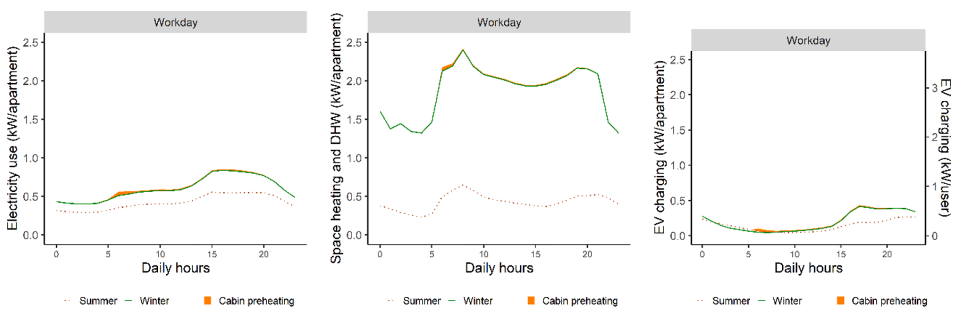

Fig. 15. Average daily profiles summer/winter: EV charging, apartment electricity use, and apartment space heating and DHW.

allows up to 4 h preheating after starting time, dependent on user preferences. The preheating duration for most of the trial sessions were between 15 and 45 min. In the trial, the preheating energy use was found to be up to 2 kWh for most EVs, while the Tesla used up to 5 kWh. Since some of the preheating sessions were interrupted by disconnecting the EVs, it is expected that the energy use can be higher.

Multiple linear regression models were developed to investigate the relationship between various variables and the energy use for preheating. Two models were selected to show the relationship between the cabin preheating energy use, outdoor temperature, and EV size/heating system (model TDSH*, R^2 0.848 for training data and 0.895 for validation data), and between the cabin preheating energy use, cabin temperature difference, preheating duration, and EV size / heating system (model CSH*, R^2 0.860 for training data and 0.752 for validation data). The two selected models can be used in parallel, since they have different input values, and therefore different advantages when applying them in analysis. For the same cabin temperature difference, the predicted preheating energy use for EVs with PTC was 2 times higher than for EVs with HP. Comparing predicted energy use for EVs with different sizes, preheating energy use for large EVs was 1.9 times higher than for small/medium EVs. Although this work has taken the first step to predict the energy consumption for grid-connected preheating of EV cabins, there are still some limitations. A larger dataset would improve the models, with an extended number of EV models, and EVs.

Hourly energy loads for EV cabin preheating were compared with other energy loads in Norwegian apartment buildings. For an example day with cold outdoor temperatures, energy for EV cabin heating increased the hourly energy peak in the morning with 48 % or 95 %, assuming 2 or 4 kWh preheating. On an aggregated level, daily energy loads for preheating were assessed for four preheating scenarios. For the four scenarios, the workday morning peak varied between 0.15 kW and 0.67 kW per EV user. This increase happens during hours where the grid is already under pressure. When comparing the daily profile for preheating with energy use in buildings on an aggregated level, it was assumed that every apartment had 0.7 EVs and that 50 % of the EVs used cabin preheating. During workdays, cabin preheating increases the average morning load during the winter with 0.5 to 2 %, including all the apartment energy loads and EV charging. Even though hourly preheating loads can be a high share of the energy use on an apartment level, the effect seems to be rather small on an aggregated level, given the assumptions in this study. Technological solutions can reduce the grid burden of EV cabin preheating. For example, the EV battery can provide energy for preheating on days where extended driving ranges are not needed. Further, even more EV models can have HPs installed, or the preheating power can be managed according to a local power limit.

The work gives insight into the power and energy use related to preheating of EVs. Such knowledge is lacking in literature, and is useful when e.g. simulating and forecasting EV energy loads on the grid in cold climates. The EV cabin preheating power and energy loads are affected by a number of parameters, such as the type of EV, the CP, the preheating duration, and the temperature levels. More research on this area is needed, including real-world testing of different EVs under various conditions, knowledge on user habits, and analyses of how preheating of EV cabins and batteries may affect the power use in buildings, and their aggregated impact on the grid loads. The research can be applied when developing new EV preheating solutions, to assure that grid requirements are met, while still maintaining the demand for extended driving ranges, comfort, and safety.

Data availability

Datasets related to this article can be found in the Data in Brief (DIB).

CRediT authorship contribution statement

Åse Lekang Sørensen: Conceptualization, Methodology, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Bjørn Ludvigsen:** Conceptualization, Investigation, Writing – review & editing. **Inger Andresen:** Writing – review & editing, Supervision.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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Main article IV

Energy profiles and electricity flexibility potential in apartment buildings with electric vehicles – A Norwegian case study

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Table: The paper's context in the thesis.

	Supplementary articles	Main article I	Main article II	Main article III	Main article IV	Data articles *(D* describes planned articles)*
RQ1: What are the energy profiles for household energy use and PV generation for apartment buildings, and how are the energy profiles influenced by climate variables?	S I. Electricity S II. Heat-DHW S III. DHW S IV. PV				Main IV. Energy profiles	D* IV. Data Main IV
RQ2: How does the user habits influence the electricity load profiles of residential EV charging, and how is the el. load affected by EV cabin preheating?	S V. Stochastic EV charging	Main I. EV charging	Main II. EV charging	Main III. EV cabin preheating		D I. Data Main I D* II. Data Main II D* III. Data Main III
RQ3: What is the potential for electricity flexibility from EVs, in relation to non-flexible apartment building loads and PV generation, in the Norwegian context?					Main IV. Flexibility	

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Energy profiles and electricity flexibility potential in apartment buildings with electric vehicles – A Norwegian case study

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ABSTRACT

Energy flexibility in buildings has the potential to reduce the grid burden of neighbourhoods, yet its practical implementation remains limited. This paper presents a data-based case study from Norway, examining the electricity flexibility potential of electric vehicles, within the context of apartment building loads and PV generation. The results highlight the significant electricity flexibility potential in apartment buildings with EVs, where EV charging can be shifted in time by means of a shared energy management system. Energy profiles are presented, showing how EV charging can increase the average electricity use in apartments by a factor of 1.5 and the power use by a factor of 3.5 to 8.6. Furthermore, the study demonstrates how electricity flexibility KPIs of optimised EV charging in apartment buildings are affected by different energy tariffs, PV generation, V2G technology, and the location of the billing meters. The simulated scenarios showed a maximum reduction of peak loads of 45 %, while a maximum of 38 % of the EV charging was covered by PV generation. The study confirms that residential EV charging emerges as a viable frontrunner in the practical realization of end-user flexibility, paving the way for effective solutions in real-life applications.

1. Introduction

1.1. Motivation

Renewable energy generation and energy efficiency of buildings are key mitigation measures, to reduce emissions under the Paris Agreement [1]. An increasing share of the energy supply is variable, which challenges the security of supply in the energy system. This challenge can be alleviated by making the energy use more flexible. The European Union has projected that the demand for flexibility in the electricity system will rise to 24 % of the total electrical demand in the EU by 2030, increasing further to 30 % by 2050 [2]. Energy use in buildings represent about 30–40 % of the total domestic energy use in many countries [3,4]. Thus, shifting the energy and power use in buildings represent a large potential for flexibility.

Several definitions of building energy flexibility can be found in literature [5,6]. IEA EBC Annex 67 defined energy flexibility of a building as [5] "the ability to manage its demand and generation according to local climate conditions, user needs and grid requirements." Different flexibility types include fast and medium regulation (within seconds or minutes, e.g. to provide frequency regulation in response to power grids), load shedding (within minutes/hours, with load curtailment during a limited period), load shifting (within hours, with loads shifted to other hours), and energy generation (where loads are covered by local generation) [7].

To increase the flexibility of energy use, demand response (DR) can play an important role. With DR, the energy consumers adjust their energy use in response to signals or incentives, for example from the grid operator or energy provider. Flexibility markets for DR are promoted by e.g. the European Commission [8]. However, the implementation of DR has not yet been fully realized in practice, due to barriers related to e.g. the regulatory framework, the market, and the lack of a proper quantification methodology [9]. Also, several other challenges remain, such as the integration of new DR systems with existing automation systems and the consideration of occupant comfort and satisfaction, as stated by [6].

When introducing DR in the residential sector, it is important to ensure it does not compromise user comfort or equipment functionality [10]. Smart applications described in literature often relate to space heating, domestic hot water (DHW) tanks, washing machines, batteries, and electric vehicles (EVs) [6,10,11]. In apartment buildings, the energy

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Nomenclature

Abbreviations

Apt	Apartment
CHP	Combined heat and power
CP	Charge point
CPO	Charge point operator
DH	District heating
DHW	Domestic hot water
DR	Demand response
DSO	Distribution System Operator
EV	Electric Vehicle
FF	Flexibility factor
FI	Flexibility index
IT230V	230 Volt IT system (distribution grid)
KPI	Key performance indicator
MILP	Mixed Integer Linear Programming
PV	Photovoltaic
SD	Standard deviation
SoC	State of charge
V2G	Vehicle-to-grid
V2X	Vehicle-to-everything
VAT	Value added tax

Sets in the optimisation model

V	Set of all electrical vehicles
E	Set of all charging events
T	Set of all time steps in the model
T_e	Set of all time steps per charging event e
M	Set of all months in the model
T_m	Set of all time steps per month in M

Variables in the optimisation model

y_t^{apt}	Electricity to the apartments (kWh/h)
$y_{v,t}^{ch}$	Electricity charged per EV (kWh/h)
y_t^{cmn}	Common electricity use (kWh/h)
$y_{v,t}^{dch}$	Electricity discharged per EV (kWh/h)
y_t^{exp}	Electricity exported to grid (kWh/h)
y_t^{imp}	Imported electricity (kWh/h)
$y_m^{\max\_imp}$	Max imported electricity per month m (kW)
z_t^{soc}	SoC of the battery (%)

Parameters in the optimisation model

D_t^{EL}	Apartment electricity demand (kWh/h)
Y_t^{PV}	Generated PV electricity (kWh/h)
$D_{v,t}^{EV}$	Uncontrolled charging demands per EV per timestep t (kWh/h)
$D_{v,e}^{EV}$	Energy demand per charging event e (kWh/h)
C^{comp}	Prosumer compensation (NOK/kWh)
C^{cons}	Energy consumption fee (NOK/kWh)
C^{eno}	Enova fee (NOK/kWh)
c^{exp}	Export income (NOK/y)
C^{fxd}	Fixed costs (NOK/y)
c^{imp}	Import cost (NOK/y)
C_m^{pty}	Peak load tariff per month m (NOK/kW)
C^{tot}	Total electricity costs (NOK/y)
C^{trans}	Energy transport fee (NOK/kWh)
C^{VAT}	Value added tax (25 %)
EV_v^{lim}	Charging power per EV (kW)
EV_v^{bat}	Battery capacity per EV (kWh)
P_t^{spot}	Spot price at hour t (NOK/kWh)
t	Timestep (h)
η^{ch}	Battery charging efficiency
η^{dch}	Battery discharging efficiency
$\Lambda_{v,t}^{EL}$	EV is connected to the CP (Boolean)

use of such applications is either part of the energy use in the apartments, or a part of the common energy use for the building association. In Norway, electricity use in apartments is metered hourly, with billing meters in each apartment [12]. Common electricity use includes energy use in common areas such as corridors, basements, and outdoors, electricity for running the central heating if relevant, and EV-charging. To realize DR in practice, it could be advantageous to start with the simplest and most accessible measures. The flexibility available in the common energy use tends to be more accessible than the energy consumption within individual apartments. Moreover, the common energy use might already be equipped with energy management systems.

Among the common energy use, smart EV charging emerges as a particularly promising solution for effective DR management. With the continued rise in EV adoption, projected to reach a 35 % sales share globally by 2030 [13], the demand for smart EV charging grows, usually as a means to reduce strain on the grid. Real-life applications of smart residential EV charging have been demonstrated in trials and in commercial offers [14–17]. Hildermeier et al. [14] analysed available tariffs and services for smart EV charging across Europe, and found that commercial services were mostly available in regions with general time-of-use tariffs, like the hourly spot prices seen in the Nordic countries. Norway, a frontrunner in EV adoption with an 88 % sales share in 2023 [13], has legally granted residents in apartment buildings the right to charge EVs at home under specific conditions [18]. However, this provision can pose challenges to local grid infrastructure. Consequently, a common charging infrastructure is often incorporated in Norwegian apartment buildings, complemented by an energy management system that limits the maximum power for simultaneous EVs charging. Since the EVs are normally connected to the charge point (CP) for a longer period than the actual charging time, there is a potential to shift the EV charging load in time. For example, residential charging loads can be shifted from high load hours in the afternoon to low load hours in the night [19]. This can be done with minimal comfort issues and involvement of residents. Using vehicle-to-grid (V2G) or vehicle-to-everything (V2X) technology allows for discharge of energy from EV batteries to the energy system.[1] Bidirectional chargers are not yet commercially available for residential users in Norway, but it is expected that they will become accessible in the near future [20]. Such DR can be a response to grid needs, or to achieve cost, energy, or climate goals for the end-users.

1.2. Literature review

EV charging and its flexibility potential have become an increasingly important topic. Numerous research articles focus on various aspects of EV charging within building infrastructures, as highlighted in recent review papers [14,21–27]. Our literature review specifically concentrates on energy use and EV charging within the residential sector. Table 1 provides an overview of the literature review, and the review findings are further elaborated in the section below.

The main data sources for EV charging studies are transportation surveys and data, data collected from vehicles, and CP data [24]. In studies that focus on residential EV charging, transportation data such as

[1] In this study, the bidirectional utilization of EV batteries is specifically referred to as V2G.

Table 1
Literature review comparison.

Ref.	Residential EV charging				Residential loads	Flexible charging	V2G	PV	Tariff comparison	Meter location comparison
	Estimation	Transport. data	CP data	Vehicle data						
[28]	–	–	–	✓	–	–	–	–	–	–
[29]	–	–	–	✓	–	–	–	–	–	–
[19,30]	–	–	✓	–	–	–	–	–	–	–
[31]	–	–	✓	–	✓	–	–	–	–	–
[32]	–	–	✓	–	–	✓	–	–	–	–
[33]	–	–	✓	–	✓	✓	–	–	–	–
[34]	–	–	✓	–	✓	✓	–	✓	✓	–
[35]	–	✓	✓	–	✓	✓	–	–	–	–
[36]	–	✓	–	–	–	–	–	–	–	–
[37]	–	✓	–	–	–	–	–	–	–	–
[38]	–	✓	–	–	✓	–	–	–	–	–
[39]	–	✓	–	–	✓	–	–	✓	–	–
[40]	–	✓	–	–	✓	✓	–	✓	–	–
[41]	–	✓	–	–	✓	✓	–	✓	–	–
[42,43]	–	✓	–	–	✓	✓	–	✓	–	–
[44]	–	✓	–	–	✓	✓	✓	✓	–	–
[45]	–	✓	–	–	✓	✓	✓	✓	–	–
[46]	–	✓	–	–	✓	✓	✓	✓	–	–
[47]	–	✓	–	–	✓	✓	–	–	✓	–
[48]	–	✓	–	–	✓	✓	–	–	✓	–
[49]	–	✓	–	–	✓	✓	–	–	✓	–
[50]	–	✓	–	–	✓	✓	–	–	–	–
[51]	–	✓	–	–	✓	✓	✓	–	–	–
[52]	✓	–	–	–	✓	✓	✓	✓	–	–
[53]	✓	–	–	–	✓	✓	✓	✓	–	–
[54]	✓	–	–	–	✓	✓	✓	✓	–	–
[55]	✓	–	–	–	✓	✓	✓	✓	✓	–
[56]	✓	–	–	–	✓	✓	–	✓	–	–
[57]	✓	–	–	–	✓	✓	–	✓	–	–
[58]	✓	–	–	–	✓	✓	–	✓	✓	–
[59]	✓	–	–	–	✓	✓	✓	✓	–	✓
[60]	–	–	–	–	✓	–	–	✓	–	✓
[61]	–	–	–	–	✓	–	–	–	–	✓
[62]	–	–	–	–	✓	–	–	–	–	✓
This paper	–	–	✓	–	✓	✓	✓	✓	✓	✓

arrival/departure time and travel distances frequently form the basis for modelling of loads and flexibility [35,36,45–51,37–44]. An example is [38], where German survey data on mobility behaviour is used for modelling individual mobility behaviour, using probability distributions and a Markov-chain. In [41], EV data are simulated based on travel distances applying a gamma distribution approach. In [37], a regional transport model from Norway is combined with data from a survey among EV owners. In other studies on EV charging in residential buildings, the needed EV charging input is simply estimated, where for example plug-in/plug-out times are based on fixed schedules [53–57,59], or modelled based on probability distributions such as the truncated Gaussian [52] or Poisson [58].

In other articles, data collected from vehicles and CP data are used to generate the residential charging load profiles [19,28–35]. According to [26], flexibility studies focussing on EV charging should incorporate realistic driving and plug-in behaviours. Also, the authors in [33] argue that it is more valuable to study the flexibility of EVs based on real-world EV charging records than simulation-based research. For example, many studies assume a standard daily EV charging session and that the EVs are continuously connected to the CP when they are parked at the residential location. This often leads to an overestimation of the actual flexibility potential from EV fleets. Therefore, it is advantageous to utilize real-world charging data as a basis for analysis, as in our study. From studies such as [19,30], actual charging demand and connection times for EV charging sessions are available. In [31], charging data and residential loads are used to study the impact of EVs on the distribution networks, but without utilizing flexibility. In [32], EV charging flexibility is studied, but without the consideration of other residential loads. In [34], aggregated load data from 4 CPs is used, but not data for each EV charging session individually. Our literature review shows that few articles combine real-world charging data with residential building loads and flexible EV charging.

Uncontrolled EV charging increases the electricity load during peak hours [27]. For the synthetic load profiles in [38], it was found that the peak loads from residential buildings increased by a factor of 1.1 to 3.6 when uncontrolled EV charging was included. At the same time, EV charging ranks among the residential energy uses with the greatest potential for flexibility [45]. Several studies have addressed flexible EV charging in residential buildings, frequently also integrating PV generation and V2G technology, as detailed in Table 1. Huang et al. [40,63] describe how minimizing the grid peak power and maximizing the self-utilization of PV electricity are important objectives for smart control of EV charging. Their case study was a building community in Sweden, including apartments, EV charging, and PV generation. Another example, [49] simulated EV charging coordination for a case study in South Korea, where charging of 1000 EVs was shifted in time to reduce the peak load of an apartment complex with 1500 apartments. The researchers concluded that EV charging coordination could reduce the peak EV charging load below a power capacity of 5 MW and reduce costs for the residents. Ramsebner et al. [35] did a field test in Austria, that included the application of controlled EV charging in a residential complex. When controlling EV charging in 27 CPs, they found that an average charging power capacity of 1.3 kW/CP was sufficient to fulfil the charging needs. They identified a potential to reduce the average charging power even further, given that more user information was combined with demand forecasts and machine learning. Studies examining household energy use, uncontrolled EV charging, and PV generation in diverse locations, such as the UK [64] and Sweden [39], have identified a mismatch between PV generation and EV charging. The review [22] encourages further research to assess how smart EV charging can improve the match with PV generation across varying locations and occupancy patterns.

Some of the studies in Table 1 also include the comparison of different end-user tariffs. Verzijlbergh [47] found that energy tariffs such as Day-Night or Time of Use resulted in peak loads that were about 25 % higher than the loads from uncoordinated EV charging. Thus, when shifting the charging loads for an EV fleet, the grid peak loads are not necessarily reduced. However, in [47], the loads were shifted to low-load hours during the night. Muñoz et al. [48] analysed the issue of overloading of distribution transformers due to EV charging, and found that the share of transformers subject to overload increased from 32 % with uncontrolled charging to 100 % with Time of Use charging. Askeland et al. [34] investigated how grid tariff optimisation with local capacity trading can facilitate an increasing amount of EV charging. Their case study was a housing cooperative in Norway with 246 apartments. The study proposed a trading mechanism to incentivize that end-users with flexible EV charging would contribute to flattening the aggregated grid load.

Apartment buildings often have a billing meter structure with separate billing meters for common energy use and individual apartments. However, there is a lack of studies addressing how this billing meter structure impacts the aggregated grid load and the self-consumption of PV electricity. In [60–62], energy use in apartment buildings is divided on common energy use in shared spaces, and energy use in apartments, but without including EV charging. To our knowledge, only [59] focuses on this division, also taking EV charging into account. In their study, they analysed household energy use and energy use for common facilities in two apartments buildings. Further, they described how the cooperative systems, such as EV charging, V2G, PV, and batteries, can be integrated into the energy management system of the apartment buildings. The researchers highlighted that the energy management systems for apartment buildings are not fully understood in literature.

The literature review shows that, while several studies focus on energy use and EV charging in residential settings, there remains a need for data-based case studies utilizing real-world data on energy and EV charging, studying load profiles and flexibility potentials in apartment buildings with EVs. We did not find any studies that also considers the billing meter location, under different end-user tariff options. Given the relevance of this scenario to numerous apartment buildings, there is a need for such studies to offer practical insights and provide input to policies.

1.3. Contributions

Our hypothesis is that apartment buildings with EVs have a particular potential for electricity flexibility, where coordination of EV charging can contribute to reducing the grid burden of the residential sector and increasing the self-consumption of PV electricity. This hypothesis is tested in a data-based case study in Norway, where the residential sector has an increasing demand for EV charging, and a growing PV utilisation. The selected case study is considered to be representative for a large share of Norwegian apartment buildings. The main research question is: *How are the electricity flexibility KPIs of optimised EV charging in apartment buildings affected by different energy tariffs, PV, V2G, and the location of the billing meters?* The contributions of this paper are as follows:

1) Utilization of real-world data: Energy data from an apartment building with 1058 apartments and EV charging data from 35,000 residential charging sessions are utilized in the case study.
2) Optimised EV charging: Data for each individual charging session (such as energy demand, plug-in, and plug-out times) and for each EV (charging power and battery capacity) are employed to generate realistic outcomes aligned with current charging patterns.
3) Billing meter structure consideration: The optimisation of EV charging considers the billing meter structure in apartment buildings. In the simulation scenarios, the common electricity use (EV, PV, V2G) is measured separately or together with the electricity use in apartments. Additionally, energy and peak load tariffs are compared in the simulation scenarios.
4) Insights and policy implications: Various scenarios involving load shifting of flexible EV charging provide insights into how these can impact the aggregated grid load and the self-consumption of PV electricity in residential neighbourhoods.

The rest of the paper is structured as follows. Section 2 presents the selected case study and its energy system. Section 3 describes the methodology, including the scenarios for optimisation, the optimisation model, and the electricity flexibility KPIs. The results are summarized in section 4, followed by discussion and policy implications in Section 5. Section 6 provides recommendations and future work, before the conclusion in Section 7.

2. The selected case study

2.1. Introduction to the case study

In this work, we aimed to select a case study which was representative for a major share of Norwegian apartments. Per 2022, about 32 % of Norwegian residents (1.7 million) live in apartments, defined as either multi-dwelling buildings or linked houses with at least 3 dwellings [65]. The remaining residents mainly live in detached houses or houses with two dwellings. The selected case study is a large housing association located in the city of Trondheim. It includes in total 1058 apartments in 121 low-rise apartment buildings, constructed in the 1970-ties, but has later been upgraded. Photos of the buildings are shown in Fig. 1. The floor area of the apartments varies from 53 to 107 m^2 (1 to 4 bedrooms), and the total floor area for the entire stock of apartments is 93,713 m^2. In 2018, the housing association consisted of 2321 residents, with a diverse mix of genders and ages [66]. A comparison between apartments in the Norwegian building stock and the selected case study can be found in Table 2.

2.2. Energy system and data

An overview of the overall energy performance of the case study is presented in Fig. 2 and Fig. 3. These figures showcase energy measurements for electricity and heating within the case study apartments, alongside data for residential EV charging. Additionally, Fig. 3 includes simulated PV generation. The purpose of these figures is to effectively illustrate the impact of EV charging on each individual apartment within the scenario involving one EV per apartment. No energy management system is currently in place.

Fig. 2 illustrates a year-long timeline featuring hourly outdoor temperatures, as well as the heating, electricity use in apartments, and EV charging. The energy loads are further described in the following sections, including space heating and DHW (section 2.2.1), electricity use in apartments (section 2.2.2), flexible and non-flexible EV charging and other common electricity use (section 2.2.3). In Fig. 3, daily average energy profiles for the same energy loads are depicted, along with simulated energy generation for four alternative PV systems (further described in section 2.4). The energy profiles in Fig. 3 are displayed for the summer (June to August) and winter (December to February), segmented by workdays and weekends. A summary of energy KPIs for the case study is presented in Table 3, and are further described in the upcoming sections. The primary data period is from 2018 and therefore predates the COVID-19 pandemic.

2.2.1. Space heating and DHW

Heating is a large share of building energy use in Norway. At the

Fig. 1. Photos of apartment buildings in the case study.

Table 2
The Norwegian building stock and the selected case study.

	Apartments in the Norwegian building stock	Selected case study
Building category	Multi-dwelling buildings or linked houses with at least 3 dwellings: 37 % of dwellings [67].	Low-rise apartment buildings with in average 8.7 dwellings per building.
Construction year	Before 1970: 35 %, between 1971 and 2000: 31 %, after 2001: 33 % [67].	1970–1973. Renovations 1993–1998 (insulation and windows) [68].
Floor space area	70 % have floor space between 50 and 120 m^2 [69].	In average 88.6 m^2 per apartment.
Residents, average	1.8 residents per household [65].	2.2 residents per household.

national level, it is estimated that about 78 % of the total energy use in households is for space heating and domestic hot water (DHW) [70]. In the case study, space heating and DHW constitute 72 % of the total delivered energy, when not including EV charging. For the case study apartments, heating is provided by district heating (DH), and the heating system is described in [71]. Delivered DH to the apartments was 138 kWh/m^2 in 2018. Heating is dominating in the wintertime, with an average daily delivered energy of 51.1 kWh/apartment. The heat use is spread quite evenly during the day (in average 2.1 kWh/h), but with a morning peak at around 08:00 during weekdays (in average 2.9 kWh/h), as shown in Fig. 3. During the summer months, the average daily delivered energy is reduced to 13.1 kWh/apartment, and with an average morning peak of 0.9 kWh/h at around 08:00. The morning peaks and the heat use during summer are mainly related to DHW use. DHW was metered in one of the sub-districts (74 apartments) in the case study in 2021 and 2022, and we found in average 8.3 kWh/apartment/day of delivered heat for DHW.

2.2.2. Electricity use in apartments

Electricity use in the apartments is metered behind billing meters in each apartment. Analysing electricity data from 505 of the apartments, the average daily energy use was found to be 14.3 kWh/apartment (standard deviation (SD) 8.5 kWh/apartment) during winter and 10.4 kWh/apartment during summer (SD 6.4 kWh/apartment). For hourly peak values, this is in average 1.4 kW during winter (SD 0.8 kW) and 1.1 kW during summer (SD 0.7 kW). During afternoons and evenings, electricity use increased by around 50 % compared to mid-day and roughly doubled compared to nighttime.

In 2018, the average electricity use in the apartments in our case study was 51 kWh/m^2, or 4527 kWh per apartment (505 units). In Fig. 4, we have compared this to the electricity use in 4 other cases studies of Norwegian apartment buildings where hourly electricity data was available from the research project COFACTOR [72]. Fig. 4 shows the daily electricity use as a function of outdoor temperature. For the apartment buildings with Apt. ID 1 to 4, the average electricity use in the apartments varied from 37 to 53 kWh/m^2/year, corresponding to 2868–4551 kWh per apartment. There is a significant seasonal difference in the electricity use, showing higher use with cold temperatures, even though all of the buildings use thermal energy for heating. We may assume that the difference is partly caused by electric floor heating in the bathrooms, and partly caused by higher electricity use for lighting and indoor activities during the winter.

2.2.3. EV charging and other common electricity use

Common electricity use in the case study includes EV charging in the garages and other electricity use in common areas (both indoor and outdoor). Excluding the electricity use in garages, we found that other common electricity uses accounts for a relatively small share of the total energy use in the case study (1 %).

In our study, we use an extended dataset for EV charging, including residential EV charging data from 12 residential locations in Norway (including the case location). The EV charging data is described in [30],

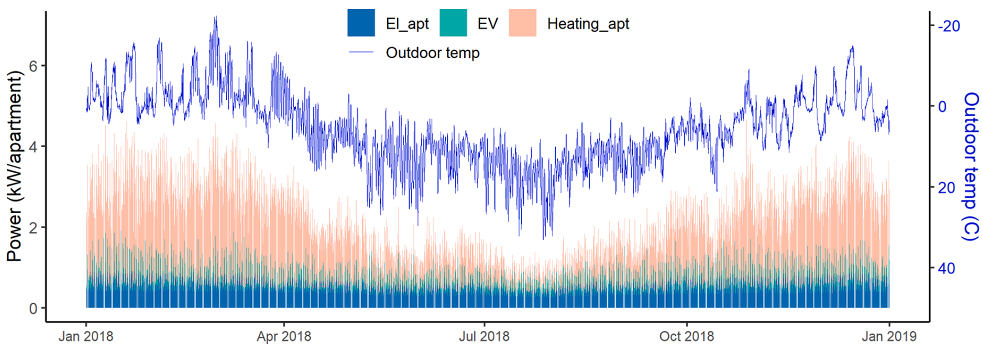


Fig. 2. Hourly energy loads in Norwegian apartment buildings during a year, with 1 EV per apartment.

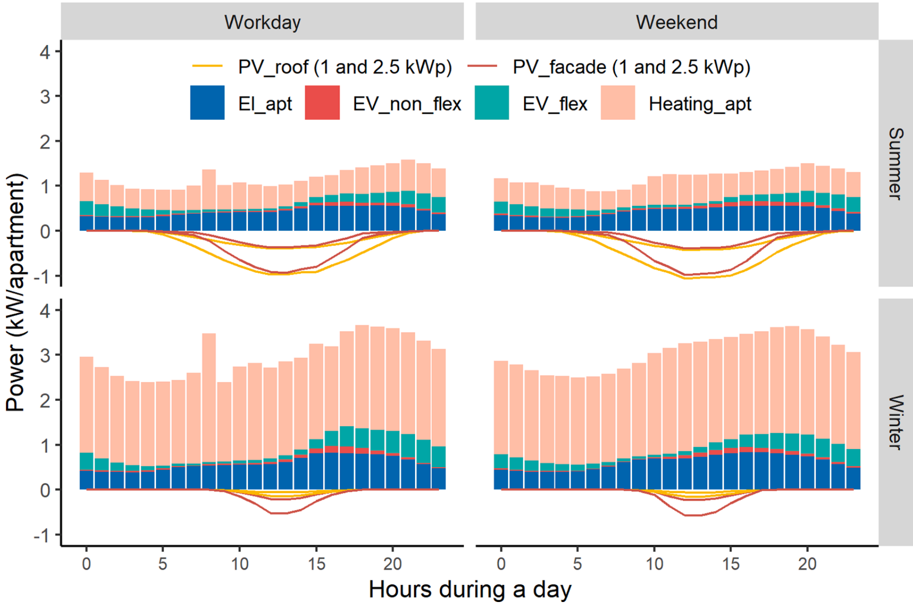


Fig. 3. Daily average energy profiles for Norwegian apartment buildings, with 1 EV per apartment.

Table 3
Energy KPIs for the apartment building of the case study.

		Delivered energy (kWh/apt/year)	Delivered energy (kWh/m²/year)	Energy share
Space heating and DHW		12 200	138	63 %
Electricity use in apartments		4 527 (SD 2 283)	51	24 %
EV charging (1 EV/ apartment)		2 314 (SD 1 445)	25.5	12 %
Other common electricity use		250	2.8	1 %
		Energy generation (kWh/apt/year)	Self-consumption (Self-sufficiency): PV to Apt and EV	Self-consumption (Self-sufficiency): PV to EV only
PV roof	1 kW$_p$:	754	98 % (11 %)	51 % (17 %)
	2.5 kW$_p$:	1 885	75 % (21 %)	29 % (24 %)
PV façade	1 kW$_p$:	799	96 % (11 %)	43 % (15 %)
	2.5 kW$_p$:	1 998	65 % (19 %)	23 % (21 %)

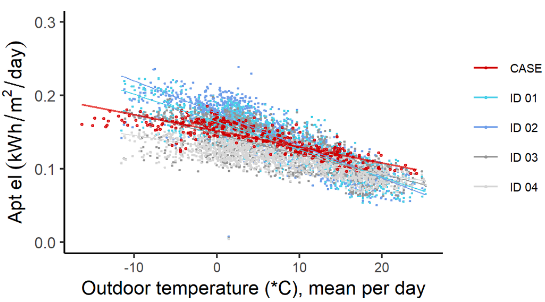


Fig. 4. Daily electricity use in 5 apartment associations, as a function of outdoor temperature.

and is based on EV charging reports with energy and time information for 35,000 EV charging sessions and 271 EV users. In [30], a charging power for each individual EV user is predicted, and the session energy is distributed hourly for each EV charging session. In the case of uncontrolled EV charging, the session energy is distributed hourly starting from the plug-in time.

The electricity use for EV charging shown in Fig. 2 and Fig. 3 is divided into flexible and non-flexible EV charging. About 25 % of the EV charging sessions have idle times less than 1 h (35 % less than 3 h) and may consequently be considered as non-flexible EV charging (in average 1.2 kWh/day). The flexible EV charging (in average 4.6 kWh/day) has in average 9.3 h idle time, and may therefore be shifted to other hours within the connection period, without necessitating changes in user behaviour.

2.3. Comparison of power and energy use for apartments and EVs

Fig. 5 shows histograms for annual and maximum hourly electricity use for each of the apartments and EVs, not including heating and other common energy use. The histograms are based on hourly measurements for electricity and heat use in about 500 apartments, together with the large dataset of residential EV charging (271 EV users). The energy histogram illustrates how the average annual electricity use in the apartments is about twice as large as the electricity use for EV charging. Adding average EV charging to average electricity use in apartments, the total energy use is increased by a factor 1.5 compared to electricity use in apartments alone. The power histogram in Fig. 5 shows how the

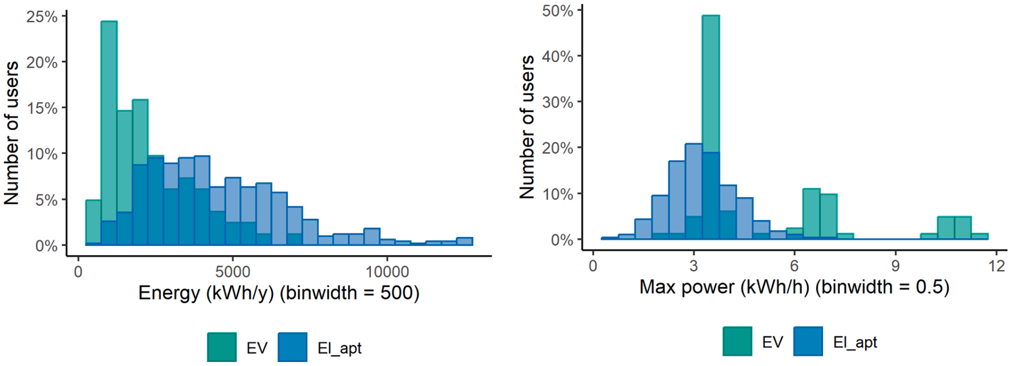


Fig. 5. Histograms with annual energy use (left) and maximum power (right) per EV and per apartment.

maximum hourly electricity use for EV charging often is higher than the hourly electricity use in the apartments. The three peaks for EV charging in the power histogram illustrates the typical charging power levels for home charging in Norway, i.e. approximately 3.5 kW, 7 kW, and 11 kW [30]. In our case study, we found that approximately 46 % of the EVs used a charging power of 3.5 kW, 38 % used a charging power of 7 kW, and 16 % used a charging power 11 kW. The charging power of these EVs is typically limited by the onboard charging power. New EVs normally have a higher onboard charging power, and the charging power is more frequently limited by the CP [30]. Adding a charging power 7 kW to the average maximum power of 1.4 kW per apartment, results in a maximum power increase by a factor 6.

2.4. Simulated PV generation and self-consumption

PV generation in apartment buildings vary with PV size, location, and weather conditions. As there are no PV systems connected to the buildings in our case study, we have simulated the PV electricity that could be generated by PV systems on the buildings. In general, there are few examples of PV systems in Norwegian apartment buildings, since the regulations did not allow sharing of electricity across billing meters until 2023. The residential PV systems currently installed in Norway are therefore mainly installed on detached houses. For the buildings in our case study, the available PV area on the roofs is estimated to be in the range of 4 kW_p per apartment (estimated for 12 of the buildings/117 apartments, using the commercial solar map [73]). Since the economic potential for PV normally is smaller than the technical potential [74], we have chosen to focus on PV sizes of 1 kW_p and 2.5 kW_p per apartment. Two alternative PV system are simulated: A rooftop system with 15° tilt orientated east and west, and a façade system with 90° tilt orientated south. The PV generation is simulated in [60], using the software PVsyst [75] and with climate data from 2018. The global radiation in Trondheim in 2018 (870 kWh/m^2) is higher than the Trondheim average from 2016 to 2022 (827 kWh/m^2), but lower than the Oslo average (953 kWh/m^2) [76].

For the simulated PV generation, we found some significant variations between the roof-mounted and façade-mounted PV systems with respect to the annual and daily energy profiles. In summer, the roof-mounted east–west system outperformed the south-facing façade-mounted system, generating an average of 4.0 kWh/kW_p/day compared to 2.9 kWh/kW_p/day, respectively. Conversely, in winter, the façade-mounted system delivered an average of 1.0 kWh/kW_p/day compared to 0.3 kWh/kW_p/day for the roof-mounted system.

The KPIs for self-consumption in Table 3 are based on hourly values, showing how PV generated electricity is utilised directly by electricity loads in apartments and for EV charging. The self-consumption of PV from the roof-mounted systems are slightly higher than those from the façade-mounted systems. This is mainly due to the fact that the roof mounted PV generates more electricity than the façade system during morning and afternoons, when there is high energy need in the apartments, as shown in Fig. 3. By increasing the size of the roof-mounted PV system from 1 to 2.5 kW_p per apartment, the self-consumption is reduced from 98 % to 75 %. By using generated PV electricity for EV charging only, the self-consumption is reduced from 51 % to 29 %, accordingly. Since a minority of the uncontrolled EVs are charging during daytime, the self-sufficiency of the generated electricity reaches a maximum of 24 % for the PV systems illustrated in Fig. 3 (roof-mounted system with capacity 2.5 kW_p/apartment).

2.5. Data selection for optimisation of residential EV charging.

Table 4 gives an overview of the data used in the optimisation. Since the main focus of the work is electricity flexibility, energy for space heating and DHW were not included in the data selection. EV charging data from 82 EV users were used in the analysis, with a full year of EV data. Electricity data from 117 apartments were included in the analysis, assuming that 70 % of the apartments were equipped with an EV. The EV rate per apartment is based on the available parking spaces for EV charging in the case study, where a common infrastructure for EV

Table 4
Input data used in the optimisation.

Data	Description	Data selection
Heating in apartments	Space heating and DHW are provided by district heating.	Not included.
Electricity in apartments	Electricity use in apartments in 2018, metered behind billing meters in each apartment [78].	Hourly data for 117 apartments.
EV charging	Dataset of residential EV charging from [30], with 271 EV users and 35,000 EV sessions in 12 residential locations in Norway, monitored from February 2018 to August 2021. Input data from EV charging reports: User ID, session ID, plug-in time, plug-out time, connection time (h), energy charged (kWh).	Predicted hourly EV charging, based on EV data for 82 EV users with full year data, pre-covid time period, transformed to fit 2018.
Other common	Other common electricity uses in the case study in 2018 [78].	Not included.
PV electricity	Simulated PV electricity generation [60], with climate data [76] from 2018. Location: Trondheim (Latitude 63.39° N, Longitude 10.44° E, Altitude 116 m).	117 kW_p roof (1 kW_p/apt).

charging was installed in 2018. In total it is possible to activate up to 764 CPs on the parking spaces, used by residents from 1113 apartments. The assumption of 70 % parking spaces for EVs is in line with the parking norms in Trondheim city (min. 0 to 0.84 parking spaces per 100 m^2 apartment building area [77]). For PV generation, the optimisation includes the roof-mounted PV system with capacity 1 kW_p per apartment.

3. Methodology

3.1. Scenarios for the optimisation

The research question of this study was addressed through a behind-the-meter optimisation of residential EV charging. The reference scenarios illustrate uncontrolled EV charging in the apartment buildings, while the simulated scenarios demonstrate a time-shifted approach for EV charging, with static electricity use in the apartments. Such EV charging control can be implemented using a common energy management system, designed to interfere as little as possible with the residents' habits. In all the scenarios, the electricity use for EV charging and the electricity use in apartments are included as key components. The scenarios for optimisation are developed considering two grid tariffs options, two billing meter locations, and two technology options (whether PV or V2G is included), as shown in Fig. 6. This makes in total 16 scenarios, as listed in Table 5.

In Norway, there is an ongoing discussion regarding the most effective tariff structure to incentivize end-user flexibility. Presently, residential customers are charged based on a combination of hourly spot prices, a monthly peak load tariff, and fixed costs. To evaluate the effect of different tariff structures, all the scenarios are analysed with the optimisation model using either the energy or peak tariff option. The tariffs that were used are described in Table 6, and are based on the tariffs that were used in the location of the case study in 2018 [79]. With the energy tariff option, it is favourable to charge the EVs during hours with low spot prices. The peak load tariff option also takes the hourly spot prices into account, in addition to reducing the monthly peak load. The optimisation was limited to the operational phase, so investment costs were not included.

Two billing meter locations are included. For the meter location labelled 'Separate', the electricity use in the apartments is measured separately from the common electricity use (EV, PV, V2G), and is not considered in the optimisation. Additionally, a common billing meter measures the shared energy systems, including EV, PV, and V2G. This billing meter option is most similar to the real-world billing location used in Norway. The option labelled 'Total' has a single billing meter for all energy options: EV, Apt, PV and V2G, meaning that the electricity use in the apartments is taken into account for the optimised control.

The technology options considered are 'PV systems' and 'V2G technology'. For PV generation, it is more profitable to use the generated electricity for energy uses behind the billing meter, compared to exporting the electricity to the grid. For V2G technology to be profitable, the cost reduction related to using V2G needs to be higher than the cost of charging, due to the round-trip efficiency losses [80]. It is most profitable to use the discharged electricity behind the billing meter, compared to exporting the electricity.

In this study, our primary focus is to examine the impact of flexible EV charging on the KPIs in various scenarios. Given the diverse range of optimised scenarios, involving different energy/peak tariffs, variations in the location of billing meters, and the presence of PV/V2G, several reference scenarios are needed to isolate the effect of EV charging in the performance. All the reference scenarios include uncontrolled EV

Table 5
Overview of scenarios for the optimisation.

Ref	*Ref*	Uncontrolled EV charging in apartment buildings	
	Ref_{PV}	Uncontrolled EV charging in apartment buildings with PV-systems	
EV-Apt	EN^{sep}	EV charging optimised with energy tariffs.	EVs are metered separately from apartments.
	EN^{tot}	EV charging optimised with energy tariffs.	EVs + apts. are metered together.
	PK^{sep}	EV charging optimised with peak tariffs.	EVs are metered separately from apartments.
	PK^{tot}	EV charging optimised with peak tariffs.	EVs + apts. are metered together.
EV-Apt-PV	EN^{sep}_{PV}	EV charging optimised with energy tariffs.	EVs + PV are metered separately from apts.
	EN^{tot}_{PV}	EV charging optimised with energy tariffs.	EVs + PV + apts. are metered together.
	PK^{sep}_{PV}	EV charging optimised with peak tariffs.	EVs + PV are metered separately from apts.
	PK^{tot}_{PV}	EV charging optimised with peak tariffs.	EVs + PV + apts. are metered together.
EV-Apt-V2G	EN^{sep}_{V2G}	EV charging + V2G optimised with energy tariffs.	EVs are metered separately from apts.
	EN^{tot}_{V2G}	EV charging + V2G optimised with energy tariffs.	EVs + apts. are metered together.
	PK^{sep}_{V2G}	EV charging + V2G optimised with peak tariffs.	EVs are metered separately from apts.
	PK^{tot}_{V2G}	EV charging + V2G optimised with peak tariffs.	EVs + apts. are metered together.
EV-Apt-PV-V2G	$EN^{sep}_{PV,V2G}$	EV charging + V2G optimised with energy tariffs.	EVs + PV are metered separately from apts.
	$EN^{tot}_{PV,V2G}$	EV charging + V2G optimised with energy tariffs.	EVs + PV + apts. are metered together.
	$PK^{sep}_{PV,V2G}$	EV charging + V2G optimised with peak tariffs.	EVs + PV are metered separately from apts.
	$PK^{tot}_{PV,V2G}$	EV charging + V2G optimised with peak tariffs.	EVs + PV + apts. are metered together.

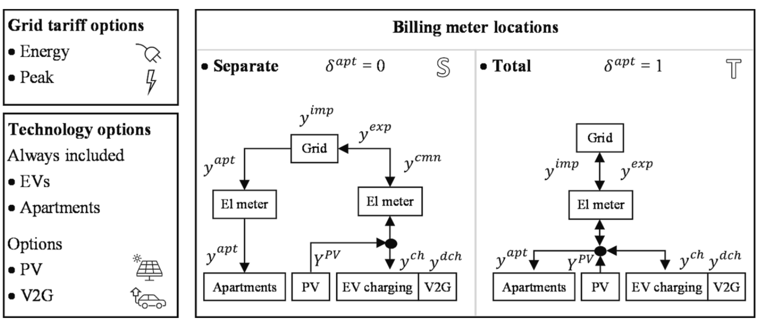


Fig. 6. Overview of the options in the optimisation scenarios.

Table 6
Tariff options: Energy and Peak per month. VAT is included in all prices.

			Energy (EN)	Peak (PK)
Grid	C^{fxd}	Fixed cost, apartments [NOK/year]	1875	1875
	C^{fxd}	Fixed cost, garage [NOK/year]	10,000	10,000
	C^{eno}	Enova tariff [NOK /kWh]	0.0125	0.0125
	C^{cons}	Consumer tariff [NOK /kWh]	0.20725	0.20725
	C^{trans}	Energy transport tariff [NOK /kWh]	0.20625	0.0625
Peak	C_m^{pty}	Peak load tariff (Jan,Feb,Nov,Dec) [NOK/month/kW]	0	75
	C_m^{pty}	Peak load tariff (Mar-Oct) [NOK/month/kW]	0	56.25
Energy	P_t^{spot}	Spot price at hour t [NOK/kWh]	Spot (2018)	Spot (2018)
PV		Self-consumed PV-electricity [NOK/kWh]	0	0
	c^{exp}	Exported electricity from PV or V2G (Jan,Feb,Nov,Dec) [NOK/kWh]	Spot x 1.065	Spot x 1.065
	c^{exp}	Exported electricity from PV or V2G (Mar-Oct) [NOK/kWh]	Spot x 1.05	Spot x 1.05

charging, with charging immediately after plug-in. When PV generation is included in a scenario, it is also included in the reference scenario. Since the tariff options and billing meter locations make an impact on the operational costs also for the reference scenarios, they are included in the reference scenarios as well.

3.2. Optimisation model

The optimisation problem is solved using Mixed Integer Linear Programming (MILP), with the optimisation model developed in [81]. Within the model, each EV charging session is simulated separately in an optimal manner, respecting the real-world values of energy demand for charging sessions, and related plug-in and plug-out times. The main objective of the optimisation is to minimize the energy costs in the operational phase, as described in Eq. (1), where the total operational electricity costs C^{tot} is the sum of annual fixed costs C^{fxd}, the import cost c^{imp} (bought electricity) and the export income c^{exp} (sold electricity). The import cost (Eq. (2)) varies for each month m and timestep t, and includes energy fees, monthly peak load tariff (if included in the scenario), and hourly spot prices. The export income (Eq. (3)) includes hourly spot prices and a prosumer compensation.

$$\min\ C^{tot} = C^{fxd} + \left(c^{imp} - c^{exp}\right) \tag{1}$$

where

$$c^{imp} = \sum_{m\in M}\sum_{t\in T_m}\left(C^{eno} + C^{cons} + C^{trans}\right)y_t^{imp} + \delta^{peak}\left(C_m^{pty} y_m^{max\_imp}\right) + P_t^{spot} y_t^{imp} C^{VAT}) \tag{2}$$

$$c^{exp} = P_t^{spot} y_t^{exp}\left(1 + C^{comp}\right) \tag{3}$$

The optimisation is subject to constraints. The energy balance constraints are described in Eqs. (4)–(6). Eq. (4) describes how imported electricity each hour y_t^{imp} is the sum of electricity to the apartments y_t^{apt} and the common electricity use y_t^{cmn}. Eq. (5) describes how the common electricity use is the sum of the electricity charged and discharged for every EV, the generated PV electricity, and the electricity exported to the grid. In this work, the electricity use in the apartments is not considered to be flexible, and is set equal to the electricity demand of the apartments D_t^{EL}, as shown in Eq. (6). Depending on the location of the billing meter, as described in section 3.1, the on-site PV electricity generation and the V2G electricity can be used for EV charging only (boolean $\delta^{apt} = 0$), or for the whole building, including both EV charging and the apartments' energy demand (boolean $\delta^{apt} = 1$).

$$y_t^{imp} = \left(1 - \delta^{apt}\right)y_t^{apt} + y_t^{cmn}\ ,\ \forall t \in \mathrm{T} \tag{4}$$

$$y_t^{cmn} - y_t^{exp} = \sum_{v\in V}\left(y_{v,t}^{ch} - \delta^{V2G} y_{v,t}^{dch}\eta^{dch}\right) + \delta^{apt} y_t^{apt} - \delta^{PV} Y_t^{PV},\ \forall t \in \mathrm{T} \tag{5}$$

$$y_t^{apt} = D_t^{EL},\ \forall t \in \mathrm{T} \tag{6}$$

The charging and discharging of each EV, v, are described in Eqs (7) and (8), where $\Lambda_{v,t}^{EL}$ is the availability of the EV at time step t (boolean), EV_v^{lim} is the fixed charging power per EV, and δ_t^{ch} is a boolean that has a value of 1 when the EV is charging. Eq. (9) ensures that the energy charged within a charging session is greater or equal to the reference charging demand (UNC). Eq. (10) ensures, for each charging session e, that the net charging (charging minus discharging) is greater or equal to the total demand of the charging session. Allowing V2G activates discharging of the EVs. Eq. (11) restricts the energy content of the battery at any hour t to be within the limits of its available SoC capacity, for EVs connected to the CP, $\Lambda_{v,t}^{EL}$. Eqs. (12) and (13) reflect the energy balance of the battery. Battery degradation is not included in the model. The values of all Λ s and δs are predefined according to real world data and/or scenario option, prior to running the model.

$$y_{v,t}^{ch} \le \Lambda_{v,t}^{EL} EV_v^{lim} \delta_t^{ch},\ \forall t \in T_e \tag{7}$$

$$y_{v,t}^{dch} \le \delta^{V2G} \Lambda_{v,t}^{EL} EV_v^{lim}\left(1 - \delta_t^{ch}\right),\ \forall t \in T_e \tag{8}$$

$$y_{v,t}^{ch} \ge \delta^{UNC} D_{v,t}^{EV},\ \forall t \in T_e \tag{9}$$

$$\sum_{t\in T_e}\left(y_{v,t}^{ch} - y_{v,t}^{dch}\right) \ge D_{v,e}^{EV},\ \forall e \in \mathrm{E}, \forall v \in \mathrm{V} \tag{10}$$

$$z_t^{soc} \le 100\% \times \Lambda_{v,t}^{EL},\ \forall t \in T_e \tag{11}$$

$$z_t^{soc} = z_{t-1}^{soc} + \frac{y_{v,t}^{ch}}{EV_v^{bat}} \times 100\% \times \eta^{ch} - \frac{y_{v,t}^{dch}}{EV_v^{bat}} \times 100\%,\ \forall e \in \mathrm{E}, \forall v \in \mathrm{V} \tag{12}$$

$$z_t^{soc} = z_{init}^{soc} + \frac{y_{v,t}^{ch}}{EV_v^{bat}} \times 100\% \times \eta^{ch} - \frac{y_{v,t}^{dch}}{EV_v^{bat}} \times 100\% \tag{13}$$

3.3. Selection of energy flexibility indicators for characterizing electricity flexibility of aggregated EV charging in the case study

Different stakeholders, such as end-users, aggregators and grid operators, require different kinds of flexibility indicators [86]. While end-users often aim to reduce their total energy costs, grid operators need to know the aggregated flexibility potential of a building stock. There is a lack of consensus and standardization about the quantification of energy flexibility in buildings [56,86,87]. The authors of [87] recommend that several methodologies should be tested when quantifying energy flexibility for a specific case study. In our case study, energy flexibility indicators from [6,83,84] are tested on the case study data, with equations and definitions as listed in Table 7.

The Energy flexibility indicators from [6] are based on a systematic review of energy flexibility KPIs for residential buildings. The energy flexibility KPIs used in our case study are listed by [6] as the five most popular KPIs found in literature, and include peak power reduction, self-consumption and self-sufficiency of locally generated energy, flexibility factor (FF), and flexibility index (FI). The FF indicates a quantity of energy during high load versus low load hours. Often the FF is used to describe the flexibility of heating systems [6,82,88], but it can also be used to describe different aspects of flexible EV charging [89]. In our study, FF is used to describe the capability to shift EV charging to periods with low load (21:00 to 6:00), to periods with PV generations, or to low-cost periods (below monthly median spot price). The FF values range from 1 to −1, where use during only low load hours gives a quantity of 1 (highest flexibility), and use during only high load hours gives a quantity of −1. The FI is the percentage of the operation cost with optimised

Table 7
Energy flexibility indicators used in the case study analysis, calculated over a period of one year.

Energy flexibility KPIs from [6]	Equation	eq. nr	Ref. case	
Peak power (kW)	P_{peak}			Power demand during peak hour.
Peak power reduction (%)	$\Delta P\% = 1 - \frac{P_{peak\ flexible}}{P_{peak\ ref}}$	(14)	Yes	Percentage of reduced power demand during peak hour due to the optimised control, taking the total reference power into account.
Self-consumption (%)	$SC = \frac{PV\ generation\ directly\ consumed}{total\ PV\ generation}$	(15)	No	SC: The share of PV generation that is used behind the same billing meter ("sep": For EV charging, "tot": For apartments and EV charging). SC_{EV}: SC for EV charging only.
Self-sufficiency (%)	$SS = \frac{PV\ generation\ directly\ consumed}{Energy\ use}$	(16)	No	SS: The share of the energy use that is covered by PV generation (behind the same billing meter). SS_{EV}: SS for EV charging only.
Flexibility factor	$FF = \frac{(E_{low\ load} - E_{high\ load})}{(E_{low\ load} + E_{high\ load})}$	(17)	No	$FF_{EV\text{-}low}$: EV charging during low load hours versus high load hours. As in [82], the low demand hours were defined as between 21:00 and 6:00 the following day. $FF_{EV\text{-}PV}$: EV charging during hours with PV generation (representing $E_{lowload}$) versus EV charging with electricity from the grid (representing $E_{highload}$). $FF_{EV\text{-}cost}$: EV charging during periods with low spot prices compared to EV charging during periods with high spot prices. As in [82], the low and high spot price hours were defined as the hours when the spot price was below and above the monthly median.
Flexibility index (%)	$FI = 1 - \frac{(Cost_{flexible})}{(Cost_{ref})}$	(18)	Yes	The operation cost with optimised control, compared to the reference case.
Energy flexibility KPIs from [83,84]			**Ref. case**	
Peak power difference (%)	$-\Delta P\%$	(19)	Yes	The difference in peak power, compared to the reference case. Equation (19) equals (14), but (14) is positive when there is a reduction and (19) is negative.
Energy stress hours difference (%)	$\Delta Estress\% = \frac{Estress_{flexible}}{Estress_{ref}}$	(20)	Yes	The difference in delivered energy during hours that are predefined as stressful for the energy system. In Norway, this is typically in the morning (7:00–11:00) and afternoon (17:00–19:00) [85]. In this case-study, the period 17:00–19:00 is selected, since this is a period with peaks in both apartment electricity use and residential EV charging.
Delivered energy difference (%)	$\Delta E\% = \frac{E_{flexible}}{E_{ref}} - 1$	(21)	Yes	The difference in delivered energy with optimised control, compared to the reference case.
Operational cost difference (%)	$\Delta cost\% = \frac{cost_{flexible}}{cost_{ref}} - 1 = -FI$	(22)	Yes	The difference in operational cost due to energy use with optimised control, compared to operational cost due to energy use in the reference case.

control, compared to a reference case.

The Research Centre on Zero Emission Neighbourhoods in Smart Cities (FME ZEN) [90] is developing a ZEN KPI assessment tool to monitor the performance of a neighbourhoods. Within the Power-category in ZEN, the KPIs refer to the energy flows between the neighbourhood and energy grids in the operational phase [83,84]. Four KPIs present the difference between a reference case and a case with flexible operation: Delivered energy difference, operational cost difference, energy stress difference, and peak load difference. In our case study, the four flexibility KPIs are summarised in a graph, showing the effect of the KPIs together, as proposed by [83,84]. These KPI graphs include two of the indicators from [6] described above; peak power reduction (named peak power difference) and FI (named operational cost difference). In our study, the peak power difference and operational cost difference are presented with a negative sign when there is a reduction (similar to [83,84], opposite to [6]).

4. Results

This section presents the results from the optimisation scenarios.

4.1. Uncontrolled EV-charging (Reference scenarios)

Fig. 7 shows the average daily load profiles for the reference scenarios. The load profiles include electricity use in the apartments, uncontrolled EV-charging, and alternatives with and without PV generation. The lines representing the net delivered electricity in the figures ("Grid") were calculated by subtracting the hourly PV generation from the total hourly electricity use (including electricity use in apartments and EV charging). Consequently, net delivered electricity represents the aggregated grid load for the apartment buildings, summarizing all the billing meters. Table 8 presents the reference scenarios, including the absolute values used to calculate the KPIs for the optimised scenarios. For the two reference scenarios with PV, the different metering locations result in varying quantities of imported and exported energy, while the net delivered electricity to the apartment buildings remains constant. The operational costs are influenced by the applied tariffs (energy tariff *EN* or peak tariff *PK*), and the placement of billing meters (tot or sep). These distinctions are captured in the reference scenarios, so the effects of optimised EV charging can be evaluated specifically, without simultaneously considering the other differences between the

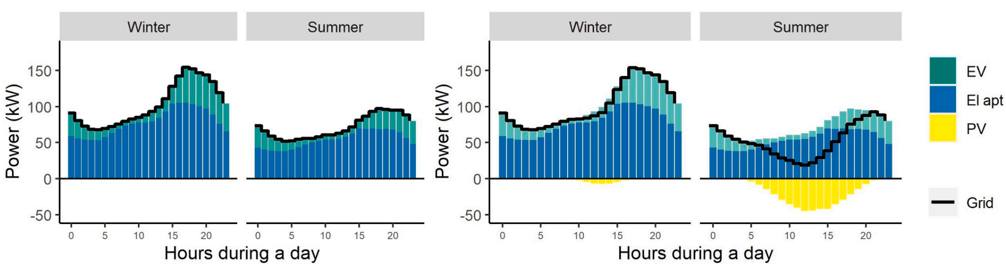


Fig. 7. Average daily profiles for uncontrolled EV-charging, without PV (left) and with PV (right).

Table 8
Reference scenarios.

	Energy use (MWh)	PV generation (MWh)	Net delivered electricity (MWh)	Imported from grid (MWh)	Exported to grid (MWh)	Energy, stress hours (MWh)	EV charging (MWh) Low load High load	EV charging (MWh) Low price High price	Cost (kNOK) EN PK
Ref	760	–	760	760	–	90	85	90	956
							99	93	976
Ref_{PV}^{sep}	760	88	672	727	55	81	85	90	897
							99	93	922
Ref_{PV}^{tot}	760	88	672	673	2	81	85	90	870
							99	93	902

scenarios.

The average daily peak is about 125 kW for the reference scenarios, both with and without PV. EV charging comprises 24 % of the average energy load during the year. The yearly peak load is 219 kW, occurring in January from 17:00 to 18:00, whereof uncontrolled EV charging contributes to 48 % of the peak. Annual delivered energy during stress hours (17:00–19:00) is 90 MWh in the reference scenarios without PV, whereof 30 % is related to EV charging. The flexibility factor value, $FF_{EV\text{-}low}$, is −0.08 for uncontrolled EV charging during low/high-load hours, as shown in Fig. 8. For the reference scenarios with PV, the delivered energy during stress hours is reduced from 90 to 81 MWh. The $FF_{EV\text{-}PV}$ value is −0.64, indicating that only a small proportion of the uncontrolled EV charging is supplied by PV generation. The self-consumption of PV is 38 % in Ref_{PV}^{sep}, when the generated PV electricity is used for EV charging only (metering location "separate"). When PV generation, EV charging, and apartments electricity use are metered together (metering location "total"), the self-consumption increases to 98 %. The $FF_{EV\text{-}cost}$ value is −0.02, for charging during low/high-cost periods.

For the operational costs, we found small differences between the reference scenarios. The operational costs for the reference scenario with peak tariffs, ^{Ref}PK, is 2 % higher than for the reference scenario with energy tariffs, ^{Ref}EN. For the scenarios with PV generation, the operational costs depend on if the generated PV electricity is used on-site or exported. When EV charging and PV generation are metered separately from apartment electricity use (Ref_{PV}^{sep}), the operational costs are about 3 % higher than when also apartment electricity use is behind the same meter (Ref_{PV}^{tot}).

4.2. *Optimised EV charging and energy loads in apartments ("EV, Apt" scenarios)*

Fig. 9 and Fig. 10 show average daily load profiles for the scenarios when the EV charging is optimised according to energy and peak tariffs (not including PV or V2G technologies). Fig. 11 presents the KPIs for the scenarios, with peak power difference, energy stress hours difference, delivered energy difference, and operational cost difference.

When EV charging is controlled according to energy tariffs, named *EN*, a large share of the EV charging is moved to the night-time, when the hourly spot prices are lower. The average daily load profile in Fig. 9 shows how this shifting creates a new peak during the night. We found a

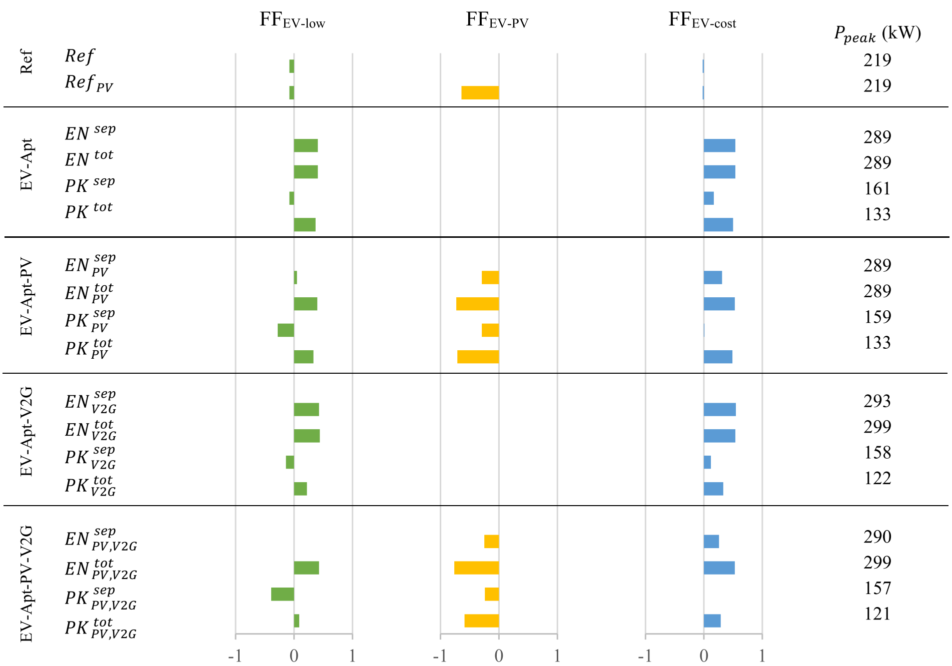


Fig. 8. Flexibility Factors and annual peak power for the scenarios.

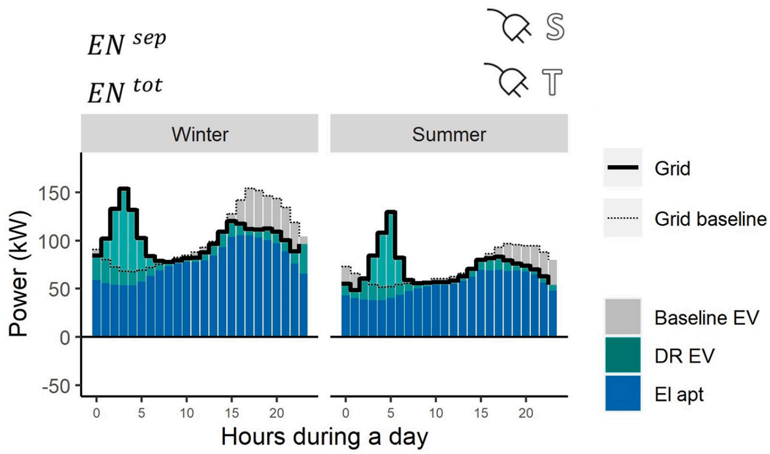


Fig. 9. Average daily profiles: "EV, Apt"-scenarios with energy tariffs.

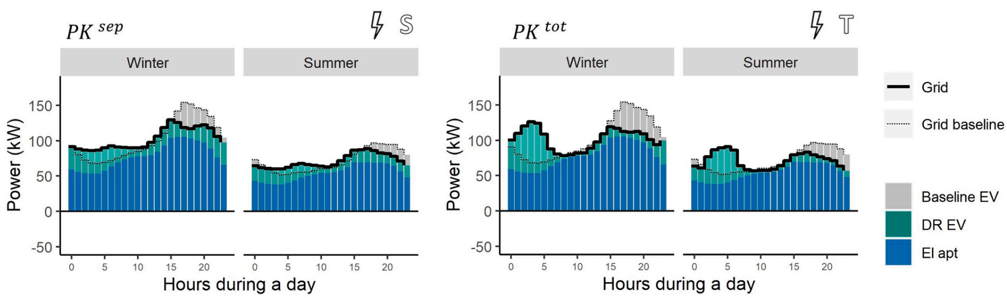


Fig. 10. Average daily profiles: "EV, Apt"-scenarios with peak tariffs.

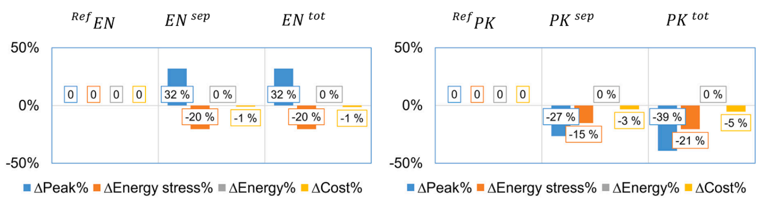


Fig. 11. Energy flexibility KPIs for the "EV, Apt"- scenarios.

yearly peak of 289 kW at night (02:00), which is 32 % higher than for the yearly peak in the reference scenarios, which occurred in the afternoon (17:00). Energy use during stress hours (17:00–19:00) is reduced by 20 % compared to the reference scenarios. FFEV-low is improved from −0.08 to 0.41, since a larger share of the EV charging occurs during low demand hours (21:00 to 6:00).

The shift in EV charging is triggered by the fact that the spot prices are different, not the magnitude of the difference. All flexible EV charging is therefore shifted to the cheapest hours, even if the profit for a certain day is small. In the case study period (2018), the differences in spot price were quite small, and the ΔCost was only −1%, compared to the reference scenarios with energy tariffs. As illustrated in Fig. 8, the $FF_{EV\text{-}cost}$ value increases from −0.02 to 0.54, showing how energy is shifted from periods with high spot prices to low spot prices. For the scenarios with energy tariffs, the location of the billing meters (separate or total) does not change the daily profile.

When controlling EV charging according to peak-tariffs, i.e. the scenarios labelled *PK*, the EV charging is optimised to reduce the monthly peak. In addition, hourly spot-prices are considered in the PK scenarios. In Fig. 10, the average daily profiles for PK^{sep} and PK^{tot} are presented. For these scenarios, the location of the energy meter affects the results. When EV charging is metered separately from electricity use in apartments (PK^{sep}), the EV charging is spread nearly evenly through the day, and the total yearly peak is 161 kW. When there is a single meter for both EV charging and apartment electricity use (PK^{tot}), a larger share of the flexible EV charging is moved to the night-time, and the yearly peak is reduced to 133 kW, 39 % lower than for the reference scenarios. Compared to the reference scenario, we found that the scenarios PK^{sep} and PK^{tot} show a reduction of the energy use during stress hours by 15 % and 21 % respectively. The ΔCost is −3% for PK^{sep} and

−5% for PK^{tot}, compared to the reference scenario with peak tariffs. The amount of shifted energy is reflected in the values for $FF_{EV\text{-}low}$ and $FF_{EV\text{-}cost}$ (Fig. 8), where $FF_{EV\text{-}low}$ is improved from −0.08 to 0.37 and $FF_{EV\text{-}cost}$ is improved from 0.17 to 0.5, going from the PK^{sep} scenario to the PK^{tot} scenario.

4.3. Optimised EV charging, energy loads in apartments, and PV ("EV, Apt, PV" scenarios)

In this section, PV technology is added to the scenarios, combining optimised EV charging, energy loads in apartments, and PV generation. The energy flexibility KPIs are summarized in Fig. 12. It is economically beneficial to increase the self-consumption of generated PV electricity, since this energy is free of charge in the operational phase. With separate metering, flexible EV charging is therefore moved to daytime for both energy and peak scenarios. Since a majority the EVs are disconnected during daytime, the share of the EV charging which could be moved to sunny hours is limited. With separate metering, the self-consumption of PV electricity is 72 % for both EN^{sep}_{PV} and PK^{sep}_{PV}, using generated PV electricity for EV charging only. When EV charging, PV generation and apartment electricity use are metered together (EN^{tot}_{PV} and PK^{tot}_{PV}), the self-consumption of PV increases to 100 %, because the PV electricity is also used in the apartments. However, in these scenarios, the flexible EV charging is not moved to daytime due to the introduction of PV, since the daytime electricity demand of the aggregated apartments exceeds the generated PV electricity. The shifting of the flexible EV charging is therefore similar to the scenarios without any PV, i.e. a shift of charging to hours with low spot prices. This is illustrated in Fig. 13, which shows the average daily profiles during summer for the scenarios with energy tariffs (EN^{sep}_{PV} and EN^{tot}_{PV}). The yearly peaks are the same as for the "EV, Apt"-scenarios, since these occur during the winter when there is little PV electricity generated. During summer, the average daily peaks are reduced from about 125 kW to 90 kW going from EN^{sep} to EN^{sep}_{PV} and from about 100 kW to 80 kW going from PK^{sep} to PK^{sep}_{PV}. This is reflected in the peak loads per month, and has a positive economic consequence for the peak-scenarios.

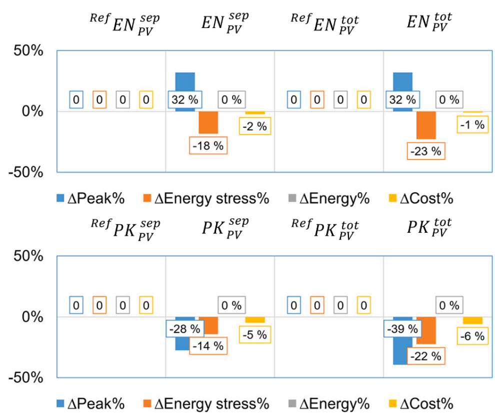
4.4. Optimised EV charging, energy loads in apartments, and V2G ("EV, Apt, V2G" scenarios)

In this section, V2G technology is included in the optimisation. The use of V2G technology has an operational cost due to the round-trip efficiency of 77 %, leading to an increased charging demand of 0.23 kWh for every discharged kWh. The use of V2G technology therefore depends on the variations in energy prices during the connection time. It has to be economical beneficial to discharge energy from the EV batteries during hours with higher spot-prices, before charging a higher amount of energy during hours with lower spot-prices. Since 2018 was a year with small variations in daily spot-prices, our results show limited use of V2G in the energy tariff-scenarios during this period. For the scenario EN^{sep}_{V2G}, we found that only 11 526 kWh was discharged during the year, while 33 191 kWh was discharged for the scenario EN^{tot}_{V2G}, i.e. when also apartment electricity is placed behind the same meter. The reason for this is that there is a higher energy demand during the hours when V2G is profitable. For both scenarios (EN^{sep}_{V2G} and EN^{tot}_{V2G}), the discharged energy is more than doubled when using the 2021-spot prices for the Oslo-region, which had more daily variations. Fig. 14 shows the "EV, Apt, V2G"-scenarios with energy tariffs during the winter seasons, which is the seasons with the largest spot price differences. Spot prices in 2018 are compared with spot prices in 2021, showing how the larger spot price variations in 2021 led to an extended use of V2G. When V2G technology is utilised with energy-tariffs, the daily peaks during night-time increased (from 289 kW with EN^{tot} to 299 kW with EN^{tot}_{V2G}), since the charging demand is increased by the round-trip efficiency. The total energy use due to the round-trip efficiency increased by 1 %, comparing the reference scenario with EN^{tot}_{V2G} scenario.

The results also show that there is not much difference between the peak-scenario with separate metering (PK^{sep}_{V2G}), and the scenario without V2G (PK^{sep}), since the charging demand is already more or less flat during the days with monthly peaks (3 700 kWh discharged). When apartment electricity is included (PK^{tot}_{V2G}), V2G technology is used more (18 828 kWh discharged), to shift electricity from afternoons during the days with highest peaks during the month, and thereby reduce the monthly peaks. Fig. 15 shows the average daily profiles during winter for PK^{sep}_{V2G} and PK^{tot}_{V2G} (2018-tarrifs). The energy flexibility KPIs for the "EV, Apt, V2G"- scenarios are shown in Fig. 16, with FF-values in Fig. 8.

4.5. Optimised EV charging, energy loads in apartments, PV, and V2G ("EV, Apt, PV, V2G" scenarios)

In this section, both PV generation and V2G technology are included in the scenarios. The average daily profiles are shown in Fig. 17 and Fig. 18, and energy flexibility KPIs in Fig. 19. For the scenarios with separate metering ($EN^{sep}_{PV,V2G}$ and $PK^{sep}_{PV,V2G}$), the combination of PV and V2G increases the self-consumption of PV (increased to 83 %, from 72 % in scenarios with PV only). V2G technology provides electricity for charging other EVs during nighttime, followed by charging the EVs the day after, utilizing PV generated electricity. For the scenarios with one billing meter for the total electricity use ($EN^{tot}_{PV,V2G}$ and $PK^{tot}_{PV,V2G}$), the



	SC (SC_{EV})	SS (SS_{EV})
Ref^{sep}_{PV}	38% (38%)	4% (18%)
Ref^{tot}_{PV}	98% (38%)	11% (18%)
EN^{sep}_{PV}	72% (72%)	8% (35%)
EN^{tot}_{PV}	100% (28%)	12% (14%)
PK^{sep}_{PV}	72% (72%)	8% (35%)
PK^{tot}_{PV}	100% (29%)	12% (14%)

Fig. 12. Energy flexibility KPIs for the "EV, Apt, PV"-scenarios.

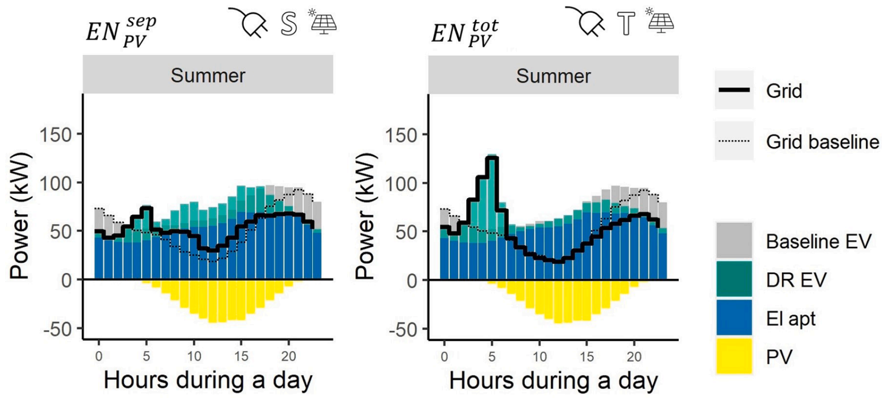


Fig. 13. Average daily profiles (summer): "EV, Apt, PV"-scenarios with energy tariffs.

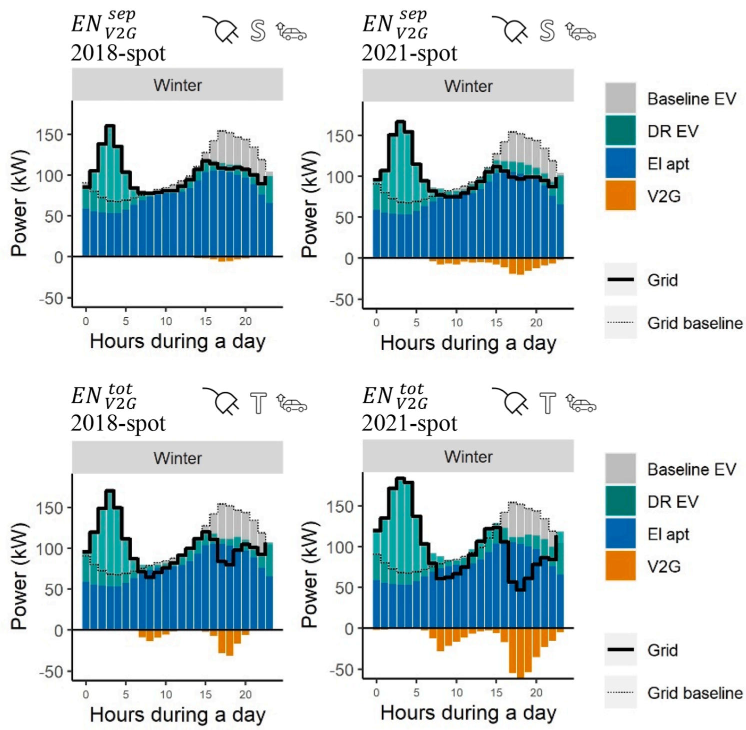


Fig. 14. Average daily profiles (winter): "EV, Apt, V2G"-scenarios with energy tariffs from 2018 and 2021.

self-consumption of PV electricity is 100 %, and the self-consumption KPI does not benefit from the V2G-PV combination. If the PV system had been larger, the self-consumption would have increased also for these scenarios. The scenario $EN_{PV,V2G}^{tot}$ uses V2G-technology more than $PK_{PV,V2G}^{tot}$, mainly to shift EV charging until hours with low spot prices during the night. Compared to the "EV, Apt, PV" scenarios without V2G, the energy use during stress hours is reduced from –23 % to –32 % going from EN_{PV}^{tot} to $EN_{PV,V2G}^{tot}$, and from –22 % to −28 % going from PK_{PV}^{tot} to $PK_{PV,V2G}^{tot}$.

5. Discussion and policy implications

This section discusses the potential for electricity flexibility from EVs under various scenarios, and how coordinated EV charging in apartment buildings can affect the aggregated grid load and the self-consumption of PV electricity in residential neighbourhoods.

5.1. How grid tariffs may impact the grid burden of residential EV charging

Uncontrolled EV charging contributed 48 % to annual peak load in

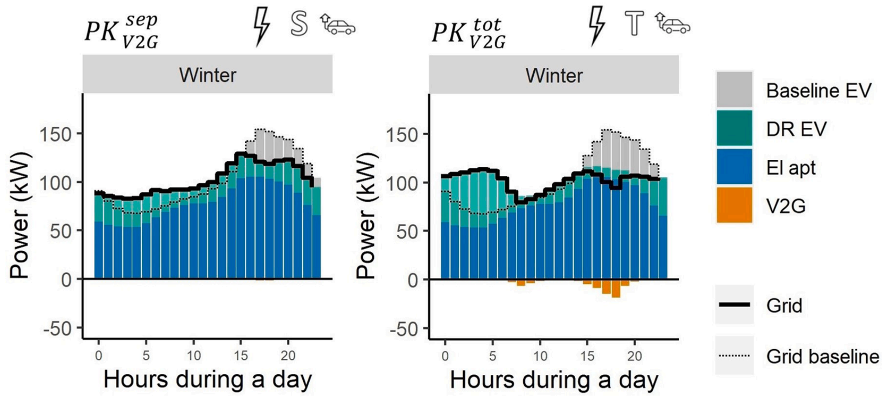


Fig. 15. Average daily profiles (winter): "EV, Apt, V2G"- scenarios with peak tariffs.

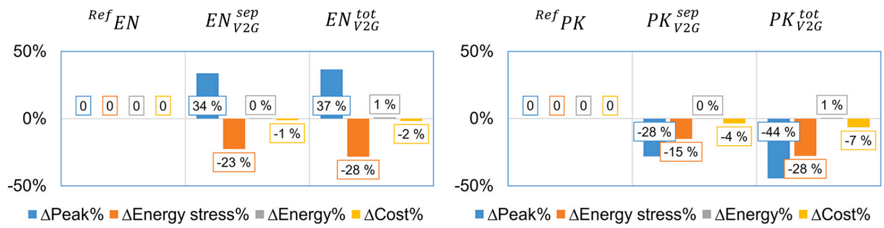


Fig. 16. Energy flexibility KPIs for the "EV, Apt, V2G"- scenarios.

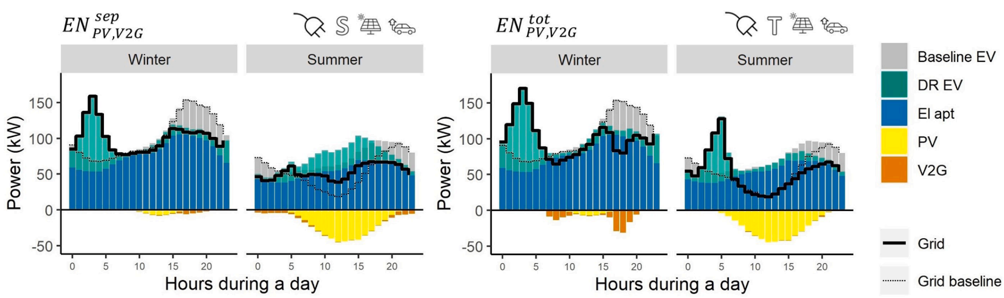


Fig. 17. Average daily profiles: "EV, Apt, PV, V2G"-scenarios with energy tariffs.

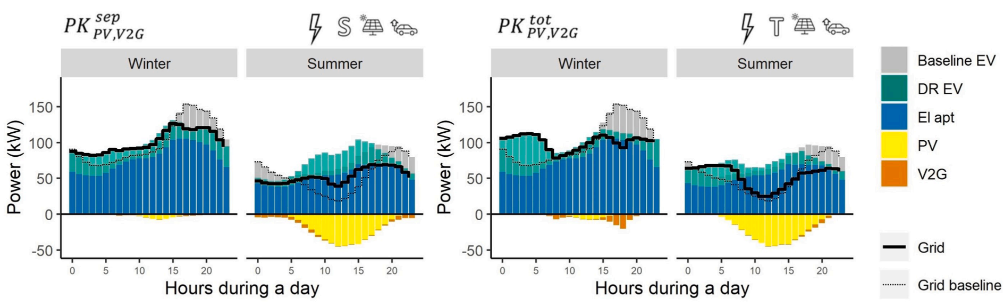
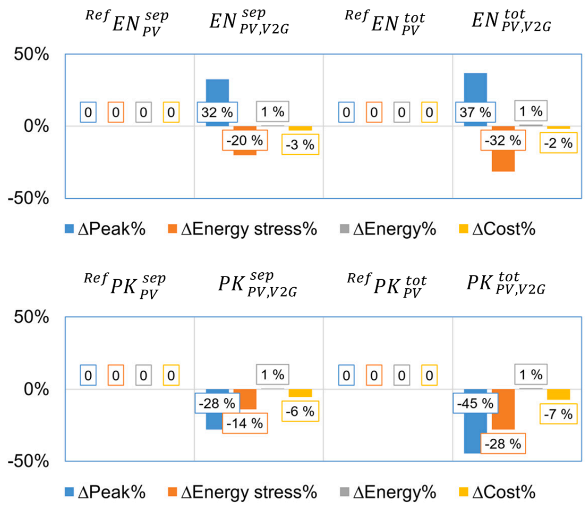


Fig. 18. Average daily profiles: "EV, Apt, PV, V2G"-scenarios with peak tariffs.



	SC (SC_{EV})	SS (SS_{EV})
Ref_{PV}^{sep}	38% (38%)	4% (18%)
Ref_{PV}^{tot}	98% (38%)	11% (18%)
$EN_{PV,V2G}^{sep}$	83% (83%)	10% (38%)
$EN_{PV,V2G}^{tot}$	100% (29%)	12% (12%)
$PK_{PV,V2G}^{sep}$	83% (83%)	10% (38%)
$PK_{PV,V2G}^{tot}$	100% (46%)	12% (20%)

Fig. 19. Energy flexibility KPIs for the "EV, Apt, PV, V2G"-scenarios.

our case study of apartment buildings with EVs. However, through optimised EV charging strategies, energy use during stress hours can be reduced. Yet, solely shifting flexible loads based on energy tariffs could induce new aggregated peaks. Implementing energy tariffs increased the annual peak for apartment buildings with EVs by up to 37 %. The peaks occurred during the night when there is typically less pressure on the grid. With energy tariffs, the billing meter location did not affect the load shifting. Peak per month tariffs reduced grid peaks by up to 39 %. With peak-tariffs, the peak loads for the total energy use (including EV charging and apartment energy) were about 20 % lower when the billing meter also included the apartment electricity use (in addition to EV charging).

Considering the practical implementation EV charging management, energy tariffs offer the advantage of simplicity, as spot prices are known the day-ahead, requiring no coordination with other EVs or building loads. Optimising EV charging loads according to peak tariffs is more challenging, as monthly peak values are not known in advance. In our study, the annual optimalisation of EV charging resulted in savings of up to 800 NOK per EV. Flexible energy loads were shifted to the most cost-effective hours, even when the price differences between hours (for spot) or between peak power levels (for peak) were small. However, building owners may hesitate to invest in energy management systems if the economic benefits are limited.

5.2. Self-consumption of PV electricity

Self-consumption of PV electricity is economical beneficial for building owners and aids to reduce high feed-in power to the grid. With uncontrolled EV charging, little residential EV charging will be covered by PV generation (18 % in our study), since few EVs are charging during the daytime. Most of the "PV-to-EV" therefore happens during the weekends, since the EVs then are more frequently connected during the daytime. With an appropriate control strategy, EV charging can be shifted to sunny hours, for EVs connected during the daytime. Our study observed this mainly in scenarios where shared energy systems (PV, EV, V2G) were metered separately, resulting in up to 38 % of EV charging using PV generation. Conversely, when apartment electricity was included behind the same billing meter, generated PV electricity was primarily consumed in the apartments. The EV charging was instead shifted to hours with low spot prices. To encourage increased use of generated PV-to-EV charging, it can therefore be an advantage to meter EV charging and PV generation separately from apartment electricity use. However, using PV electricity also in the apartments have an economical positive consequence for building owners, due to the increased self-consumption, and may therefore motivate PV investments.

5.3. Integrating V2G in the EV charging optimisation

Under energy tariffs, V2G is hardly used in our case due to small differences in daily spot prices. V2G, due to its round-trip efficiency, increases the night-time peaks induced by energy tariffs. However, V2G can reduce monthly peaks under peak tariffs. In practical scenarios where monthly peaks are not known in advance, this management approach is more complex, necessitating increased reliance on V2G-technology to achieve similar peak power reductions. V2G has greater potential when apartment energy loads are included behind the same energy meter, allowing discharged energy to cover apartment loads during expensive hours. Compared to EV charging alone, days with sufficient variations in daily energy prices can therefore more frequently take advantage of the V2G capacity.

In our study, V2G improves the KPIs, but to a limited degree, and it may not justify the needed investments in V2G technology, battery degradation, and advanced energy management systems. However, in real life, the use of V2G may be more frequent than shown in our study, since the study has some limitations: 1) Charging can happen in several locations, not only in the building where the discharging happens as in our study, 2) EV users can facilitate for V2G by applying longer connection times and employing more flexibility when it comes to end-SoC, 3) In the future, the spot prices will most likely be higher, with larger differences during a day.

When introducing V2G, the energy management system should consider user needs, to make sure that the SoC level is at an acceptable level at plug-out time. In addition, battery conditions should be taken into account. The battery stress during V2G operation depends on a number of factors, such as SoC usage range, the number of cycles, current throughput, and battery temperature [91]. Wei et al. [92] concluded that for V2G-operation, a SoC range of 30–70 % is most beneficial for the battery life. They found that discharging the battery from 90 to 65 % SoC may actually extend the battery life, compared to parking the car with 90–100 % SoC, due to calendar aging. These factors should therefore be considered when developing an energy management system for EV charging and V2G.

6. Recommendations and future work

Our study highlights the potential for coordinating EV charging in apartment buildings. Current CP management systems, commonly available in these buildings, could play a major role in load shifting. Such management systems control the charging loads of the EVs, e.g., to keep the loads below a specific power limit. Effective implementation of DR requires information about building energy loads, local energy generation, and price/grid signals. In addition, information from the users is required, i.e., regarding expected plug-out times and charging needs per session. In real life implementation it is not feasible to have complete knowledge of the building energy use, PV generation, and EV plug-out times and energy charged, as we have in this study. Thus, the real potential for EV charging coordination may be lower than our calculations indicate. Nonetheless, the potential for coordinating residential EV charging remains significant. Achieving this in practice favours simple yet effective solutions, ensuring primary benefits such as cost reduction, grid load reduction, and increased self-consumption of PV electricity. As we have demonstrated in this study, several KPIs can be combined to address the needs of various user groups, including apartment building associations, CPOs/energy management companies, DSOs, authorities, and entities facilitating end-use flexibility. Areas for further research include:

- Research on real-life implementation of smart and robust EV charging solutions in apartments buildings.
- Research on energy profiles and EV charging flexibility in other building categories, such as office buildings, utilizing real-world data on energy loads and EV charging.
- Research on the interaction between different building categories, with e.g. PV generation in commercial buildings and V2G technology in residential buildings.
- Research on the impact of varying EV charging facilities and tariff structures, such as those at residences, workplaces, and public charging stations, on energy profiles and the flexibility of EV charging across different building categories.

7. Conclusion

In this study, we examined the energy profiles and electricity flexibility potential in apartment buildings with EVs. Our analysis was based on residential energy and EV data from an extensive case study in Norway. The work acknowledged how apartment buildings differ from detached houses, due to their more complex structure in ownership and energy metering. Adding EV charging to household electricity use (excluding heat demand), delivered electricity increased by a factor of 1.5 for an average apartment and EV. The impact on load peaks was even larger, increasing the power demand by a factor of 3.5 to 8.6. For 117 apartments with uncontrolled EV charging from 82 EVs, the aggregated annual peak was 219 kW, whereof 48 % were caused by uncontrolled EV charging. The annual peak appeared in the afternoon at wintertime, during high load hours in the grid.

Our study investigated optimisation of the residential EV charging with the objective to minimize the energy costs. The grid burden of EV charging was affected by different tariffs (energy tariffs or monthly peak tariffs), billing metering locations, and the introduction of PV and V2G technologies. We found that energy tariffs shifted EV charging to low price hours, increasing the peaks by up to 37 % compared to uncoordinated charging. The shifted peaks occurred during night hours, which are typically low load periods for the grid. The peak tariff scenarios reduced the peak loads by up to 45 %. For apartment buildings with PV, the study confirmed how relatively few residential EVs are connected to a CP during daytime. In our case study, maximum 38 % of the EV charging was covered by PV generation. Utilisation of V2G depends on differences in daily spot prices, and our study showed that V2G had a limited effect due to small daily variations in spot price.

This study strengthened the hypothesis that apartment buildings with EVs have a considerable potential for electricity flexibility. It is common that apartment buildings have CP management tools in place, to make sure that the aggregated EV charging load does not exceed a certain power limit. Such CP management tools can be further developed, providing opportunities to shift EV charging loads in time, e.g. to reduce the grid burden of the neighbourhood, and/or to reduce the energy costs for the residents. Residential EV charging is therefore a viable frontrunner in the practical realization of end-user flexibility, paving the way for effective solutions in real-life applications.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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C. Supplementary publications

Supplementary article I

Electricity analysis for energy management in neighbourhoods: Case study of a large housing cooperative in Norway

Åse Lekang Sørensen, Igor Sartori, Karen Byskov Lindberg, Inger Andresen

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Table: The paper's context in the thesis.

	Supplementary articles	Main article I	Main article II	Main article III	Main article IV	Data articles *(D* describes planned articles)*
RQ1: What are the energy profiles for household energy use and PV generation for apartment buildings, and how are the energy profiles influenced by climate variables?	S I. Electricity S II. Heat-DHW S III. DHW S IV. PV				Main IV. Energy profiles	D* IV. Data Main IV
RQ2: How does the user habits influence the electricity load profiles of residential EV charging, and how is the el. load affected by EV cabin preheating?	S V. Stochastic EV charging	Main I. EV charging	Main II. EV charging	Main III. EV cabin preheating		D I. Data Main I D* II. Data Main II D* III. Data Main III
RQ3: What is the potential for electricity flexibility from EVs, in relation to non-flexible apartment building loads and PV generation, in the Norwegian context?					Main IV. Flexibility	

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Electricity analysis for energy management in neighbourhoods: Case study of a large housing cooperative in Norway

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Abstract. As a basis for energy management in apartment blocks, this paper characterises electricity use in a Norwegian housing cooperative with 1,058 apartments. In 2018, the average specific electricity delivery to apartments and common areas is 56.7 kWh/m^2 or 2,301 kWh per resident, in addition to heat delivery from district heating. Average annual electricity use in the apartments is 4,362 kWh and average maximum hourly load is 3.2 kWh/h. The electricity coincidence factor is 0.323. The study suggests a potential for shifting electricity loads in time on a neighbourhood level, where especially EV charging can be utilized as a flexible load.

1. Introduction

In zero emission neighbourhoods, thermal and electric energy should be managed in a flexible way, to achieve reduced power peaks, reduced energy use, reduced CO_2-emissions and increased self-consumption of locally produced energy [1], [2]. Further, smart management of building loads can provide energy flexibility services to distribution system operators (DSOs) and district heating companies. As a basis for energy management in apartment blocks, this paper characterises the electricity use in a large housing cooperative in Norway, built in the 1970s.

The Risvollan housing cooperative consists of 1,058 apartments with a total of 93,713 m^2 heated floor area, distributed on 121 similar apartment blocks. There are apartments with one bedroom (52.9 m^2), two bedrooms (83.5 m^2), three bedrooms (104.8 m^2) and four bedrooms (107.2 m^2), where 78% are two- or three-bedroom apartments. In total 2,321 residents live in the apartments, 53% female and 47% male, where 24% are under 20 years old, 40% between 20 and 50 and 33% above 50 years old [3].

Space heating and domestic hot water (DHW) is provided by district heating, which is analysed in a parallel study [4]. A majority of the apartments have electric floor heating in the bathrooms. In 2018, it was possible to charge around 55 electric vehicles (EVs) in the parking houses, but within the next three years, up to 764 charging points will be available to residents on request. The housing cooperative is considering installing photovoltaic (PV) systems on some of their buildings, to be partly self-sufficient with electricity. PV generation is simulated in a parallel study [5].

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2. Methods

Electricity measurements from AMS meters (Advanced Metering System) installed in 2017 and 2018 are provided by the utility company, with hourly resolution. Each measurement gives accumulated electricity delivery for the previous hour. Electricity measurements are available from 1,044 of the 1,058 apartments at Risvollan (99%), but the exact address and size of each apartment is unknown. Apartments with a measurement period of less than 80% of the year (7000 hours) were excluded from the analysis, resulting in data from 1,009 apartments (95%). When summarizing electricity use for the housing cooperative in total, average electricity use is assumed for the 49 missing apartments. Still some missing measurement periods remain, mainly in January 2018, where only 72% of the apartments are measured. From February 2018, most AMS meters are installed. There are also measurements available from 114 meters that provide electricity to common areas and EVs, with a known address for the meter locations. 25 of the meters are located in garages and 89 in other common areas. 8 of the cooperative meters have missing measurements periods of around 7000 hours, since these AMS meters were installed late in 2018. 33 cooperative meters have shorter missing periods from 400 to 2700 hours. When summarizing electricity use for the housing cooperative in total, electricity delivery is estimated for the missing periods, based on average hourly electricity delivery for each specific meter.

The electricity measurements are analysed using the statistical computing environment R [6]. From the utility company, the hourly values are marked as measured values (M) or estimates (E). 99% of the hourly values for apartments are measured as well as 98% of the values for the garages / other common areas. Since the share of estimates are so small, also the estimated values are included in the analysis, except for the analysis of max values. The data quality is evaluated as good, with few zero-values. Only one measurement error is corrected, which occurred in most apartments for two hours May 29th.

Outdoor temperatures from eKlima [7] are collected mainly from a weather station at Risvollan, where a few missing values is replaced with data from the weather station Voll, 2.5 km away. Holidays are identified as days where the primary schools are closed in Trondheim [8], including national bank holidays. If the schools are closed on a Friday or Monday, the weekends are marked as holiday-weekends. The annual seasons have three months each, where spring season starts in March.

3. Results and discussion

3.1. Electricity delivery to Risvollan in 2018

Table 1 shows electricity delivery to Risvollan in 2018. The average specific electricity delivery to apartments, garages and common areas is 56.7 kWh/m^2 heated floor area or 2,301 kWh per resident. 87% of the electricity is used in apartments, 8% in the garages and 5% in other common areas. To apartments only, the electricity delivery is 49.2 kWh/m^2 or 1,997 kWh per resident. The delivered electricity is similar to values found by [9], where average specific electricity delivery for 40 Norwegian apartment buildings is 64 kWh/m^2. Delivered heat to Risvollan in 2018 is 139 kWh/m^2, giving a total of 196 kWh/m^2 specific delivered energy. The total delivered energy is in the range of the national average for households, which is 185 kWh/m^2 [10]. Heating is 70% of the energy delivery at Risvollan, which is higher that the estimate from [9] of 60% heating share for apartments built in the period 1971–1988.

Table 1. Electricity delivery to Risvollan housing cooperative in 2018, with in total 2,321 residents.

	Heated area m^2	**# Apt (# meters)**	**Total el deliv.** MWh/yr	**Division of use**	**El pr. res** kWh/res.	**Specific el. deliv.** kWh/m^2	**Aggregated average load** kWh/h	**Aggregated peak load** kWh/h
Apartments	93,713	1,058 *(1,009)*	4,614	87%	1,997	49.2	527	1028
Garages	(16,397)	*(25)*	438	8%	189	4.7	50	104
Common areas		*(89)*	266	5%	115	2.8	30	73
Total	93,713	1,058	5,318	100%	2,301	56.7	607	1146

Abbreviations: Apt: Apartments. Res: Residents. Deliv: Delivery. El: Electricity.

Electricity delivered to apartments, garages and other common areas each hour is shown in Figure 1, as well as duration curves for the total electricity delivery. For simplification, hourly electricity delivery (kWh/h) is described as power (kW) in the figures. The highest electricity peaks in 2018 are Christmas Eve and New Year's Eve, also shown in Figure 2. Figure 3 shows the electricity signatures for apartments, garages and common areas, reflecting the relationship between electricity use and different outdoor temperatures. Since the housing cooperative is connected to district heating, the temperature dependency is rather small. Both heating and lighting are reasons for the increased electricity use wintertime.

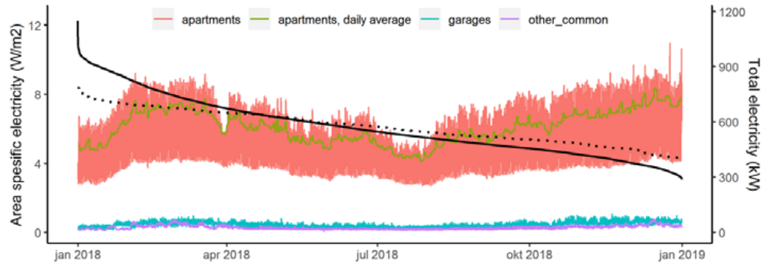

Figure 1. Electricity delivered to Risvollan housing cooperative each hour in 2018, divided on apartments, garages and other common areas. Duration curves show total electricity delivered each hour (black line) and daily average electricity per hour (dotted line).

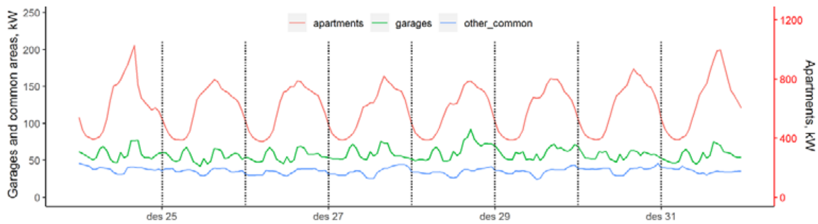

Figure 2. Electricity delivered to Risvollan housing cooperative during the Christmas week 2018, divided on apartments, garages and other common areas (scale difference of 5).

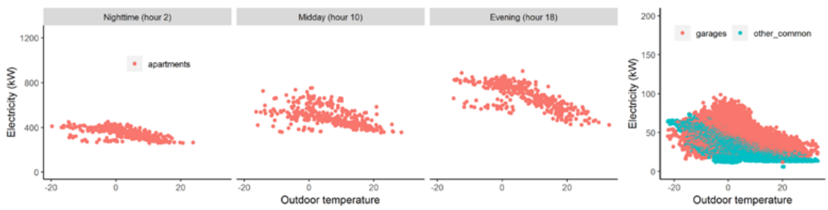

Figure 3. Hourly electricity signatures for electricity delivered to Risvollan in 2018, showing relationships between electricity use and outdoor temperature.

3.2. Variations of electricity delivery between apartments in Risvollan and coincident peak loads

Figure 4 shows variations of electricity use between 1,009 apartments in Risvollan in 2018. The average electricity delivery per apartment is 4,362 kWh, not including electricity delivery to garages and other common areas. Minimum electricity use is 324 kWh, first quartile 2,713 kWh, median 4,036 kWh, third quartile 5,642 kWh and maximum 13,654 kWh. Removing the apartments with 5% lowest and 5% highest electricity delivery, the electricity delivery varies from 1,443 to 8,391 kWh per year. Since the exact address of each apartment meter is unknown, the variations cannot be compared with area specific electricity use or number of residents, as in [11], where annual electricity use is measured in 1,300 apartments in Sweden for six years. [11] found an average increase in electricity use with increasing number of residents, but with large variations in the use. For example, variations in average electricity power for different apartments with one resident is between 80 W and 450 W, while it is between 140

W and 440 W for apartments with two residents. At Risvollan, the average electricity power for all apartments is about 500 W. There is in average 2.2 residents per apartment.

Analyzing maximum hourly values for each apartment in 2018, the average max. value is 3.2 kWh/h, see Figure 4b. The distribution of max. values in the apartments has a minimum value of 0.1 kWh/h, first quartile is 2.5 kWh/h, median is 3.2 kWh/h, third quartile 3.8 kWh/h and maximum hourly value is 7.3 kWh/h. Maximum capacity available for most apartments is 35 A or 8 kW.

The electricity coincidence factor for the in total 1174 meters is 0.323, based on hourly values. This factor is defined as the ratio between maximum load for the aggregated measurements studied (1,146 kWh/h) and the sum of each meters maximum load (3,552 kWh/h), and is always less or equal to unity [12]. The coincidence factor at Risvollan is similar to the value found by [12] for single family houses and apartment blocks, of 0.387. Looking at apartments, garages and other common electricity areas separately, the coincidence factors for Risvollan are 0.316, 0.588 and 0.624 accordingly.

The total aggregated peak load at Risvollan in 2018 is 1,146 kWh/h. To size the distribution grids, Velander's formula is widely used to calculate expected peak loads in a neighbourhood [13]. When using the formula and typical apartment blocks coefficient values as described in [13], the calculated peak load for Risvollan is 1,370 kWh/h, 20% higher than the measured peak load in 2018.

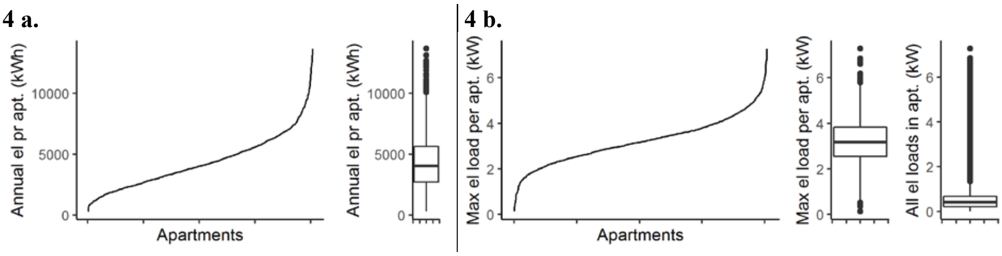

Figure 4. Variations between 1,009 apartments: Annual (a) and hourly (b) electricity delivery in 2018.

3.3. Electricity delivery to garages

The total electricity delivery to the garages was 438 MWh or 4.7 kWh/m^2 apartment area. Assuming an annual driving length of 12,000km and 0.2kWh/km, charging 55 EVs would use about 30% of the electricity delivered to the garages. Fans and lighting are among the other electricity uses in the garages. Assuming the annual driving length as above, charging the facilitated max. nr of 764 EVs would demand 19.5 kWh/m^2 apartment area. In 2018, the max hourly electricity use in all the garages aggregated was 104 kWh/h, 9% of the total aggregated peak load at Risvollan. If the number of EVs increases from todays 55 to 764, also the aggregated peak load use will increase. How the peak load will increase for the total housing cooperative, depends on the energy management and future timing of the EV charging.

3.4. Average daily electricity load profiles for Risvollan

Average daily electricity load profiles are shown in Figure 5 and Figure 6, with hourly values as the sample mean values. Apartments and garages have a similar daily profile, but with a scale difference of about 10. Both apartments and garages have an afternoon/evening peak in delivered electricity, from about 3 pm to 9 pm. During workdays, apartments have the average minimum hourly electricity delivery during night, of about 4 Wh/m^2/h, increasing to about 5 Wh/m^2/h in the morning and to 7.5 Wh/m^2/h in the afternoon, between 3 pm and 9 pm. During the weekends, the electricity delivery during daytime is higher, in average about 6.5 Wh/m^2/h from around 9 am, but with a similar afternoon/evening peak as during weekdays. The daily electricity profiles for apartments are similar to profiles found by [12], analyzing 38 single family houses and apartment blocks. The garages also have a morning peak, most likely caused by the start-up of fans and lighting when cars are collected in the garage. Figure 6 c shows the average load profiles for the 101 apartments (10%) with minimum and maximum electricity use during the year. The hourly daily profiles for the min/max apartments are similar to the average daily profile for all the apartments.

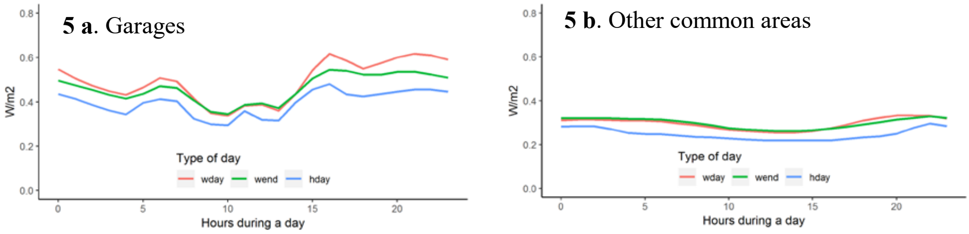

Figure 5. Average daily electricity load profiles for the common electricity delivered to Risvollan, divided on electricity to garages (**a**) and electricity to other common areas (**b**).

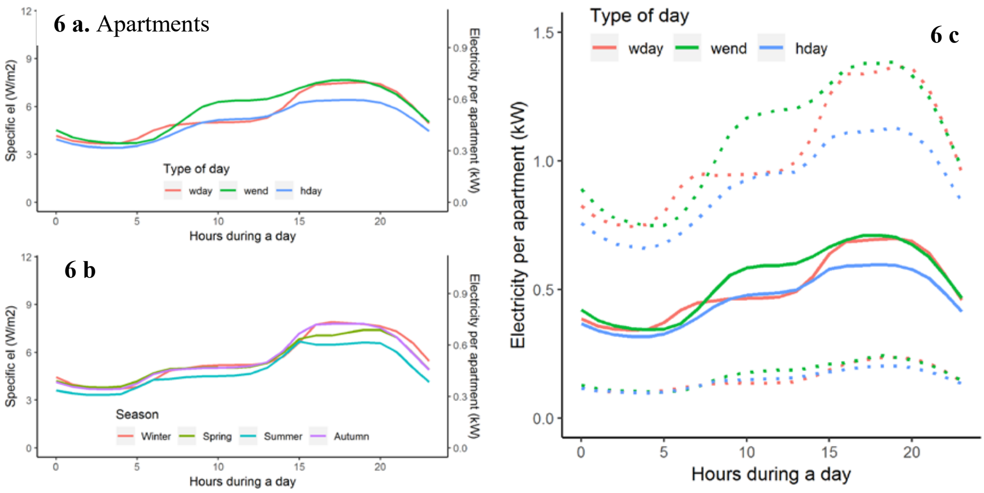

Figure 6. Average daily electricity load profiles for apartments at Risvollan in 2018, divided by weekdays and holidays (**a**), for weekdays only during different annual seasons (**b**) and average load profiles for the 101 apartments (10%) with minimum and maximum electricity use during the year (**c**).

3.5. Potential for electricity flexibility

Flexible electricity loads can be shifted in time or regulated lower or higher. How flexible a load can be, without disrupting the consumer, vary between load categories [14]. For example, changes in cooking, lighting, and television will require changes in user behaviour, while EV charging can happen independently from the user. Examples of electricity loads with flexibility potential are electric heating, electric water boilers, EV charging, washing machines and refrigerators [14], [15], [16].

EV charging is a main source of flexible electricity use in Norwegian apartment buildings. Besides often being flexible with respect to starting time, duration and charging power [17], EV charging infrastructure is the responsibility of the Risvollan cooperative, already being part of the energy management system. Electric DHW tanks are another flexible electricity load, often available in apartment blocks. Since district heating provides DHW to Risvollan, this is not relevant for this site. However, most apartments have electric floor heating in some rooms. Also, other electricity loads in the apartments can become flexible, such as dishwashers, washing machines, tumble dryers or refrigerators, which can be shifted in time. However, such electricity loads are not always easily available for an energy management system on a neighbourhood level. Batteries could be used for electricity storage, e.g. shifting electricity from the nighttime to evening peak hours. Besides stationary batteries, batteries in the EVs can be used in a V2G solution, were the battery in the EV delivers power back to the source.

4. Conclusion

As a basis for energy management in apartment blocks, this paper characterises electricity use in Risvollan housing cooperative in Norway, built in the 1970s, with in total 1,058 apartments. The average specific electricity delivery to apartments, garages and common areas is 56.7 kWh/m^2 or 2,301 kWh per resident. In 2018 the average annual electricity use in the apartments is 4,362 kWh, with variation from first quartile of 2,713 kWh to third quartile of 5,642 kWh. For maximum hourly load, the average max. value is 3.2 kWh/h, first quartile is 2.5 and third quartile 3.8 kWh/h. The average maximum load during a day is in the afternoons/evenings. The electricity coincidence factor for the in total 1174 meters is 0.323, based on hourly values. The study suggests a potential for shifting electricity loads in time on a neighbourhood level, where especially the EV charging can be utilized as a flexible load. The analysis will be used in further work, together with analysis of heat use at Risvollan, aiming to contribute to answering how effective management of power and energy at neighbourhood level can be realized.

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Supplementary article II

Heat analysis for energy management in neighbourhoods: Case study of a large housing cooperative in Norway

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	Supplementary articles	Main article I	Main article II	Main article III	Main article IV	Data articles (*D* describes planned articles)*
RQ1: What are the energy profiles for household energy use and PV generation for apartment buildings, and how are the energy profiles influenced by climate variables?	S I. Electricity S II. Heat-DHW S III. DHW S IV. PV				Main IV. Energy profiles	D* IV. Data Main IV
RQ2: How does the user habits influence the electricity load profiles of residential EV charging, and how is the el. load affected by EV cabin preheating?	S V. Stochastic EV charging	Main I. EV charging	Main II. EV charging	Main III. EV cabin preheating		D I. Data Main I D* II. Data Main II D* III. Data Main III
RQ3: What is the potential for electricity flexibility from EVs, in relation to non-flexible apartment building loads and PV generation, in the Norwegian context?					Main IV. Flexibility	

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Heat analysis for energy management in neighbourhoods: case study of a large housing cooperative in Norway

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Abstract. As a basis for energy management in apartment blocks, this paper characterises heat use in a large housing cooperative in Norway, with in total 1,058 apartments. Heat measurements with hourly resolution are available from 20 heating substations. Average specific heat delivery is 139 kWh per heated floor area. A linear regression model is described, modelling specific heat delivered to the apartments. Models are also used for separating heat to domestic hot water (DHW) from the total heat delivery, with a modelled DHW heat delivery of 34 kWh/m^2. Daily heat load profiles are presented, for delivered heat during weekdays and holidays in the annual seasons. The study shows a potential for shifting heat loads in time on a neighbourhood level.

1. Introduction

In zero emission neighbourhoods, thermal and electric energy should be managed in a flexible way [1], to achieve reduced power peaks, reduced energy use, reduced CO_2-emissions and increased self-consumption of locally produced energy. As a basis for energy management in apartment blocks, this paper characterises heat use in a large housing cooperative in Trondheim, Norway, built in the 1970s.

In Risvollan housing cooperative, there are 1,058 apartments with in total 93,713 m^2 heated floor area, distributed on 121 similar apartment blocks. 2,321 residents live in the apartments: 53% female and 47% male residents [2]. 24% are under 20 years old, 40% between 20 and 50 and 33% above 50 years old. District heating (DH) provides space heating and domestic hot water (DHW) to the apartments, as illustrated in Figure 1. DH is distributed to 20 heating substations (SUBs) through three distribution lines (DL), with a supply set point temperature of 76°C all year. The 20 SUBs cover from 25 to 74 apartment units per SUB. The DHW set point temperature is 60°C. The temperature in the space heating system can be changed on SUB-level, by changing the outdoor temperature compensation curves in the SD-system. The applied settings for these temperature curves are similar for all the SUBs, as shown in Figure 1.

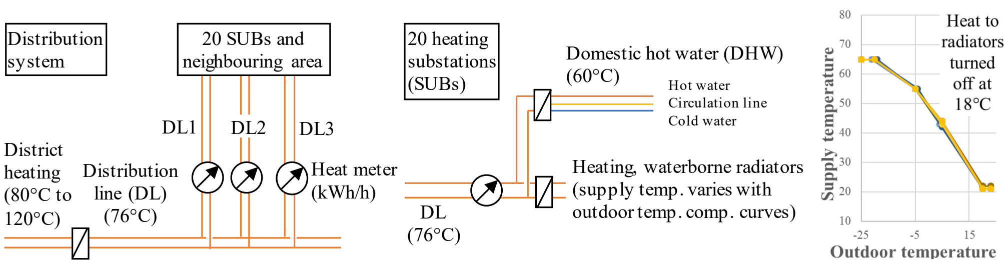

Figure 1. Heat distribution (left) and delivery of DHW and heating from the 20 SUBs (middle) to the 1,058 apartments in Risvollan. Right: Outdoor temperature compensation curves for the 20 SUBs.

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Residents can also adjust the valves on the waterborne radiators in the apartments. However, O&M staff experiences that most resident do not frequently manually regulate their heat supply. When the outdoor temperature exceeds 18°C, the heating circulation to radiators is automatically turned off.

2. Data

2.1. Data collection and quality assurance

Heat measurements from 20 SUBs are available from an energy monitoring system, starting from 2018 [3]. The meters measure space heating and DHW combined, where each measurement gives accumulated heat delivery the previous hour. In this research, the data are analysed using the statistical computing environment R [4]. The data quality is analysed with visual inspection and by studying peak- and zero-values. For 13 SUBs, the heat measurements have a resolution of 10 kWh per hour, while the remaining 7 SUBs have a resolution of 100 kWh per hour. Low measurement resolution may affect load profiles by shifting the load to the subsequent hour [5], which is the case especially for the 100 kWh-resolution measurements. After evaluating the measurement resolution and data quality, all the 7 SUBs with 100 kWh and 3 SUBs with 10 kWh resolution were excluded from the detailed analysis, analysing daily heat load profiles and peak values. The measurements are still used when evaluating annual heat delivery. The 10 SUBs used in the detailed analysis, cover about half of the housing cooperative: 536 apartment units with a heated floor area of 46,030 m^2 and 1,161 residents.

The climate data are collected from eKlima [6]. The outdoor temperatures (code TA) are mainly from a weather station at Risvollan, where a few missing values are replaced with data from weather station Voll, 2.5 km away. The wind data (code DD and FF) are also from Voll, while the global radiation (code QSI) and minutes of sunshine each hour (code OT) are from the weather station Gløshaugen, 3 km away.

Holidays are identified as days where the primary schools are closed in Trondheim [7], including national bank holidays. If the schools are closed on a Friday or Monday, the weekends are marked as holiday-weekends. The annual seasons have three months each, where the spring season starts in March.

Table 1. Heat delivery to the 121 apartment blocks in Risvollan housing cooperative in 2018.

	Area	**Bldg**	**Apt**	**Res**	**Heat deliv.**	**Heat pr. res**	**Specific heat deliv.**	**If incl. garages**	**Max hourly**	**Max daily**
	m^2	Nr.	Nr.	Nr.	MWh/yr	kWh/res/yr	kWh/m^2/yr	kWh/m^2/yr	kWh/m^2/h	kWh/m^2/h
SUB-1	5,258	6	56	137	770	5,624	147	147	0.059	0.83
SUB-2	4,758	5	56	128	483	3,775	102	102	0.048	0.61
SUB-3	3,790	5	44	99	492	4,971	130	130	0.053	0.71
SUB-4	4,663	5	54	122	653	5,352	140	140	0.056	0.92
SUB-5	3,680	6	43	98	506	5,161	137	137	0.052	0.73
SUB-6	4,887	6	62	115	650	5,654	133	133	0.053	0.71
SUB-7	4,197	5	45	107	770	7,192	183	110	0.086	1.10
SUB-8 *	6,139	5	74	139	830	5,974	135	115	0.052	0.72
SUB-9	4,507	5	54	116	605	5,216	134	134	0.053	0.73
SUB-10	4,150	4	48	100	578	5,776	139	139	0.055	0.81
SUBs in analysis	46,030	52	536	1,161	6,337	5,458	138	127	Accumulated 0.051	0.75
SUBs remaining *	47,684	69	522	1,150	6,698	5,825	140	111		
Total	93,713	121	1,058	2,311	13,036	5,641	139	118		

* Heat delivery is estimated for 3 months for SUB-8 and 1 month for two of the remaining SUBs. However, only actual measurements are included in model development and for load profile analysis.

Abbreviations: Bldg: Buildings. Apt: Apartments. Res: Residents. Deliv: Delivery. SUB: Heating substation.

2.2. Heat delivery to the Risvollan apartments in 2018

Table 1 shows heat delivery to Risvollan in 2018. The average specific heat delivery from the 20 SUBs is 139 kWh/m^2. SUB2 and SUB7 stand out, with a low heat delivery of 102 kWh/m^2 and a high heat delivery of 183 kWh/m^2. Heated garage area is the main reason for these differences, as shown in the table. Garages are not included in the heated floor area, but heat delivered to garages is included in the measurements. Other explanatory variables may be differences in heat losses and occupant behaviour. The average heat delivery per resident is 5,641 kWh per person. The max hourly value for the 10 SUBs in the analysis vary from 0.048 to 0.086 kWh/m^2/h, where most of the SUBs have a max value from 0.05 to 0.06 kWh/m^2/h. Variations are also to be expected within each SUB, on apartment level [8].

Figure 2a) shows specific heat delivered from the 10 SUBs included in the analysis. The figure also shows duration curves for specific heat, delivered 1) each hour and 2) daily average energy per hour. The difference between the duration curves illustrate the potential for reducing peak values, if a heat storage was available for 24 hours heat delivery. Figure 2b) illustrates an example of daily coincidence curves, for March 2nd, 2018. The figure shows 10 SUBs individually, the 10 SUBs accumulated, and three DL heat meters accumulated. This date is chosen since it has the highest 2018-hourly peak for *all* the three DL heat meters. The curves show a morning and afternoon peak in the heat delivery.

The coincidence factor for the 10 SUBs is 0.90, based on hourly values. This factor is defined as the ratio between maximum load for the accumulated measurements studied and the sum of each SUBs maximum load [5], and is always less or equal to unity. As a comparison, [5] found district heating coincidence factor for clusters with app. 10 buildings (single family houses and apartment blocks) to be 0.711. The coincidence factor is dependent on the number of customers served, and if the customers represent a homogeneous or heterogeneous group [5]. At Risvollan there is a rather large and homogeneous customer group and buildings per SUB, which can explain the high coincidence factor.

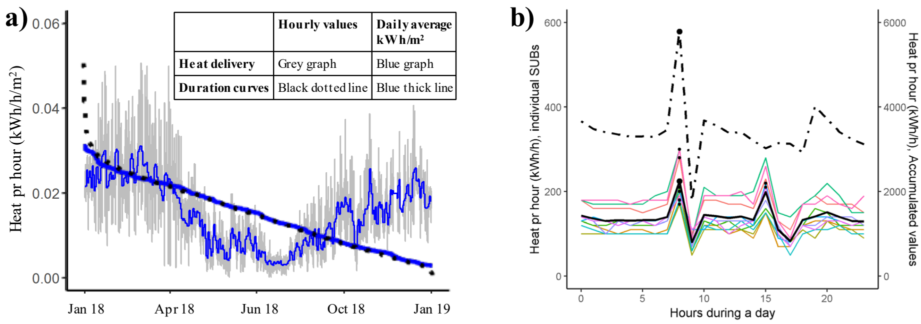

Figure 2 (a). Specific heat delivered from 10 SUBs each hour and daily average energy per hour. Lines show duration curves for specific heat delivered each hour and daily average energy per hour. **(b).** Coincidence curves for March 2nd, 2018, with hourly heat and max points for 1) 10 SUBs (coloured), 2) total heat for 10 SUBs (black line), 3) total heat for 3 DL meters (dotted).

3. Methods

Linear regression models [9] are developed based on data from 2018, for predicting heat delivered to space heating and DHW. For the heat modelling, only the high-quality data from the 10 SUBs are included. Measurements from three days in April and October are removed, since the water temperature was raised these days to prevent legionella growth.

The methodology used for modelling is mainly based on methods described by [5, 10]. Quantitative and categorical explanatory variables are tested, to specify a linear regression model for the response variable "heat per area per hour". The quantitative variables tested are outdoor temperature, average outdoor temperature (TMA) the last 3, 6, 9, 12, 15, 18, 21 and 24 hours, wind speed, solar radiation, minutes of sun each hour and residents per area. The categorical variables tested are hour of the day, weekdays / weekends, holidays, SUBs and wind direction. Weekdays, weekends and holidays are tested in both separate and joined models. In the joined model, the categorical variable "hour of the day" is divided in weekday (wd), weekend (we), weekday holiday (wd_h), weekend holiday (we_h), with 24 values per category, in total 96 values. Also, interaction between temperature and daily hours are tested in the model, giving different slope and intercept for each line [11]. Lastly, models are tested with a break point, with segmented relationships between the response and the explanatory variables [12, 13]. When comparing the models, the adjusted R^2 and the significance of the terms are considered. For the most promising models, predictions and residuals are analysed. The chosen model is tested on data from January to February 2019. When estimating energy for DHW, revised models are used (Named A and B). The DHW models are based on heat data from 2018 until May 2019, setting the outdoor temperature to the approximate break-point temperature of the model. The DHW estimation is compared with a DHW measurement period of one months in one of the SUBs, during May 2019.

4. Results

An excerpt of the linear regression models evaluated are shown in Table 2, with the chosen model 8 in equation 1. Model 8 is chosen instead of nr. 9, since hourly predictions for wind and solar data are not sufficiently reliable for Risvollan. This would affect the result if using the model for prediction. The chosen model has a break point for outdoor temperature of 19.0°C. Adjusted R^2 is 0.8438. Model A and B-8 are used for DHW estimation, where model A is for Risvollan while model B-8 is for SUB-8 only.

Table 2. An excerpt of the linear regression models evaluated for heat delivery to Risvollan.

	Variables						*Interactions*							
Mod	**T**	**h**	**sub**	**TMA18**	**W**	**S**	**T:h**	**T:sub**	**Sub: TMA18**	**T:h: sub**	**T:h:sub: TMA18**	**Break-point T**	**df**	**Adjusted R^2**
1													107	0.8149
2													202	0.8196
3													211	0.8345
4													1066	0.8357
5													220	0.8379
6													1075	0.8389
7													1067	0.8306
8												19.01°C	222	**0.8438**
9												17.96°C	224	0.8515
A												18.77°C	212	**0.7973**
B-8			SUB-8									20.60°C	194	**0.7744**

$$y_t = \beta_0 + \beta_T T_t + \beta_h D_h + \beta_{sub} D_{sub} + \beta_{TMA18} TMA18_t + \beta_{Th} T_t D_h + \beta_{Tsub} T_t D_{sub} + \beta_{subTMA18} D_{sub} TMA18_t + \mathcal{Y}_{t,T>bp} + \varepsilon_t \quad (1)$$

Table 3. Variables and symbols / indexes used in Table 2 and equation 1.

Variables	Description	Symbols	Description
t	Any hour t throughout the year (1-8760)	β_0	Fixed time independent effect
y_t	Specific heat delivered in hour t (kWh/m²/h)	β_h	Effect on hour-of the day (1-96)
D	Dummy variable for categorical variables, h and sub	β_{sub}	Effect on SUB (1-10)
T_t	Outdoor temperature in hour t	β_{TMA18}	Effect on TMA18 in hour t
h	Hour-of the day (1-96, as wd, we, wd_h and we_h)	β_{Thsub}	Effect on interaction between T, h and sub
$TMA18_t$	18 hour moving average of T_t	$\mathcal{Y}_{t,T>bp}$	Effect when T_t is above break-point temp.
sub	Heating substation	ε_t	Error term of regression
W	Wind speed in hour t	df	Degrees of Freedom: Measure in statistics of how many values can vary
S	Global radiation (QSI) in hour t		

The modelled value of specific heat delivered to the 10 SUBs is 138 kWh/m² in 2018, which equals the measured value. When testing the model for January and February 2019, the specific heat modelled for 9 SUBs these two months is 32.2 kWh/m², while the measured value is 33.2 kWh/m². Delivered heat to DHW is estimated by setting the outdoor temperature to 19°C all hours. With this method, delivered energy to DHW is 34 kWh/m² or 1,360 kWh per resident in 2018, equivalent to 24% of the heat delivery.

The energy signature reflects the relationship between energy use and different outdoor temperatures. For most of the hours the slope is similar, but for hour 8, representing the time slot from 7 to 8 in the morning, the slope is steeper, illustrating that delivered heat is higher this hour, see Figure 3.

Figure 4 shows daily heat load profiles for delivered heat during weekdays and weekends in the summer and winter season, with holidays separated. For the daily heat load profiles, the hourly values are the sample mean values. The figure shows the fit between the modelled hourly means and the 2018-measurements. The daily heat load profiles show a morning peak from 7 to 8 during working days and a delayed morning peak during weekends. The peaks are primarily linked to DHW use. During holiday periods the heat delivery is reduced. The modelling result of DHW is shown in Figure 5, together with available DHW measurements from SUB-8 during May 2019.

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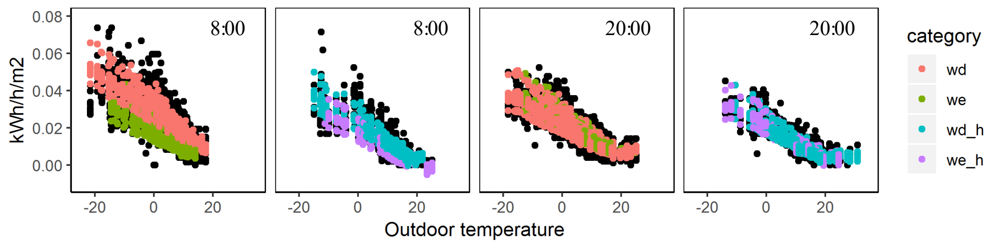

Figure 3. Hourly energy signatures of Risvollan, at the hour 8:00 and 20:00, divided on working days and holidays. The modelled data points are coloured, while the 2018-measurements are black dots.

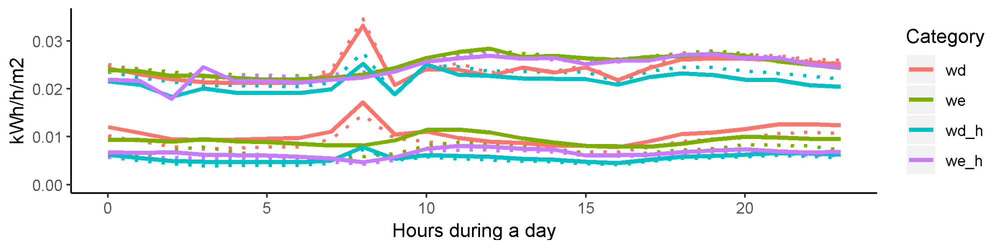

Figure 4. Average daily heat load profiles at Risvollan during summer (Jun-Aug, lower plots) and winter (Dec-Feb, higher plots). Modelled hourly means (lines) are based on 2018-data (dotted).

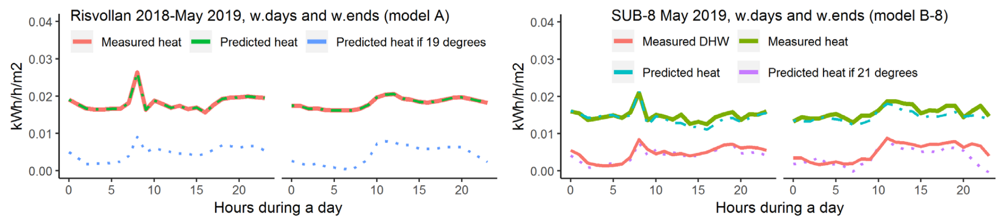

Figure 5. Daily heat load profiles for Risvollan (left) and SUB-8 only (right). The two models are based on measurements from Jan 2018 to May 2019. For DHW estimation, heat prediction is shown for outdoor temperatures above break point temperature (19°C or 21°C), every hour of the year.

5. Discussion

This paper characterises heat use in Risvollan housing cooperative. The linear regression model described, represents well the specific heat delivered in 2018. The testing period of two months in 2019 also give a modelling result close to reality, with modelled heat delivery 3% less than measured heat delivery. The input values of the model are easily available also for predicting heat delivery, since it only includes outdoor temperature as climate data. The model can be developed further, preparing for short-term forecasting in an energy management system, e.g. by analysing the autocorrelation function for the model residuals [14]. When improving the model, also measurements after 2018 are available.

Total delivered heat in 2018 was 138 kWh/m^2 or 5,458 kWh per resident. Compared to low energy buildings the heat delivery per area is high, and the project EBLE measured delivered heat between 23 to 58 kWh/m^2 in 19 passive houses [15]. DHW heat delivery is modelled to 34 kWh/m^2 or 1,360 kWh per resident, by setting outdoor temperature to 19°C all hours. There are few data points above 19°C, especially for non-holidays and night time. When modelling DHW, a temperature close to break-point temperature was therefore used, to make the results as reliable as possible. The DHW result is in the range of the limited DHW measurements available, in SUB-8 during May 2019. The value 34 kWh/m^2 is also comparable with the Norwegian norm value of 29.8 kWh/m^2 [16]. The project EBLE measured energy for DHW in 29 houses or apartments, with values from 18 to 42 kWh/m^2 [15]. Seasonal variations in delivered DHW [17] is not considered in the model, due to few DHW measurements.

The study shows a potential for shifting heat loads in time, on a SUB or neighbourhood level. The following possibilities are identified: 1) Duration curves, coincidence curves and daily heat load profiles show that heat loads can be shifted in time. Especially the morning peak can be shifted from peak hours to the night-time, by installing heat accumulation tanks in the SUBs. On an *average* working day during winter (Dec-Feb, ref. figure 4), the increase to *average* morning peak from 7 to 8 is in the range of 0.01 kWh/m^2, which need a storage volume of app. 0.2 $litre/m^2$. 2) The peaks are primarily linked to DHW use. If delivered temperature is increased before the peak hours, the need for delivered space heating could be reduced during DHW peak hours. This could be arranged by changing the set-points in the compensation curves. However, if this should be tested in practice, O&M staff needs to be sure that the comfort of the residents will not be reduced. A pilot test in five multifamily residential buildings in Sweden, indicate that buildings with a structural core of concrete can tolerate relatively large variations in heat deliveries while still maintaining a good indoor climate [18]. 3) It may also be possible to increase the temperature in the distribution line. If the temperature set-point is increased during off-peak periods, e.g. during the night, the distribution line can function as a heat storage, reducing the need for district heating delivery during peak hours. When evaluating such an approach, thermal stresses should be taken into account, since there will be a more frequent cycling between higher and lower temperatures [19].

6. Conclusion

This paper characterises heat use in a large housing cooperative in Norway, built in the 1970s, with in total 1,058 apartments. A linear regression model is described, modelling the specific heat delivered to the apartments. The model is also used for estimating the share of heat for DHW. The study shows a potential for shifting heat loads in time on a SUB or neighbourhood level. The analysis and model will be used in further work, together with analysis of electricity use at Risvollan, to address how effective management of power and energy in neighbourhoods can be realized.

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Supplementary article III

Energy flexibility potential of domestic hot water systems in apartment buildings

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Table: The paper's context in the thesis.

	Supplementary articles	Main article I	Main article II	Main article III	Main article IV	Data articles *(D* describes planned articles)*
RQ1: What are the energy profiles for household energy use and PV generation for apartment buildings, and how are the energy profiles influenced by climate variables?	S I. Electricity S II. Heat-DHW S III. DHW S IV. PV				Main IV. Energy profiles	D* IV. Data Main IV
RQ2: How does the user habits influence the electricity load profiles of residential EV charging, and how is the el. load affected by EV cabin preheating?	S V. Stochastic EV charging	Main I. EV charging	Main II. EV charging	Main III. EV cabin preheating		D I. Data Main I D* II. Data Main II D* III. Data Main III
RQ3: What is the potential for electricity flexibility from EVs, in relation to non-flexible apartment building loads and PV generation, in the Norwegian context?					Main IV. Flexibility	

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Energy flexibility potential of domestic hot water systems in apartment buildings

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Abstract. Domestic Hot Water (DHW) storage tanks are identified as a main source of flexible energy use in buildings. As a basis for energy management in apartment buildings, this paper describes the aggregated DHW use in a case building, and analyses the potential for DHW energy flexibility by simulating different control options. The case study for the work is an apartment building in Oslo with 56 apartments and a shared DHW system. Energy measurements are available for consumed hot water, hot water circulation, and energy supplied to the DHW tanks. The measurements are presented with minute, hourly and daily values. Aggregated daily energy use for the consumed hot water is in average 362 kWh, while the energy supplied is 555 kWh. The potential for energy flexibility is analysed for a base case and for four different rule-based control options: Power limitation, Spot price savings, Flexibility sale and Solar energy. Economic consequences of the control options are compared. With the Norwegian tariff structure, maximum hourly power use has the main impact on the cost. Control systems that aim to reduce the maximum power use may be combined with spot price savings or to offer end-user flexibility services to the grid.

1 Introduction

1.1 Flexibility potential of DHW systems

Moving towards zero emission buildings and neighbourhoods, thermal and electric energy loads can be managed in a flexible way to achieve i.e. reduced power peaks, reduced energy use, reduced CO_2-emissions, and increased self-consumption of locally produced energy. Further, smart management of building loads can provide energy flexibility services to energy companies.

Domestic Hot Water (DHW) storage tanks are identified as a main source of flexible energy use in buildings [1]. As buildings are becoming more energy efficient, the share of DHW energy is increasing. However, so far, there has been relatively limited efforts in the field of energy-efficient DHW [2].

With demand side management (DSM) it is possible to influence the end-use of energy in a number of ways, by reducing (peak shaving), increasing (valley filling) or rescheduling (load shifting) the energy demand [3]. For the DHW system, load shifting of the energy profile is possible, i.e. by preheating the storage tanks or delaying the heating of the hot water. The flexibility capacity of DHW systems is largely based on the volume of the storage tank [1]. When storing DHW there are heat losses; [2] found ranges from 2% to 36% heat losses in the storage tanks depending on the system solution. The VarmtVann2030 project found annual heat loss values in the range of 4 kWh per litre stored [4].

DHW use in individual households has been analysed by e.g. [5], [6], [7] and [8]. Balint and Kazmi [5] analysed energy flexibility of DHW, where each household has a 200 litre storage tank. They found that the energy flexibility is influenced by ambient conditions, control algorithm and occupant behaviour. Ericson [6] analysed data from 475 households, where electric water heaters were automatically disconnected during peak periods of the day. The results show reductions in electricity use during the disconnections, but also indicate a risk for new system peaks if several DHW tanks are reconnected all at once. [7] analysed the stochastic nature of DHW demand in residential houses, used machine learning to predict the behaviour in 6 individual houses, and investigated the potential for energy reduction by an adapting hot water system. [8] analysed DHW consumption profiles from 95 residential houses and aggregated information. They found that the aggregate consumption profile is more predictable than individual consumption profiles.

Many apartment buildings have shared electric DHW tanks in a heating central, where load shifting of the electricity use could be possible. DHW use in buildings is affected by user behaviour [9]. Compared to DHW use in individual households, aggregated DHW use in apartment buildings is expected to be more predictable, influenced by parameters such as time of day, day of the week, months, and holiday periods [10].

As a basis for energy management in Norwegian apartment blocks, this study analyses DHW measurements in a typical apartment building located in Oslo. The work gives general recommendations for

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possible rule-based control (RBC) options, utilizing the energy flexibility potential. The research question of the work is: How can an apartment building reduce energy costs by shifting aggregated DHW energy loads in time, provided a limited storage volume? The analysis will also provide the basis for more advanced analysis planned, as described in section 3.2.

1.2 The case study apartment building

The case study for the work is an apartment building in Oslo with 56 apartments and in total 3,752 m^2 heated floor area. Each apartment has a floor area of 67 m^2 and has two bedrooms.

DHW is heated by a local heating network based on heat pumps (preheating) and electricity, see Table 1. The heating and storage capacities are dimensioned to fulfil the residents need for DHW, with temperature-based control of the DHW tanks, but there is otherwise no active DSM of the DHW system. The DHW is supplied to the apartments from a technical room in the basement. DHW is permanently circulated in pipes on the basement level, to keep the water hot, compensating for heat losses. There is no circulation system from the basement and up to each apartment.

Energy measurements are available on an aggregated level, and include energy need for DHW (without losses, as defined by [11]), energy losses in the DHW circulation, and energy supplied to the DHW tanks (to cover DHW energy need and all losses). In this article, the total DHW heating and storage capacities are analysed, not separating between the preheating and electricity heating systems.

Table 1. DHW heating and storage capacities in the case.

Source	Capacity (kW)	Storage (litre)	Storage (kWh) *
Preheating via heat exchanger	60	(4 x 400) 1,600	96
Electricity	(3 x 14) 42	(3 x 400) 1,200	72
Total values (used in article)	**102**	**2,800**	**168**

* Storage multiplied by accumulation factor 0.06 kWh/litre.

1.3 Economic motivation for energy flexibility

This section describes existing tariff structure and economic conditions, which may motivate building owners to realize their DHW energy flexibility potential.

1) Power limitation: In Norway, electricity production and transmission capacity during peak-load hours is a main concern for the distribution grid [6], especially during winter months. Therefore, larger customers usually pay hourly power tariffs, e.g. if they exceed 100,000 kWh annual electricity use behind a meter. For the case building, the power tariffs are monthly, with tariffs varying from 2.2 euros/kW (7 summer months), 6.7 euros/kW (2 spring/autumn months) and 12 euros/kW (3 winter months) [12] (1 euro = 10 NOK).

2) Spot price savings: Day-ahead spot prices are available from NordPool [13]. This is a market price of power, determined by supply and demand. The prices are normally higher during peak load hours, in the morning and afternoon. For most days during the year, the hourly price differences during a day are rather small. However, there are exceptions, where the spot prices increase substantially for a few hours during the day. For example, during the winter day 12 February 2021, the hourly prices increased from about 0.05 euro/kWh during the night hours to about 0.25 euro/kWh during the morning peak. Figure 1 shows normalized spot prices for each day in the period January 2019 to February 2021, the prices during the 23-days data period used in this article, as well as the prices during corresponding 23 dates in 2021. In the figure, the absolute price difference for each hour is shown, as the difference between the spot prices each hour and the average hourly spot price during the same day.

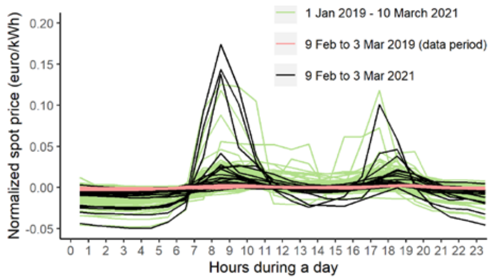

Figure 1. Normalized hourly spot prices during a day, with line colours illustrating three time periods.

3) Energy flexibility services to energy companies: End-user flexibility may become valuable for the Distribution System Operator (DSO). A market may be developed, where building owners are paid for not using energy during peak hours. However, it is difficult to quantify the value of such flexibility services, since related tariffs are not yet existing in Norway. The project EMPOWER [14] presents a local energy market concept, with compensation in the form of a strike price and an activation reward. In an example, they suggest 11 euros strike price and 4 euros activation reward for a 1.5 kW flexible load, with given activation criteria (up to 2.5 hours activation mornings and evenings weekdays).

4) Increased self-consumption of locally produced energy: If there are solar energy supply systems on-site, there is an economic advantage of using the energy in the building, including thermal energy from solar collectors and electricity from photovoltaic (PV) systems. For thermal solar energy, unused energy has no value (given that it cannot be exported). For solar electricity, within the Norwegian tariff structure, the income of electricity exported to the grid is mainly the spot price, while the price of electricity imported from the grid is about the double, including also grid costs and taxes [15]. It is therefore beneficial to shift DHW loads to the daytime (direct use of solar energy) or to store hot water in DHW tanks. There is no solar energy technologies installed in the case building, but the article

analyses the effects of solar electricity from a theoretical PV-system.

5) Energy use: Utilizing the flexibility of a DHW system may increase the use of the storage system, which would increase the heat losses of the system. The variable electricity price for end-use customers is in the range of 0.08 euro/kWh, including spot price and taxes [16]. If the annual heat losses related to the storage tanks are about 4 kWh/litre [4], the energy costs of an additional litre stored is around 0.32 euro/year. The annual heat loss for the current 2,800 litre heat storage in the case building may thus cost about 900 euros/year.

6) Investment costs and technical lifetime of DHW systems: Use of flexibility will also change the operation of the energy systems, which may change their technical lifetime [17]. For example, more constant power delivered from heat pumps may increase their lifetimes and may also reduce the capacity size needed for heat pumps and heat exchangers. However, such systems may require increased storage volume. Also, investments in monitoring equipment and building energy management systems (EMS) may be needed. [18] analysed practical performance of heat pump systems, finding universal challenges such as over-sized capacity design and unreasonable control strategies. To improve the energy efficiency, they suggest decentralized and reasonable system design, as well as accurate and efficient control strategies.

In this article, the economic consequences of 1) to 4) are included, while the consequences of 5) and 6) are not analysed.

Nomenclature

CO	Control option
CHW	Consumed hot water
DHW	Domestic hot water
DaySES	Daily supplied energy setpoint
DSM	Demand side management
DSO	Distribution system operator
EMS	Energy management system
HWC	Hot water circulation
RBC	Rule-based control
SoC	State of charge

2 Methodology

2.1 Method for DHW measurements

DHW measurements for this study were extracted from the following sources: The project VarmtVann2030 [19] performed a measurement campaign where energy for consumed hot water (CHW) and distribution losses in the hot water circulation (HWC) were measured. The EMS in the building measures energy supplied to the DHW tanks.

The measurement campaign lasted for 7 weeks, from 16 January to 6 March 2019. Flow and temperature measurements were performed on the main supply pipe for the apartment building. Clamp-on ultrasonic flow meters were used for flow measurement and Type-T thermocouples where mounted on the pipe wall. Flow rates and temperatures were measured with an interval of 1 second, and then averaged to 2 seconds before analysis. Measurement equipment and energy calculations are described in [20].

Energy supplied to the DHW tanks was measured hourly. The measurements are available for 3 full weeks and 4 weekends, from 9 February to 3 March. In the EMS, both thermal energy (preheating) and electricity to the DHW tanks were measured, and the total hourly energy supplied is used in these analysis.

Due to the storage tanks, there is a time difference between CHW and energy supplied. In addition, there is an absolute difference between energy supplied and energy needed for CHW and HWC. This difference is calculated as the heat losses in the technical room, and is related to heat exchanger, storage, valves, pipes, etc.

2.2 Method for DHW energy analysis

The following data are used in the energy analysis:
50 days measurement-period (16.01 - 06.03.2019):
• CHW, resampled to 1 minute and 1 hour time steps,
• HWC, resampled to 1 minute and 1 hour time steps,
23 days measurement-period (09.02 - 03.03.2019):
• Energy supplied (sum of preheating and electricity), 1 hour time steps,
• Heat losses in the technical room (calculated difference as described above), 1 hour time steps.

Calendar data were added to the energy data, such as time of day and weekdays. DHW energy need and supplied energy are analysed. For CHW and HWC, the time steps of 1 minute and 1 hour are compared. For the heat losses in the technical room, the hourly analyses show average heat losses, not heat losses hour-by-hour, since the hourly values includes the time-delay between CHW and supplied energy.

2.3 Control options for utilizing flexibility

The potential for energy flexibility is analysed by simulating a base case and four different control options (COs), named control option 1 "Power limitation", control option 2 "Spot price savings", control option 3 "Flexibility sale", and control option 4 "Solar energy". The control options are rule-based with additional constraints [21], aiming to account for physical limitations of the systems, and to make sure DHW is always available for the users.

Input parameters for the control options are:
• CHW (all COs): Hourly values, 23-day period.
• HWC (all COs): Hourly values, 23-day period.
• Heat loss in technical room (all COs): Hourly average heat loss value is used for all hours: 4.7 kW.
• Daily supplied energy setpoint, DaySES (all COs): Assumed maximum energy supply during a day, set 10% above the measured value of 613 kWh: 672 kWh per day.
• Power limitation setpoint: Because of the existing hourly power tariffs, there is a power limitation in most of the COs (except the base case and the CO 2 case):

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- Base case: No limitation, except by actual installed total capacity: 102 kWh/h.
- CO 1: Even distribution DaySES: 672/24=28 kWh/h.
- CO 2: The spot prices are divided into three levels each day: 1) Low-price level: 12 hours, limited by actual installed capacity (102 kWh/h), 2) Medium-price level: 8 hours, limited to energy use that hour (no energy is supplied to the storage tanks), and 3) High-price level: 4 hours, no energy supply.
- CO 3: Two peak load hours with no supplied energy: One in the morning (from 07:00 weekdays and 10:00 weekends) and one in the afternoon (from 16:00 all days). Even distribution of DaySES on the remaining hours: 672/22=30.5 kWh/h.
- CO 4: Solar electricity is prioritized, when available. A 50 kW_p system is assumed, based on a solar map for Oslo [22]. Hourly electricity generation is simulated for 2019, using the tool renewables.ninja [23] (Dataset MERRA-2, 0.1 system loss, 30° tilt, 135° azimuth). In addition: Even distribution of DaySES: 672/24=28 kWh/h.

• State of charge (SoC) storage tank (all COs): Limited to the total storage volume available in the technical room: 168 kWh. For the first hour, the storage volume is full. Then, calculated for each hour (i) as:

$$E_{tank(i)}=E_{tank(i-1)}+E_{PV(i)}+E_{setpoint(i)}-E_{CHW(i)}-E_{HWC(i)}-E_{losses(i)}$$
$$\text{Condition: If } E_{tank(i)}>E_{tank\text{-}cap} \text{ then } E_{tank(i)}=E_{tank\text{-}cap} \quad (1)$$

$E_{setpoint(i)}$ is the hourly power limitation setpoint, while $E_{tank\text{-}cap}$ is the storage tank capacity. Hourly solar energy ($E_{PV(i)}$) is zero for all COs except CO 4.

• Energy supply (varies with the CO): Hourly energy supply, calculated for each hour (i) as:

$$E_{supply(i)}=E_{tank(i)}-E_{tank(i-1)}-E_{PV(i)}+E_{CHW(i)}+E_{HWC(i)}+E_{losses(i)} \quad (2)$$

3 Results and discussion

3.1 DHW energy need and supplied energy

This section describes the actual energy need and supplied energy to the DHW tanks in the case building. Figure 2 shows CHW and HWC during the 50-days measurement period, and supplied energy during the 23-days measurement period. Figure 3 shows the duration curve for CHW and HWC separately, comparing minute and hourly time steps. Comparing the time steps, the max. power averaged during a minute is about 3 times higher than the max. power averaged during an hour. For hourly resolution of CHW, the max power is 53.3 kW, while the 95-percentile is 33.9 kW. For the minute resolution of CHW, the max power is 171.9 kW, while the 95-percentile is 49.6 kW. The substantial variations within one hour should be taken into account when analysing hourly averages and indeed when dimensioning DHW systems and preparing control systems.

Table 2 shows hourly and daily values for CHW, HWC, supplied energy, and heat losses. The HWC-values show that energy losses in the distribution are fairly constant during the day. The total heat losses are 35% of the supplied energy. Figure 4 shows CHW, HWC and supplied energy each day during the 50 days measurement period. There are not very large daily variations. The daily CHW values vary from 276 to 436 kWh per day during the period, while HWC values vary from 68 to 94 kWh per day. There was a holiday period from 18 to 24 February, but it appears that there is not any significant change in DHW use.

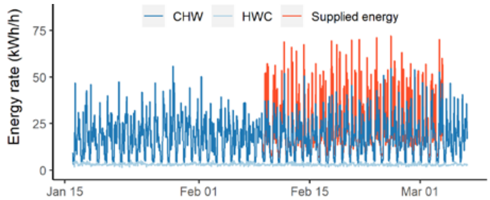

Figure 2. CHW, HWC and supplied energy on a timeline with 1 hour time-steps (data series are stacked in columns).

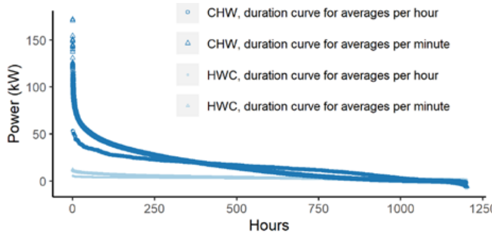

Figure 3. Duration curve for CHW and HWC separately. Comparing 1 minute and 1 hour time-steps.

Table 2. Hourly and daily values for CHW, HWC, supplied energy and heat losses.

DHW (kWh)	Average hourly	95-percentile hourly	Max hourly	Average daily	Max daily
CHW	15.1	33.9	53.3	362	436
HWC	3.3	4.4	5.6	78	94
Supplied	23.1	54.6	72.1	555	613
Heat losses	4.7	-	-	112	142

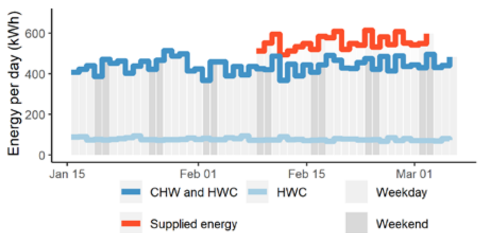

Figure 4. Daily CHW, HWC and supplied energy during weekdays and weekends.

Hourly average values are shown in the daily profile in Figure 5. CHW, HWC, heat losses, and supplied energy are shown separately, with their individual 90% confidence interval. For heat losses, an average value is shown. The daily values show an increased CHW during the morning, from about 06:00 during the weekdays and about during 08:00 weekends. There is a morning and afternoon peak, as also observed in other apartment

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buildings [24], but also the DHW uses during other daytime hours are quite high. An explanation for this could be that residents with small children or elderly are overrepresented, which is reasonable given that the apartments have two bedrooms only. If so, a higher share of the residents may be home during daytime, compared to other buildings with more mixed or larger apartment sizes. For CHW, Table 3 provides more details, with hourly average values during weekdays and weekends.

In the case study, supplied energy during peak hours is higher than the CHW, even though DHW tanks are present. This is explained by the design of the preheating control system. Using the storage capacity actively, it may be possible to shift loads from peak hours to off-peak hours. This is further investigated in the next section.

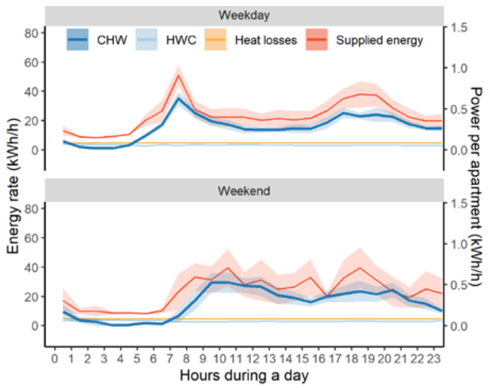

Figure 5. Average daily profiles for CHW, HWC, heat losses, and supplied energy, shown separately, with their individual 90% confidence interval (1 hour time-steps).

Table 3. Average CHW for weekday/weekend hours (kWh).

Daily hour	Week-days	Week-end	Daily hour	Week-days	Week-end
00-01	6.7	9.8	**12-13**	12.3	24.7
01-02	2.3	5.5	**13-14**	13.1	21.1
02-03	1.1	2.6	**14-15**	16.2	18.8
03-04	0.8	0.6	**15-16**	16.2	17.0
04-05	2.6	0.4	**16-17**	20.9	18.6
05-06	9.0	1.9	**17-18**	25.0	21.4
06-07	16.8	1.0	**18-19**	24.5	19.6
07-08	31.8	6.6	**19-20**	24.2	20.3
08-09	21.6	17.4	**20-21**	24.0	22.7
09-10	17.2	27.2	**21-22**	17.2	18.4
10-11	16.4	31.0	**22-23**	16.3	14.4
11-12	12.7	28.3	**23-24**	14.8	9.8
Average daily CHW (kWh/day):				**363.9**	**359.1**

3.2 Energy flexibility potential of DHW systems

This section analyses the potential for energy flexibility by simulating a base case and four control options. For each option, the average daily profile and an example day are shown in Figure 6 and Figure 7, while Table 4 provides some key results. The average day has a CHW demand of 367 kWh and a max. hourly CHW load of 52.5 kWh/h, based on the 23-day measurement period. Including losses, the daily demand is 554.8 kWh and the max. hourly load is 59.3 kWh/h. The example day Sunday 3 March 2019 is chosen, since it has the highest daily demand (606 kWh incl. losses) and the third highest hourly load (57.3 kWh/h) during the 23-day period.

For the base case, the heat production capacity of 102 kWh/h can deliver all needed energy, hour-by-hour. The storage capacity therefore remains at maximum level on an hourly basis. The max. hourly energy supply is 59.3 kWh/h.

CO 1 "Power limitation" aims to distribute the supplied energy evenly through the day, to reduce the power tariff costs. For both the average day and the example day, the supplied energy is limited by the DHW tank volume during night-hours. The minimum SoC for the storage tank during the 23-day period is 65.5 kWh (39%), which implies that the tank volume is sufficient. If it becomes necessary to increase the hourly energy supply, this increase should happen slowly, since large power jumps over a short period has higher economical costs than a smaller power increase during a longer period. Since hourly values are analysed, a safety margin should be considered, to make sure that the needed energy can be provided within the hour. This is illustrated in Figure 8, showing the example day with minute timesteps, which can be directly compared with CO 1 in Figure 7. A DWH tank may be emptied due to variations within the hour, even though the tank is large enough for the hourly averages.

With CO 2 "Spot price savings", the supplied energy is distributed according to the day-ahead spot prices. The spot prices vary during the day, with higher spot prices during energy peak periods. With CO 2, this results in less energy production during hours with DHW demand, both for the average day and the example day. The result is that CO 2 struggles to supply the needed energy, given the available DHW storage. With all the heat production capacity available, the minimum SoC for the storage tank during the period is 21.8 kWh (13%). This is during a day where all the four high-price level hours (with no energy supply) are in sequence. The maximum hourly load is high, since there are no limitations (102 kWh/h). Also for this control option, a maximum level could be set for the hourly energy supply. In addition, other conditions could be tested, e.g. limiting the number of high-price level hours in sequence, reducing the number of hours with high-price or medium-price level, or increasing the available storage volume.

With CO 3 "Flexibility sale", there is no energy supply during 2 peak hours. Like for CO 1, the power level is limited by the DHW tank volume during night-hours. The minimum SoC for the storage tank during the period is 35.8 kWh (21%), which means that it may be necessary to increase either the hourly energy supply or the tank volume in order to provide flexibility services every day. Another option is to only offer flexibility services when sufficient capacity is available, if this becomes a possible option within the flexibility market.

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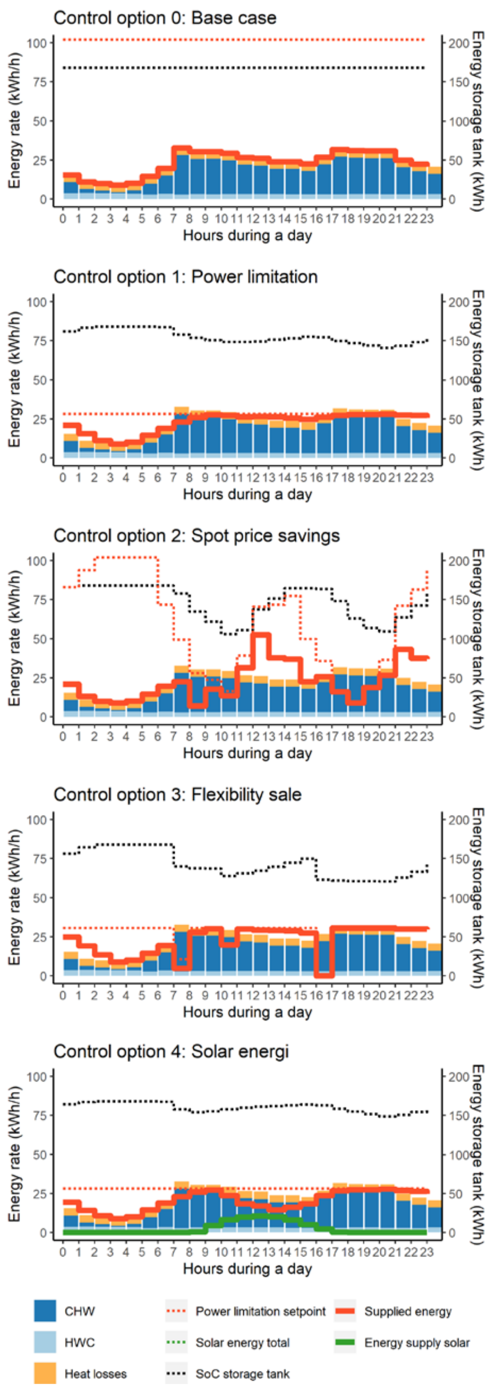

Figure 6. Average daily profiles for the control strategies.

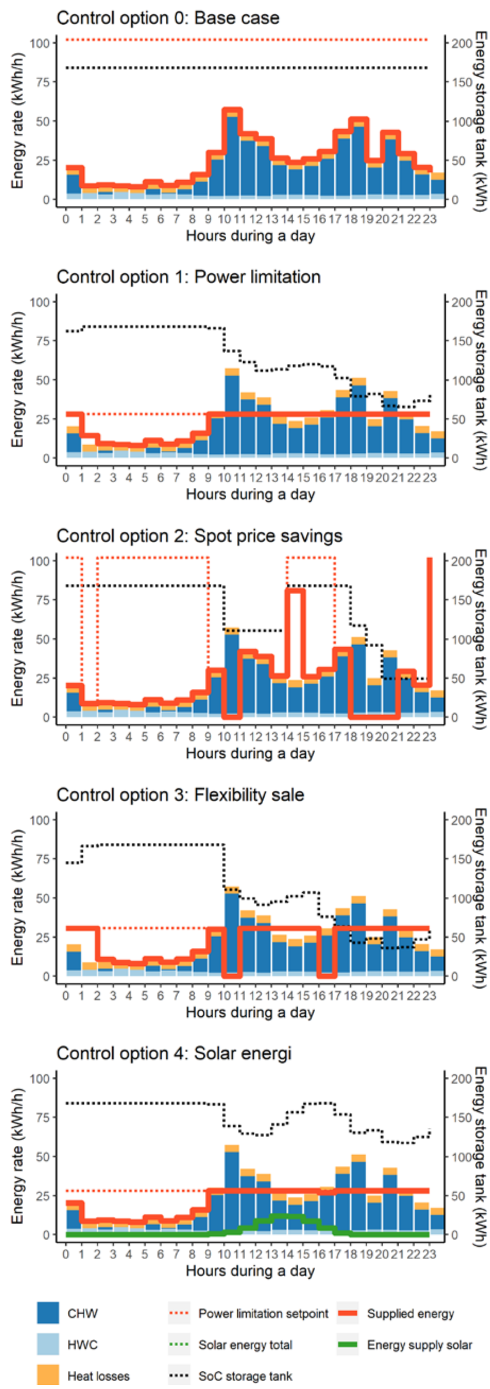

Figure 7. Daily profiles for example day 2019-03-03.

CO 4 "Solar energy" is like CO 1, but with a PV-system added. The solar electricity is used directly, either to supply the DHW demand or to be stored in the tanks (limited by tank capacity). Solar electricity is prioritized when available, and the power limitation in

CO 1 is relevant for grid electricity only, not solar electricity. In the 23-day period, the average PV generation is 62 kWh per day (Figure 6). The minimum SoC for the storage tank is 113 kWh (67%). The daily PV generation March 3 is 53 kWh (Figure 7). During the year 2019, the average daily PV generation is 123 kWh, with maximum 341 kWh/day.

Table 4. Analysis of control strategies (23-days period)

	Energy supply (kWh)	Power max (kW)	Average SoC storage (kWh)	Min. SoC storage (kWh)
CO 0	12,760	59.3	168	168
CO 1	12,676	28.0	154.8	65.5 (39%)
CO 2	12,725	102.0	146.4	21.8 (13%)
CO 3	12,652	30.5	142.2	35.8 (21%)
CO 4	11,349 +PV 1,378	28.0	160.2	113 (67%)

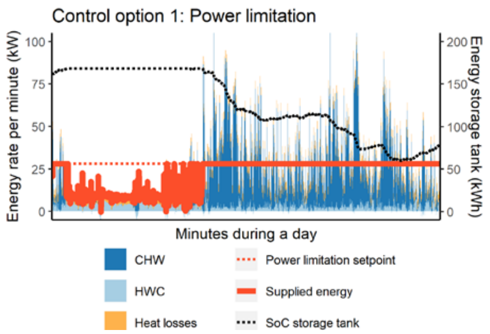

Figure 8. Daily profile for example day 2019-03-03, with minute timesteps.

Table 5. Economic consequences of the control strategies

	Power tariffs (€/month) summer-winter	Spot-price (€/23 days) 2019	Spot-price (€/23 days) 2021	Other (€/23 days)
CO 0	130-712	553	669	
CO 1	62-336 (47%)	548 (-5)	653 (-16)	
CO 2	224-1,224 (172%)	545 (-8)	601 (-68)	
CO 3	67-366 (51%)	546 (-7)	644 (-25)	Flex services 0.5 €/kW: 398
CO 4	62-336 (47%)	491 (-62)	592 (-77)	El. savings 0.05 €/kWh: 69

The economic consequences of the four control strategies are analysed, with key results in Table 5. In the analysis, it is assumed that a reduction in energy supplied to the DHW tanks also reduces electricity delivered from the grid (independent on the use of preheating or other energy use in the building).

For customers with power tariffs, it is an advantage to reduce max. hourly energy supply each month. During a year, there is a saving potential of 2,028 euros when moving from the base case to CO 1.

With the conditions in this work, the daily difference in spot prices seem too low to justify a management system focusing on spot price savings. It was not achieved lower spot price with CO 2 than the other control options, using spot prices during the 23 days measurement period in 2019. Spot prices vary, and if using 2021-prices for the same dates (not adjusting for change of weekdays, and assuming that the CHW habits are not directly dependent on spot prices), the savings increase from 8 euro to 68 euro during the periode, compared to base case. Spot price savings may be combined with other control options. In the future, also Norwegian grid tariffs may depend on time of day, which may increase the savings.

It is challenging to estimate the potential income from flexibility services in CO 3, since related tariffs are not yet existing in Norway. If assuming an activation reward of 0.5 euro/kW each flexible hour, using the hourly energy supply in CO 1 as the reference, a reduction from 28 kW to 0 kW during a peak hour will generate 14 euro. For two peak hours each weekday only, the potential income during the 23 days is 398 euro (or 6,898 euro/year).

If solar energy is available, either thermal or electric, the average DHW loads in the case building fit well with the potential solar energy production, even if the whole demand cannot be covered, such as the morning loads during weekdays. Larger storage volume would increase the self-consumption potential of solar energy.

The analysis in this article uses a simple input-output storage tank model, with energy flows in and out of the tank. RBC can yield significant improvements with regards to demand response and flexibility [21]. RBC is also easy to implement, with few requirements for historic data and control system. However, RBC may lead to non-optimal solutions, since the control rules are predefined [17]. In future work, more advanced analyses are planned. The internal state of the storage tank will then be included, with temperature levels in the tank. In addition, optimalisation options will be introduced. In general, Model Predictive Control (MPC) is expected to further improve the results [21], [25], optimizing DHW operation by modelling future DHW need, technological constraints, and additional influencing parameters. In this article, we have not separated between the preheating and electricity heating systems, thus analysing the total DHW heating and storage capacity only. In real life, it would normally be an advantage to increase the preheating share of the system A deeper analysis of technical options, control algorithms and economic consequences is intended in further studies.

4 Conclusion

The research question of this work is: How can an apartment building reduce energy costs by shifting aggregated DHW energy loads in time, provided a limited storage volume? The case study is a building with 56 apartments. The potential for energy flexibility is simulated for a base case and four RBC options, based on hourly timesteps. The flexibility capacity of DHW systems is largely based on the volume of the storage tank. In the analysis, the volumes of the tanks are limited to the actual sizes available in the case study.

The economic analysis shows that for customers with power tariffs, it is an advantage to reduce the maximum hourly energy supply. This can be done by setting a maximum power level for delivered energy. The power level should be high enough to avoid short-term power jumps, which would increase the tariff costs. When hourly values are used as a basis for setting the power level, a safety margin should be included, since there are variations within an hour. A management system with maximum power level can be combined with other control options, such as spot price savings or flexibility services. With the conditions in this work, the daily difference in spot prices is too low to justify a management system focusing on spot price savings alone. It is possible for apartment buildings to provide flexibility services to the DSO by avoiding to use energy for DHW during peak load hours in the grid. If so, the power tariffs for the building may increase and investments in larger storage volume may be needed. The interests in offering flexibility services will therefore depend on the economic conditions for the services.

The results of the study support the theory that aggregated DHW need is a significant source of flexible energy use in Norwegian apartment buildings. A deeper analysis of technical options, control algorithms and economic consequences is intended in further studies.

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Supplementary article IV

Analysing electricity demand in neighbourhoods with electricity generation from solar power systems: A case study of a large housing cooperative in Norway

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Table: The paper's context in the thesis.

	Supplementary articles	Main article I	Main article II	Main article III	Main article IV	Data articles *(D* describes planned articles)*
RQ1: What are the energy profiles for household energy use and PV generation for apartment buildings, and how are the energy profiles influenced by climate variables?	S I. Electricity S II. Heat-DHW S III. DHW S IV. PV				Main IV. Energy profiles	D* IV. Data Main IV
RQ2: How does the user habits influence the electricity load profiles of residential EV charging, and how is the el. load affected by EV cabin preheating?	S V. Stochastic EV charging	Main I. EV charging	Main II. EV charging	Main III. EV cabin preheating		D I. Data Main I D* II. Data Main II D* III. Data Main III
RQ3: What is the potential for electricity flexibility from EVs, in relation to non-flexible apartment building loads and PV generation, in the Norwegian context?					Main IV. Flexibility	

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Analysing electricity demand in neighbourhoods with electricity generation from solar power systems: A case study of a large housing cooperative in Norway

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Abstract. An energy management system can be introduced on a neighbourhood level, to achieve energy goals such as increased self-consumption of locally produced energy. In this case-study, electricity generation from photovoltaic (PV) systems is simulated at Risvollan housing cooperative, a large housing cooperative in Norway. The electricity generation from PV systems of different orientations and capacities are analysed with the electricity load. Key performance indicators (KPIs) such as self-generation, self-consumption and generation multiple are described, based on hourly values. The electricity generation from the south-oriented building façade PV systems are about 5-6% higher than for the east-west oriented rooftop PV systems on an annual basis, since the façade PV systems generate more electricity in the spring and autumn. The self-consumption factor is the most important KPI in Norway, due to the national tariff structure. For the total housing cooperative, a PV capacity of about 1,000 kW_p seem suitable, giving a self-consumption factor of 97% for a rooftop system, based on 2018 electricity and climate data. From the perspective of the housing cooperative, it is financial beneficial to aggregate electricity loads for common areas and apartments, since a higher share of the electricity can be used by the cooperative. For this to be possible, also housing cooperatives with PV must be facilitated for in the prosumer agreement. Comparing a single 1,100 kW_p PV system providing electricity to the total cooperative with 22 PV systems of 50 kW_p behind 22 garage meters, the self-consumption factor decreases from 95% to average 14%, resulting in a 41% lower financial value for the PV electricity.

1. Introduction

In zero emission neighbourhoods, thermal and electric energy should be managed in a flexible way, to achieve reduced power peaks, reduced energy use, reduced CO_2-emissions and increased self-consumption of locally produced energy [1]. Further, smart energy management systems (EMS) with building loads can provide energy flexibility services to distribution system operators (DSOs) and district heating companies, both on a building and a neighbourhood level.

A prosumer agreement exists in Norway, for locally produced electricity [2]. AMS meters (Advanced Metering System) at each customer measure net electricity export and import on an hourly basis. Financially, consumers normally receive less payment for electricity sold to the energy company than what they pay for buying electricity. This makes it beneficial to maximise self-consumption, i.e. minimising export of electricity to the grid.

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Risvollan housing cooperative is a large housing cooperative in Trondheim, built in the 1970s. Risvollan cooperates with energy companies and researchers to develop a neighbourhood EMS. In Risvollan, there are 1,058 apartments with in total 93,713 m^2 heated floor area, distributed on 121 similar apartment blocks, as shown in Figure 1. In total 2,321 residents live in the apartments: 53% female and 47% male [3], as shown in Figure 2. Previously, measurements of electricity and heat loads of Risvollan in 2018 have been analysed in respectively [4] and [5]. The electricity loads also include around 55 electric vehicles (EVs) in the parking houses, which is expected to increase within the next years. Space heating and domestic hot water (DHW) is provided by district heating.

To be partly self-sufficient with electricity, the housing cooperative considers installing photovoltaic (PV) systems on some of their buildings. This article analyses the electricity demand at Risvollan together with possible electricity generation from the PV systems. In this article the electricity delivery is also referred to as electricity use, demand or load.

Figure 1. Example of apartment blocks at Risvollan housing cooperative, with 121 similar building blocks.

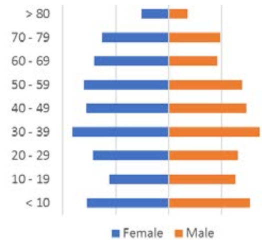

Figure 2. Age and gender distribution of the 2,321 residents.

2. Methods

Future scenarios for PV systems are developed, with varying installed PV capacity. PV generation is simulated with hourly resolution, using the software PVsyst [6]. Input data and system information is shown in Table 1. The PV systems are placed in two directions: 1) rooftop PV systems on flat roofs, with a 15° tilt orientated east and west, and 2) building façade PV systems, south oriented with a 90° tilt. No shadings are defined for the systems. Snow cover is considered by increasing the albedo values during the winter months, as shown in the table. Two system sizes are simulated in each orientation, to develop a scalable 1 kW$_p$ PV system based on the average, since variations can occur between simulated systems in PVsyst. The area suitable for PV on the 121 building blocks varies. Analysing internet maps, it seems that around 600 m^2 roof area may be available on the most suitable buildings, while other building might be evaluated as not suitable at all, due to shadings or roof conditions. In this article, it is roughly estimated that a 50 kW$_p$ system can be placed on one third of the buildings, giving a total of 2,000 kW$_p$ on the roofs. For the systems placed on the façades, less suitable area is available. Assuming that a 12 kW$_p$ system can be placed on one third of the buildings, the total potential is about 500 kW$_p$ on the façades.

Climate data for 2018 collected from eKlima [7] is imported to PVsyst. The outdoor temperatures are mainly from a weather station at Risvollan, where a few missing values are replaced with data from weather station Voll, 2.5 km away. The wind data are also from Voll, while the global radiation is from the weather station Gløshaugen, 3 km away. Based on the 2018-climate data, PVsyst creates hourly meteo-data for the simulations, where the annual horizontal global irradiation is 868.3 kWh/m^2, the horizontal diffuse irradiation 432.96 kWh/m^2 and ambient temperature 5.49°C.

Based on analysis of electricity loads in 2018 [4], this analysis uses load data from 1,009 apartments (95%), 22 electricity meters in garages (88%) and 82 electricity meters in other common areas (92%), excluding metering points with less than 7000 hours of data. Still some missing measurement periods remain, mainly in January, where only 67% of garages, 76% of other common areas and 72% of the apartments are measured. From February, most AMS meters are installed.

To evaluate the results, the self-generation, self-consumption and generation multiple factors are calculated based on hourly values. The 'self-generation factor', is the percentage of the electrical demand that is covered by on-site electricity generation [8]. The 'self-consumption factor' is defined as the percentage of the on-site generation that is used by the buildings [8]. 'Generation multiple factor' is the ratio between exported and imported peak powers [8].

A range of PV capacities are chosen, up to the maximum of 2,000 kW_p rooftop and 500 kW_p façade PV systems, with capacity steps of 0, 50, 100, 500, 1,000 and 2,000 kW_p. The aim of the chosen steps is to illustrate changes in the key performance indicators (KPIs) with changing PV capacities. In the analysis, the main focus in on the KPI self-consumption, since this is a financial important KPI with the Norwegian tariff structure. When comparing KPIs for several smaller PV systems to a large PV-system, the smallest capacity step of 50 kW_p is chosen for the 22 individual systems, with an aggregated capacity of 1,100 kW_p, which is the capacity used for the single large system. Both the electricity loads and the simulated PV electricity generation are analysed using the statistical computing environment R [9].

Table 1. Input data and system information for the simulated PV systems, with climate data for 2018.

Location	Latitude 63.39° N, Longitude 10.44° E, Altitude 116 m					
Horizon	From GVGIS website API					
Monthly albedo values	Dec, Jan, Feb, Mar, Apr: 0.4, May, Jun, Jul, Aug, Sep, Oct, Nov: 0.2					
PV module	Si-poly, 285 W_p, 72 cells (generic), 14.78% efficiency at STC					
Inverter	12 kWac inverter (generic)					
Orientations, tilts/azimuths	**Rooftop**: 15°/-90° and 15°/90°			**Façade**: 90°/0°		
PV capacity (kW_p)	42.8	68.4	**1**	12.82	42.8	**1**
Nb. modules	150	240	**-**	45	150	**-**
Module area (m^2)	291	466	**6.8**	87.3	291	**6.8**
Nb. inverters	3	5	-	1	3	-
Inverter power (kW_{ac})	36	60	-	12	36	-
Produced electricity (MWh/year)	32.25	51.58	**0.75**	10.26	34.18	**0.80**
Specific prod. (kWh/kWp/year)	754	754	**754**	800	800	**800**

3. Results

The total average specific electricity use in 2018 was approx. 56.7 kWh/m^2, used in apartments and common areas [4]. Average specific use of district heating was approximately 139 kWh per heated floor area [5]. In this article, only the electricity use is analysed with simulated PV electricity.

3.1. Analysing electricity generation from PV with electricity use in the housing cooperative

Table 2 summarizes KPIs for analysing electricity demand at Risvollan with simulated PV electricity. Both electricity and climate data are from 2018. The results are for the housing cooperative in total, where hourly electricity load from several AMS meters are aggregated.

In the following, the results are analysed for the common areas only, followed by the total Risvollan. For the common areas it is simulated that a 50 kW_p, 100 kW_p or a 2,000 kW_p PV system on the roof could cover about 6.5%, 12.3% or 35.3% respectively, of the electricity use on an hourly basis (self-generation factor). For the façade systems, the self-generation factor for a 50 kW_p PV system is 6% higher than for the rooftop system, and 30% lower for the larger 500 kW_p system. For the 50 kW_p rooftop PV system, nearly all (99.9%) of the generated electricity can be used by the common areas (self-consumption factor). For larger rooftop systems of 500 kW_p or 2,000 kW_p, the self-generation factor is declined to 41.5% or 13.5% respectively. For the façade systems, the range of the self-consumption factor for the common areas is from 100% for the smallest PV system at 50 kW_p, down to 27.6% for the largest PV system at 500 kW_p. For both the roof and wall systems, the ratio between exported and imported peak powers is 0.1 for the 50 kW_p PV system and 0.3 for the 100 kW_p PV system (generation multiple factor). For a 500 kW_p system the generation multiple factor increases to 2.4 for a rooftop system and to 3.1 for a building façade system. For the 2,000 kW_p rooftop system the generation multiple factor is increased to 10.4.

For the total Risvollan, the three KPI factors change. It is simulated that a 500 kW_p PV system would cover about 8% of the loads and a 2,000 kW_p PV system would cover about 23.3%, on an hourly basis. For the façade systems, with maximum capacity of 500 kW_p PV, the self-generation factor is slightly higher than for the rooftop system. The self-consumption factor for a 500 kW_p PV system on both roof and the façades is about 100%. For a 2,000 kW_p PV system, the self-consumption factor is around 77% for a rooftop system, with a ratio between exported and imported peak powers of 0.8.

Table 2. KPIs for analysing electricity use with simulated PV electricity (2018- electricity/climate data).

Type of user (# el meters)	Electricity demand (MWh/y)	Max. load (kWh/h)	PV capacity (kW_p)		Simulated gen. (MWh/y)		Self-gen. (%)		Self-cons. (%)		Gen. multiple	
			Roof	Façade	Roof	Façade	Roof	Façade	Roof	Façade	Roof	Façade
Electricity common areas	576	129	50	50	38	40	6.5	6.9	99.9	100	0.1	0.1
			100	100	75	80	12.3	12.7	94.0	91.3	0.3	0.3
(hourly sum of 104 el meters)			500	500	377	400	27.2	19.1	41.5	27.6	2.4	3.1
			1,000		754		31.9		24.4		5.0	
			2,000		1,507		35.3		13.5		10.4	
Total electricity, apartments and common areas	4,977	1,126	50	50	38	40	0.8	0.8	100	100	-	-
			100	100	75	80	1.5	1.6	100	100	-	-
			500	500	377	400	7.6	8.0	100	100	-	-
(hourly sum of 1,113 el meters)			1,000		754		14.7		96.8		0.2	
			2,000		1,507		23.3		77.1		0.8	

Figure 3 shows analysis of electricity demand with simulated PV generation, using electricity and climate data from 2018. The electricity demand shown is for the common areas (figures in column 1), and in total, also including apartments (figures in column 2). The sizes of the PV systems shown are 100 or 500 kW_p for the common areas and 500, 1,000 or 2,000 kW_p for the total housing cooperative. The electricity load and PV generation on a monthly basis is shown in Figure 3 a) and b), for PV systems on the roof or façade. The figures show that the façade-placed south oriented systems generate more electricity during the swing seasons, compared to the rooftop east-west oriented systems, but have a lower electricity generation during the summer months. In Figure c) and d), hourly duration curves are shown, for net electricity load (positive values: import from grid, and negative values: export to grid). The figures show how the export increases, if the PV system is large compared to the electricity demand, giving a high generation multiple factor. Figure e) and f) shows example of hourly load and generation during a week in April, showing daily variations in electricity use and PV generation. Average daily electricity profiles is shown in Figure 3 g) and h), for load and PV generation on roofs or façades during spring (Mar, Apr, May) and summer (Jun, Jul, Aug).

3.2. Comparing KPIs for a large PV-system to several smaller PV systems

Table 3 summarizes KPIs for several smaller PV system, compared to one large PV system with the same aggregated PV capacity. AMS measurements from the garages are analysed individually, where hourly electricity generation from 22 rooftop PV systems, each with a capacity of 50 kW_p, are located behind the meter of each of the 22 garages. As a comparison, a single large rooftop PV system with a capacity of 1,100 kW_p is delivering electricity to the garages aggregated, to the common areas (including garages), or to the total Risvollan housing cooperative (including common areas and apartments). Figure 4 shows hourly duration curves for net electricity from or to the grid, comparing the 22 rooftop 50 kW_p PV systems with a single rooftop 1,200 kW_p PV system.

Due to the tariff structure in Norway, it is normally financially beneficial to maximise self-consumption, i.e. minimising export of electricity to the grid. Table 4 compares the financial values of four system solutions; 1) 22 PV systems of 50 kW_p, providing electricity to 22 garages only, 2) 1 PV system of 1,100 kW_p providing electricity to 22 garages only, 3) 1 PV system of 1,100 kW_p providing electricity to all common areas (incl. garages) and 4) 1 PV system of 1,100 kW_p providing electricity to all of Risvollan (incl. apartments and common areas). The tariff estimations are based on [10] and [11], and is 1 NOK/kWh for self-consumed PV-electricity, which is the estimated end-user cost for electricity from the grid, and 0.5 NOK/kWh for exported PV-electricity. Only electricity costs are considered, assuming that the choice of PV system solution would not change the investment costs.

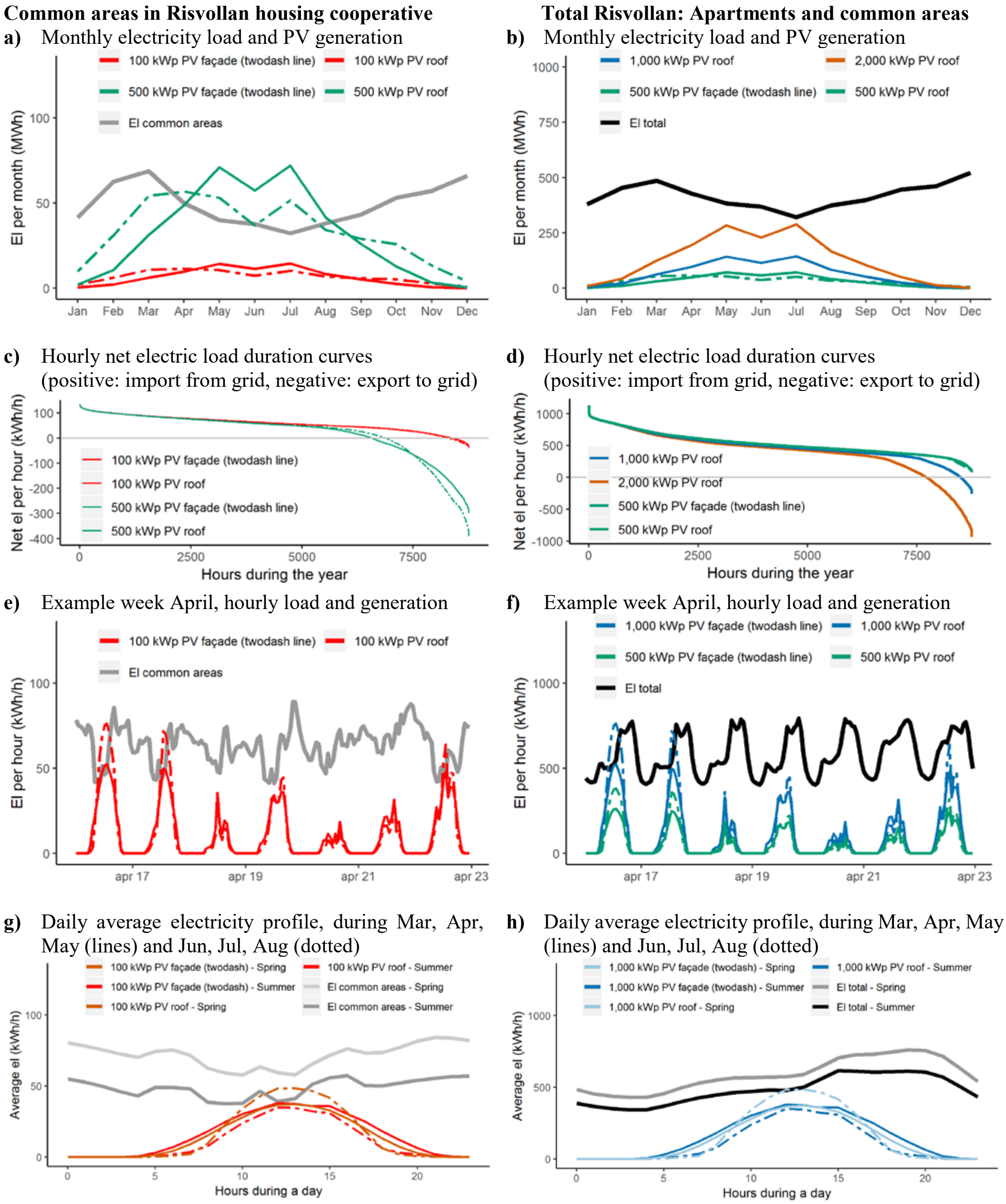

Figure 3. Analysing electricity use in Risvollan housing cooperative with simulated PV generation.

Table 3. KPIs for analysing electricity use with simulated PV electricity (2018- electricity/climate data). All the PV systems are east-west oriented rooftop systems with a total capacity of 1,100 kW_p.

KPIs for 22 individual PV systems, located behind 22 garage meters:

	Electricity (MWh/y)	Max. load (kWh/h)	PV capacity (kW_p)	Simulated gen. (MWh/y)	Self-gen. (%)	Self-cons. (%)	Gen. multiple
El garages (22 el meters)	Per garage: Max: 56 Mean: 17 Min: 5	Per garage: Max: 34 Mean: 7 Min: 3	22·50 Tot: 1,100	22·38 Tot: 829	Per garage: Max: 46.4 Mean: 34.9 Min: 17.1	Per garage: Max: 31.8 Mean: 14.3 Min: 3.2	Per garage: Max: 11.0 Mean: 6.0 Min: 1.0

KPIs for one large PV system, with aggregated load:

	Electricity (MWh/y)	Max. load (kWh/h)	PV capacity (kW_p)	Simulated gen. (MWh/y)	Self-gen. (%)	Self-cons. (%)	Gen. multiple
El garages	363	91	1,100	829	35.0	15.3	8.1
El common areas	576	129	1,100	829	32.5	22.6	5.6
El total Risvollan	4,977	1,126	1,100	829	15.8	95.0	0.3

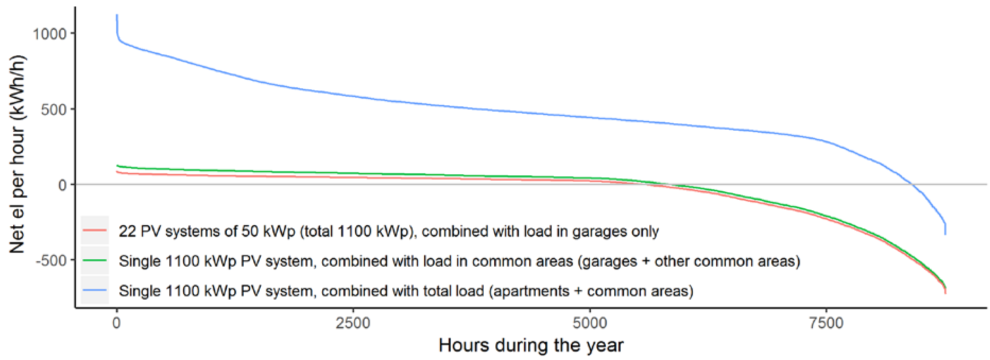

Figure 4. Hourly duration curves for net electricity from/to grid, with 22 rooftop 50 kW_p PV systems or a single rooftop 1,100 kW_p PV system. PV generation from the 22 PV systems cover electricity load in 22 garages. PV generation from the single large PV system cover aggregated electricity loads in all common areas or in the total housing cooperative, including apartments and common areas.

Table 4. Estimation of financial value of PV electricity, comparing four cases with different electricity use, each with a total capacity of 1,100 kW_p rooftop PV system.

Case	Simulated gen.	Self-cons. (%)	Value self-use	Value export	Total annual value
22 PV systems a 50 kW_p, providing electricity to 22 garages only	22·38, Tot: 829 MWh/y	Per garage: Mean: 14.3	121 MWh: 121,000 NOK	708 MWh: 354,000 NOK	475,000 NOK
1 PV system a 1,100 kW_p, providing electricity to 22 garages aggregated	829 MWh/y	15.3	127 MWh: 127,000 NOK	702 MWh: 351,000 NOK	478,000 NOK
1 PV system a 1,100 kW_p, providing electricity to all common areas	829 MWh/y	22.6	187 MWh: 187,000 NOK	642 MWh: 321,000 NOK	508,000 NOK
1 PV system a 1,100 kW_p, providing electricity to all of Risvollan (incl. apartments and common areas)	829 MWh/y	95.0	788 MWh: 788,000 NOK	41 MWh: 20,000 NOK	808,000 NOK

4. Discussion

As a basis for energy management in apartment blocks, this article analyses the electricity demand at Risvollan together with simulated electricity generation from several different PV systems. The total electricity use included in the analysis is 4,977 MWh, where 12% is used in common areas and 88% in 1.009 apartments. It is estimated that the total electricity delivery to Risvollan in 2018 was 5,318 MWh [4], meaning that 6% of the annual electricity use is excluded or missing from this analysis. If all measurements had been available, the KPI factors would have changed slightly. Electricity generation from PV is simulated based on climate data from 2018. The climate data is therefore not general, and

2018 was a year with higher temperatures and less rain than normally [12]. In addition, no shadings were assumed in the simulations, which is rather optimistic. The simulated PV generation may therefore be higher than can be expected in real life.

Comparing the simulated electricity generation on roofs and walls, the façade systems generate about 5-6% more electricity than the rooftop systems on an annual basis. The systems on the façades generate more electricity in the spring, autumn and winter, because of the steeper PV array angle [13]. A south-oriented 100 kW_p system on the façade generates 11% of its electricity during winter, 41% in the spring, 31% in the summer and 17% in the autumn, while the seasonal division for the east-west oriented rooftop system is 4%, 40%, 45% and 11% accordingly. This is positive for the self-generation and self-consumption factors, since PV electricity can cover electricity demand in the swing seasons. However, the wall-placed system is orientated towards south, which gives a higher midday peak than the rooftop east-west oriented systems. More PV power is available during morning or afternoon hours for east west oriented systems [13]. A higher electricity generation early and late in the day is positive for the matching with electricity use. The systems with highest self-generation factor therefore varies: For the smaller PV capacities it is the rooftop systems and for the larger PV capacities it is the façade systems. For the self-consumption factors, the rooftop systems have the highest values. More electricity is exported with the façade systems, giving a higher generation multiple factor. In general, the performance of the façade systems is somehow better than the rooftop systems. However, the area available for façade systems is limited, and it may be advisable with a combination of the two orientations.

The KPIs are calculated based on hourly values. If calculating the factors based on 15 minutes, daily or monthly intervals, the results would differ. For example, for the 500 kW_p PV system providing electricity to all common areas, the self-consumption factor of 27.2% based on hourly measurements, increases to 45% or 48% if calculated based on daily or monthly values. The self-generation factor is 41.5% based on hourly values and increases to 69% or 74% based on daily or monthly values. The generation multiple factor of 2.4 based on hourly values, decreases to 1.0 or 0.6 based on daily or monthly values. It is expected that the self-consumption and self-generation factors would be somewhat lower, using 15 minutes instead of hourly measurements. For load and generation power flows, shorter time steps give more realistic values for how a real system works. However, when estimating financial values, it is usually more relevant to use time steps from the tariff structure.

The self-consumption factor is the most important KPI in Norway, due to the Norwegian tariff structure. When the self-consumption factor is close to 100%, the self-generation factor is around 10% and the generation multiple factor is close to zero, since very little electricity is exported. From the perspective of the housing cooperative, it is therefore beneficial to locate the PV system and the load behind the same AMS meter, or to aggregate electricity loads in the common areas and the apartments. To aggregate electricity load from several AMS meters is currently not possible in Norway, but the authorities plan to facilitate also for housing cooperatives with PV in the prosumer agreement [14]. In principle, all electricity loads in common areas can be behind one AMS meter, but at Risvollan there are 104 such meters, 22 in garages and 82 in other common areas. The annual financial value of the 22 single PV systems of 50 kW_p, providing electricity to 22 garages only was at 475,000 NOK, whereas a single 1,100 kW_p PV system, providing electricity to all common areas (incl. garages), the total value increases with 6%. For the housing cooperative, the best financial option would be to provide PV electricity both to apartments and common areas, increasing the financial value with 70%, to approximately 808,000 NOK per year.

Energy flexibility of Risvollan housing cooperative will be a topic in the further work. According to Annex 67 [15], Energy Flexible Building Clusters should *demonstrate the capacity to react to forcing factors in order to minimize CO_2 emissions and maximize the use of Renewable Energy Sources (RES)*. Electricity loads can be adapted to PV generation, by increasing use of electricity during sunny periods or by storing electricity in heat storages or EVs [13]. EV charging is a main source of flexible electricity use in Norwegian apartment buildings. Besides often being flexible in starting time, duration and charging power [16], EV charging infrastructure is the responsibility of the Risvollan cooperative. A neighbourhood battery could also increase the self-consumption of PV generated electricity.

5. Conclusion

This article analyses the electricity use at Risvollan housing cooperative together with possible electricity generation from PV systems. Risvollan is a large housing cooperative in Norway, built in the 1970s, with in total 1,058 apartments. The study shows that the electricity generation from south-oriented systems on the building façades are about 5-6% higher than for east-west oriented rooftop systems on an annual basis, since the façade systems generate more electricity in the spring and autumn. However, more PV power is available during morning and afternoon hours for the rooftop east-west oriented systems. A combination of PV systems on the roofs and façades seem advisable. The self-consumption factor is the most important KPI in Norway, due to the national tariff structure. For the total housing cooperative, a PV capacity of about 1,000 kW_p seem suitable, giving a self-consumption factor of 97% for a rooftop system, based on 2018 electricity and climate data. From the perspective of the housing cooperative, it is financial beneficial to aggregate electricity loads for common areas and apartments, since a higher share of the electricity can be used by the cooperative. For this to be possible, also housing cooperatives with PV must be facilitated for in the prosumer agreement. Comparing a single 1,100 kW_p PV system providing electricity to the total cooperative with 22 PV systems of 50 kW_p behind 22 garage meters, the self-consumption factor decreases from 95% to average 14%, resulting in a 41% lower financial value for the PV electricity. The analysis will be used in further work, together with analysis of electricity and heat load patterns at Risvollan, aiming to play a role answering how effective management of power and energy at neighbourhood level can be realized.

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Supplementary article V

Stochastic load profile generator for residential EV charging

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Table: The paper's context in the thesis.

	Supplementary articles	Main article I	Main article II	Main article III	Main article IV	Data articles (*D* describes planned articles)*
RQ1: What are the energy profiles for household energy use and PV generation for apartment buildings, and how are the energy profiles influenced by climate variables?	S I. Electricity S II. Heat-DHW S III. DHW S IV. PV				Main IV. Energy profiles	D* IV. Data Main IV
RQ2: How does the user habits influence the electricity load profiles of residential EV charging, and how is the el. load affected by EV cabin preheating?	S V. Stochastic EV charging	Main I. EV charging	Main II. EV charging	Main III. EV cabin preheating		D I. Data Main I D* II. Data Main II D* III. Data Main III
RQ3: What is the potential for electricity flexibility from EVs, in relation to non-flexible apartment building loads and PV generation, in the Norwegian context?					Main IV. Flexibility	

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Stochastic load profile generator for residential EV charging

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Abstract

Electric vehicle (EV) charging loads have an impact on the power grid, but also represent a potential for energy flexibility. There is a need for EV data to evaluate effects on the power grid and optimal EV charging strategies. A stochastic bottom-up model is developed for residential EV charging, taking outdoor temperatures into account. The model input is based on real-world data from residential charging in Norway. The load profile generator provides hourly load profiles for any number and combination of small and large EVs, assuming immediate charging after plug-in. It is found that the model generates realistic load profiles for residential EV charging, reflecting today's charging patterns. Data generated can be used for load and flexibility simulations for residential EV charging.

Introduction

The worldwide use of EVs is increasing rapidly (IEA, 2021). EV charging loads may have a severe impact on the peak loads in the power grid, however charging of EVs also represent a potential for energy flexibility (Gonzalez Venegas et al., 2021). When evaluating effects on the power grid and optimal EV charging strategies, knowledge is needed on EV charging habits, load profiles and flexibility potential (Calearo et al., 2021). However, the availability of such real-world EV data is scarce (Calearo et al., 2021).

Norway had a 75% sales share of EVs in 2020 (IEA, 2021), and EVs are becoming the major car choice of the population. The main locations for EV charging are at home and work, where the charging power is limited by the charge points (CPs) and the AC onboard charger in the EVs. The number of CPs is increasing in Norway, with 3.6 to 7.4 kW as typical charging power limitations (Figenbaum & Amundsen, 2022).

EV charging habits have a sporadic nature, with e.g. varying plug-in/plug-out time, weekly charging frequency, and energy charged per charging session. Several CP operators (CPOs) provide charging reports to their users, with information on the individual charging sessions. Such CPO reports have formed the basis for recent research on residential charging habits, load profiles and flexibility potential (Sørensen et al., 2021a). It is found that EV load profiles also depend on the characteristics of the EV, such as onboard charging power and battery capacity (Sørensen et al., 2022). EVs with a smaller charging power and battery capacity tends to be charged more frequently, and have a lower annual charging need, compared to EVs with larger capacity values. The flexibility potential is related to the non-charging idle time of the charging sessions, when the EV is connected to the CP without charging, thus potentially offering smart charging or Vehicle-to-grid (V2G) services. High charging power, frequent connections, and long connection times are positive elements for reaching a high flexibility potential (Sørensen et al., 2022).

It can be challenging to access quality time series with residential EV data and load profiles. In some situations, there is an advantage to use a model to generate stochastic load profiles, compared to analysing original EV data and load profiles directly. A stochastic load profile generator can provide load profiles for any number of EVs, and with EV parameters for different types of EV fleets. In addition, local parameters can also be taken into account, such as climate or traffic data.

Several studies have been carried out to model the stochastic nature of EV charging, where the probability distributions are typically based on factors such as driving distances, plug-in/plug-out times, and start state of charge (SoC) estimations. Fischer et al. (2019) presented a stochastic bottom-up model to assess EVs' impact on load profiles at different parking locations. Influencing factors and probability distributions were identified, based on analysis of a German mobility dataset, with e.g. driven distances, driving and parking durations. The model outputs were presence at a CP and its corresponding electricity demand. Ayyadi et al. (2019) applied probability distributions for driven distances and plug-in/plug-out times by using Monte Carlo simulations. The probability distributions were based on a driving behaviour survey with GPS data in China. Other studies model energy charged instead of driven distances and SoC. Flammini et al. (2019) analysed real-world EV data from public CPs in the Netherlands, based on data similar to the CPO reports used in our work. The researchers provided probability distributions for plug-in/plug-out times, connected, charge and idle times, and energy charged per charging session, by applying a Beta Mixture Model approach.

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This paper presents a stochastic load-profile generator for residential EV charging. The methodology used is similar to the approach presented by Fischer et al. (2015). The methodology is improved by including outdoor temperature as an explanatory variable, since a dependency is identified between energy charged and outdoor temperature. The contributions of the paper are:

1) The model is based on information typically available in CPO reports in Norway, reflecting real charging patterns in Norway.
2) The generator provides hourly charging load profiles for individual or aggregated EVs, where the charging happens at private CPs, located at the residents own parking spaces.
3) The hourly charging loads are generated for a full year, and can be used as input in EV load and flexibility simulations.
4) The composition of an EV fleet can be defined in the generator, including "small" EVs, "large" EVs, or a mix of EV types. Such distinguishment makes it possible to generate load data for the current EV fleet in a certain location, as well as future EV fleet composition scenarios.

Data

CPO reports for residential EV charging

The load-profile generator is developed based on data from residential charging in Risvollan, Norway, with 5466 charging sessions from residents using 56 private CPs (Sørensen et al., 2021a; Sørensen et al., 2021b). The number of CPs are increasing during the period, from zero in December 2018 to 56 in January 2020. Each charging session includes the following data: user ID, plug-in and plug-out times, connection time, and charged energy for each charging session. Risvollan housing cooperative (lat. 63.39470, long. 10.43028) is located approx. 4 km from Trondheim city. In our paper EV charging is in focus, but also other energy analyses from the apartment buildings are available in Sørensen et al. (2019a; 2019b; 2019c).

Outdoor temperature dependency of EV charging

The vehicle range of EVs is reduced in cold temperatures, e.g. due to the heating the EVs cabin (Al-Wreikat et al., 2022). Due to the sporadic nature of EV charging, long time series are advantageous for identifying whether charged energy per user ID may be influenced by outdoor temperatures. For the studied data series, only 7 of the 56 user IDs have a full year data period. Figure 1 shows weekly charging need and average outdoor temperatures for six of these EV users (the 7th user has few sessions).

The stochastic character of EV charging is clear in the figures. Still, for some users and periods, a temperature dependency is visible. Pearson's correlation coefficient (Maechler, 2022) is calculated , for weekly charging need and outdoor temperatures during week 10 to 52. The three users with highest correlation values (TRO_R_AsO2-1, TRO_R_Bl2-1, TRO_R_Bl2-2)", have correlation coefficients from -0.46 to -0.27 (with p-values from 0.002 to 0.091), which indicate a correlation. For the three remaining users the correlation is weak, with p-values from 0.5-0.7.

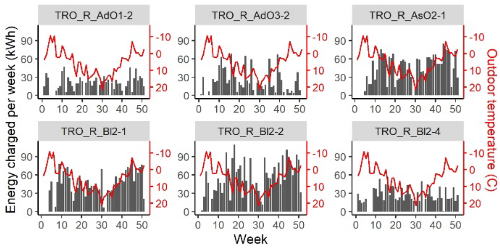

Figure 1: Real weekly charging need and average outdoor temperatures for six EV users.

Classifying EV user types for the user IDs

Each EV user ID in the dataset is classified as a "small" EV or a "large" EV depending on the maximum charged energy per session (which is a proxy for the battery size of the car). If < 25 kWh, the user is classified as a "small EV", and if > 25 kWh as a "large EV" (see overview in Table 1). The battery threshold value of 25 kWh is determined based on EV market information (Sørensen et al., 2021a), where most EVs with smaller batteries are either plug-in hybrid EVs (PHEVs) or earlier models of battery EVs (BEVs), which often have onboard charger capacity of about 3.6 kW. Newer BEVs normally have larger battery capacity > 25 kWh, and onboard charger capacity of at least 7.2 kW.

The maximum average charging power per user ID is evaluated, as shown in Figure 2. Based on this, an average charging power of either 3.6 kW or 7.2 kW is allocated to each of the user IDs. For the allocation it is assumed that at least one session per user ID is ended before the EV is fully charged, as described in Sørensen et al. (2022).

Table 1: Classification of EV types for dataset user IDs.

	3.6 kW	7.2 kW	Total user IDs
Small EV	84% (26 IDs)	16% (5 IDs)	55% (31 IDs)
Large EV	12% (3 IDs)	88% (22 IDs)	45% (25 IDs)

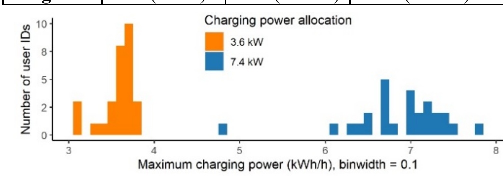

Figure 2: Maximum average charging power per user ID, and their allocation to a charging power level.

Methods

Overall description of the EV load profile generator

The stochastic bottom-up model is developed in Westad (2021), and simulates hourly load profiles for individual EVs during a year, assuming immediate charging after plug-in. Any number of EVs can be simulated by the model, with a specified share of "large" or "small" EVs, referring to the charging power and battery sizes of the cars. In addition to the hourly load profiles for each EV user, the plug-in and plug-out time, charged energy, and non-charging idle hours are provided. Based on the individual load profiles, aggregated load profiles are created. An illustration of the process for generating EV load profiles is shown in Figure 3, while Table 2 lists the probability distributions, model parameters, variables used, and model outputs from the load profile generator. The model is written in the Python programming language (Python Software Foundation, 2022).

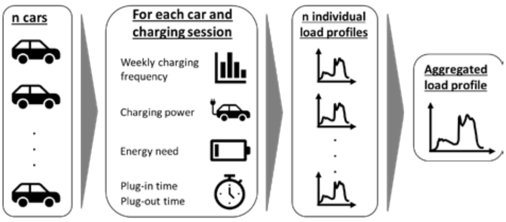

Figure 3: Process for generating EV load profiles.

Table 2: Probability distributions, model parameters, variables, and outputs from the load profile generator.

Probability distributions from the data		
Name	**Description**	**Units**
F	Weekly charging frequency	-
E	Charging need per session	kWh
T^S	Plug-in time of session	h
T^E	Plug-out time of session	h
Model parameters from the generator user		
U	Number of EV users	-
	Percentage EV user types (Large EV, Small EV). If no input: No distinction	%
	Share of charging power for the respective EV type (3.6 kW, 7.2 kW)	%
	Daily temperatures for the modelled year, starting on Monday week 1	°C
Model parameters from the data		
P_u	Charging power for EV user *u*	kW
F_u	Weekly charging frequency (1...7)	-
$E_{d,u}$	Charging need per session at day *d*	kWh
L_t	Duration of period *t* (1 year)	h
$T^S_{d,u}$	Plug-in time of session (1...24)	h
$T^E_{d,u}$	Plug-out time of session (1...24)	h
$C_{d,u}$	Connection duration of session (1...24)	h
$\Gamma_{d,u}$	EV user u plugs-in at day d	0/1
Generator variables		
$y_{t,d,u}$	Load at time *t*, day *d*, for EV user *u*	kWh/h
$z_{t,d,u}$	Remaining charging need at time *t*, day *d*, for EV user *u*	kWh
$\alpha_{t,d,u}$	EV user u is charging at time *t*, day *d*	0/1
$\beta_{t,d,u}$	EV user u is connected at time *t*, day *d*	0/1
Model outputs from the generator		
• EV user type (Small EV, Large EV)		
• Charging power per user (3.6 kW, 7.2 kW)		kW
• Plug-in time each day for a year (1...24)		h:m
• Plug-out time each day for a year (1...24)		h:m
• Connection time each session		h:m
• Energy need per session		kWh
• Connection profile per hour for a year		0/1
• Charging profile per hour for a year		kWh/h
• Aggregated charging profile for a year		kWh/h

Identifying probability distributions

The load profile generator uses 4 stochastic parameters for each user ID and day: 1) weekly charging frequency, 2) charging need per session, and 3) plug-in and 4) plug-out time of session. The flow chart in Figure 4 shows how the stochastic model parameters are obtained from the identified probability distributions based on the dataset.

Several probability distributions were evaluated in the process, and a Kolmogorov–Smirnov test was used to estimate the goodness of fit between the data and the tested distributions, to find the best-fitted distribution for the stochastic parameters. A selection of the chosen probability distributions is shown in Figure 5 - Figure 6.

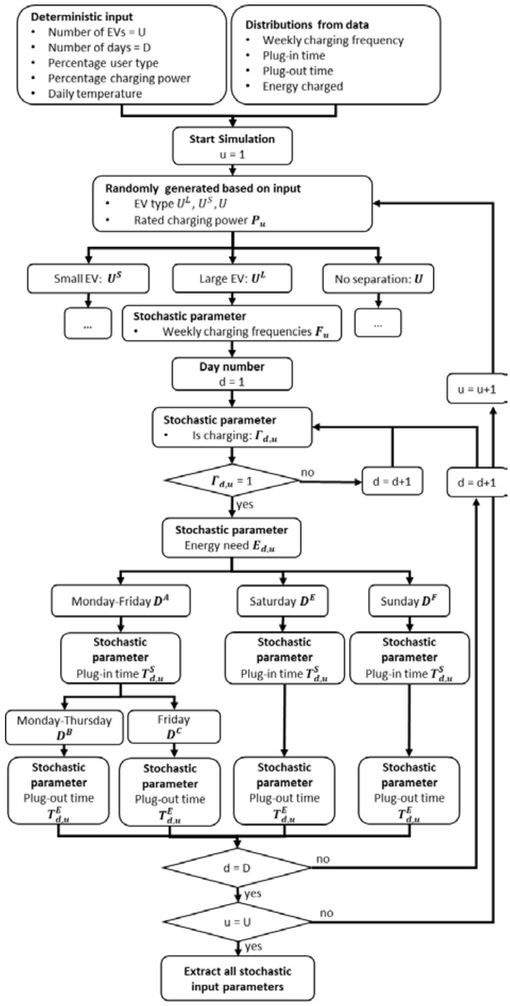

Figure 4: Detailed flow chart for obtaining stochastic model parameters in the load profile generator.

1) and 2) Weekly charging frequency and charging need per session: In the profile generator, the weekly charging frequency is limited to maximum one plug-in per day, for simplification. In the dataset, 74% of the

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charging sessions happen during weeks with maximum 7 plug-ins, if removing possible faulty sessions (energy charged < 1 kWh and 1 user Bl2-5). As shown in Figure 5a, EVs classified as "small" has higher plug-in frequencies than the large EVs, due to their smaller battery sizes. The distribution for charging needs per session depends on both the EV type, and the weekly charging frequency, as shown in Figure 5b-c.

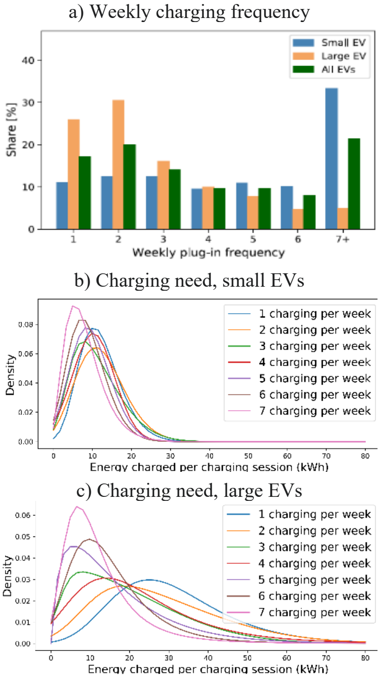

Figure 5: Probability distributions used in generator for weekly charging frequency and session charging need.

3) and 4) Plug-in and plug-out times of session: The plug-in and plug-out times are only dependent on the type of day (workday/Saturday/Sunday). A combination of different distributions was necessary to describe the plug-in and plug-out times, since they do not fit well with a single distribution, as illustrated in Figure 6a-e.

The plug-in and plug-out times are found by first randomly drawing which distribution to use, and then randomly drawing a daily hour from this distribution. The plug-in time is separated by type of day only, while the plug-out time during workdays is additionally related to the plug-in time. The distributions for plug-in times are identified for the following groups "Early and late-night (0-6)", "Early morning (6-9)", "Late morning (9-12)", "Early afternoon (12-15)", "Late afternoon (15-18"), "Early evening (18-21)" and "Late evening (21-23)". When the plug-in day is a Friday, Saturday or Sunday, the plug-out time is related to the day of the plug-in, not the hour since there is less data available for these days.

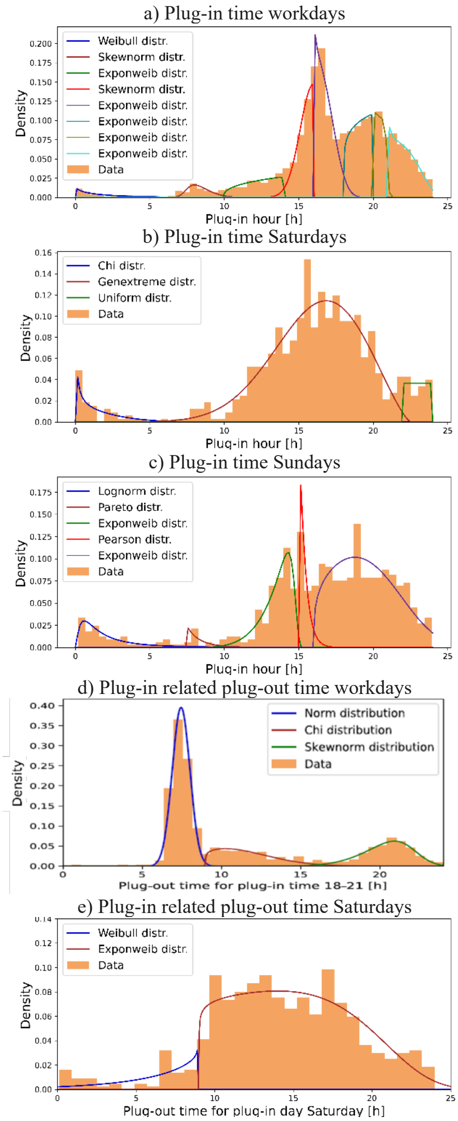

Figure 6: Probability distributions used in generator for plug-in and plug-out times.

Other parameters

Connection time limitation: In the generator, connection time is limited to a maximum of 24 hours, for simplification. Less than 1% of the charging sessions in the data are connected for longer than 24 hours. Since the generator assumes EV charging immediately after connection, this simplification will normally not affect the charging load results. However, the simplification may underestimate the generated non-charging idle times. In addition, the connection time one day may be limited by the plug-in time the next day, since there are no requirements of minimum time between charging sessions. For the sessions connected long enough, charging will continue until the charged energy is equal to the energy need. When this is not the case, charging will last the entire connection duration of maximum 24 hours.

Outdoor temperature dependency is included in the generator. The intention was to use the real-world data to calculate the dependency, however since the data period is relatively short and knowledge on driving ranges were lacking, the scaling factor is based on a temperature-dependent driving range estimation for Nissan Leaf EVs (Nissan, 2022), which per March 2022 is the most sold EV in Norway (Edvardsen, 2022). The reference temperature is set to 5°C, since this is the average temperature for the data period. Charging need per session is multiplied with a scaling factor, as shown in Figure 7.

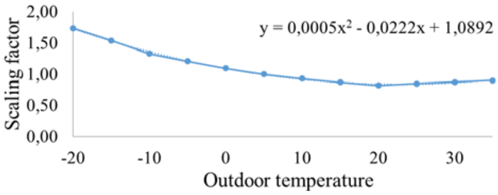

Figure 7: Scaling factor for temperature dependency of charging need, with reference temperature 5°C.

Model

Mathematical equations

The mathematical equations of the generator are expressed in equation 1-7. The connection duration (equation 1) is a result of the plug-in and plug-out times. The hourly load profile (equation 2) depends on the maximum charging power level for the EV, and whether the EV is charging (equation 3). For the remaining charging need at each hour, the calculation depends on whether the EV is connected overnight, meaning that $T^S_{d,u} + C_{d,u} \leq 24$ and $T^E_{d,u} > T^S_{d,u}$.

When the EV is not connected overnight (equation 4), the remaining charging need is expressed by the session charging need, and if the EV is connected (equation 5). When the EV is connected overnight, the charging session's remaining charging need is transferred to the next day, expressed by the transferred charging need (equation 6), and if the EV is connected (equation 7).

$$C_{d,u} = \begin{cases} T^E_{d,u} - T^S_{d,u}, & \text{if } T^E_{d,u} \geq T^S_{d,u} \\ 24 - T^S_{d,u} + T^E_{d,u}, & \text{if } T^E_{d,u} < T^S_{d,u} \end{cases} \tag{1}$$

$$y_{t,d,u} = P_u \times \alpha_{t,d,u} \tag{2}$$

$$\alpha_{t,d,u} = \begin{cases} 1, & \text{if } z_{t,d,u} > 0 \text{ and } \beta_{t,d,u} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

$$z_{t,d,u} = E_{d,u} - \sum_{t=T^S_{d,u}}^{N} P_u \times \beta_{t,d,u} \times L_t, \quad \text{for } T^S_{d,u} \leq t \leq 24 \tag{4}$$

$$\beta_{t,d,u} = \begin{cases} 1, & \text{if } T^S_{d,u} \leq t \leq T^E_{d,u} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

$$z_{t,d+1,u} = z_{24,d,u} - \sum_{t=1}^{T^E_{d,u}} P_u \times \beta_{t,d+1,u} \times L_t, \quad \text{for } 1 \leq t \leq T^E_{d,u} \tag{6}$$

$$\beta_{t,d,u} = \begin{cases} 1, & \text{if } T^S_{d,u} \leq t \leq 24 \\ 0, & \text{otherwise} \end{cases} \qquad \beta_{t,d+1,u} = \begin{cases} 1, & \text{if } 1 \leq t \leq T^E_{d,u} \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

Scenarios

Generating load profiles

To illustrate the output from the load generator, hourly load profiles for a whole year are simulated for 1000 EVs. Three scenarios are investigated, each with a different mix of user types:

1. "BASE": the mix of "small" and "large" EVs types and charging power are identical to the original data (ref. Table 1),
2. "LOW": "small" EVs only, 3.6 kW charging power,
3. "HIGH": "large" EVs only, 7.2 kW charging power.

The Root Mean Squared Error (RMSE) is used to evaluate the performance, comparing the original data with BASE.

Coincidence factors

Coincidence factors are used to calculate the simultaneous demand of several customers, while coincident peak demand describes the maximum demand for a group of customers during periods of peak system demand (Dickert & Schegner, 2010). To investigate the coincidence factor c and peak load $Y^{\max}$ per EV for an increasing number of EVs, a fleet of 100 single load profiles is used. By drawing n single load profiles from this fleet, the aggregated load profile is found $y_t^{\text{sum}}(n) = \sum_{u=1}^{n} y_{t,u}$, and the coincidence factor *c(n)* and average individual peak load $Y^{\max,\text{avg}}(n)$ are calculated using equation 8 and 9. This is done for *n* = 1, ..., 50. The procedure is repeated 50 times for each *n*, and the maximum, minimum and mean results are collected.

$$c(n) = \frac{\max\left(y_t^{\text{sum}}(n)\right)}{\sum_{u=1}^{n} \max\left(y_{t,u}\right)} = \frac{Y^{\text{sum,max}}(n)}{\sum_{u=1}^{n} Y_u^{\max}} \tag{8}$$

$$Y^{\max,\text{avg}}(n) = \frac{Y^{\text{sum,max}}(n)}{n} \tag{9}$$

Results and discussion

Aggregated load profiles

Load profiles are simulated for 1000 EVs, where the EV mix is either BASE, LOW or HIGH. Table 3 presents the main results for the three EV scenarios and for the original data. The values for the BASE case are closest to the original data, which is as expected since this scenario reflects the original mix of EV types. The annual charging need is about 2500 kWh for BASE, and is 25% higher for HIGH compared to LOW. This can be explained by higher energy demand for larger EVs and/or longer annual driving ranges. However, the difference may also

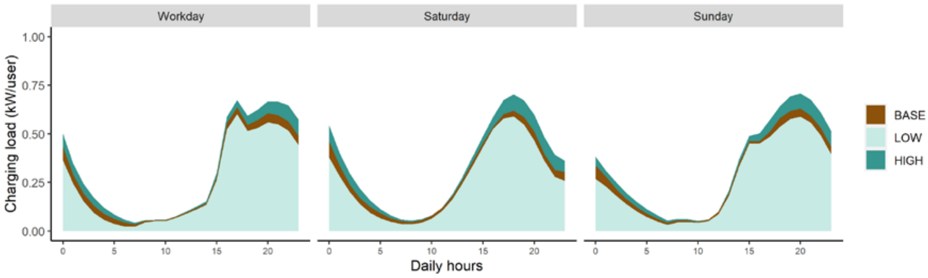

Figure 8: Daily average EV load profile per EV user for three scenarios of EV user types. (unstacked)

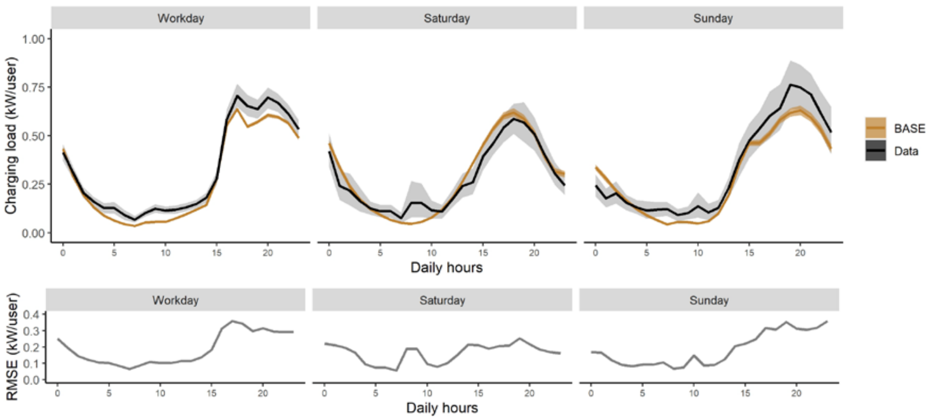

Figure 9: Top: Daily average EV load profile per EV user for original dataset (n = 18 to 56 EV users) and the BASE scenario (n = 1000 EV users), with 95% conf.int. Bottom: Root-mean-square error (RMSE) for each hour of the day.

be influenced by the model limitation of maximum one charging session per day, since "small" EVs are more affected by this simplification. The EVs in LOW charge 1.7 times more frequent and about half the amount of energy per session, compared to HIGH.

Table 3: Main results for dataset and three scenarios.

PER EV USER	Data	BASE	LOW	HIGH
Charging need per year (kWh)	2380	2480	2240	2790
Sessions per week (#)	4.1	3.9	4.7	2.8
Charging need per session (kWh)	11.2	12.6	9.3	19.4
Charging time (h/week)	9.5	10.0	12.2	7.6
Non-charging idle time (h/week)	42.4	32.2	38.5	24.1
Idle energy capacity (kWh/week)	206	164	139	173

Charging time and non-charging idle time are part of the output for each user, making it possible to analyse EV flexibility potentials. The BASE value for average idle time per week is 32.2 hours, considerably lower than in the original data of 42.4 hours. This can most likely be explained by the limitations of maximum one charging session per day, and maximum 24 hours connection time. Since HIGH has fewer weekly charging sessions compared with LOW, the weekly connection time is also shorter. HIGH needs less time to charge, but the non-charging idle time is still shorter than for LOW and BASE. However, the potential to move the charging in time is higher for HIGH, due to the increased charging power: 139 kWh idle energy capacity per week for LOW compared to 173 kWh per week for HIGH.

The average daily load profiles per EV user are shown in Figure 8. In all three scenarios, the average daily peak load occurs between hour 17 and 18 on workdays, between hour 18 and 19 on Saturdays, and between hour 19 and 20 on Sundays. This is in line with the original data (Sørensen et al., 2021a) as shown in Figure 9, and also similar to average daily load profiles analysed for other residential locations (Sørensen et al., 2022). A 95% confidence interval is shown in the figure, where the original dataset, with n = 18 to 56 EV users, has a greater variability than the BASE scenario, with n = 1000 EV users. This is in line with general expectations, that larger samples would produce a narrower confidence interval. However, a dependency between charging need and type of day is indicated in the data. Especially Saturdays stand out, with about 15% lower charging need compared to the other days. This dependency is not included in the generator, resulting in a similar charging need for all type of days. Figure 9 also shows the RMSE for each hour of the day, comparing the original dataset with the BASE scenario. Smaller RSME values indicate higher accuracy. The average error is 0.18 kW/user.

Effect of the outdoor temperature dependency

Figure 10 shows aggregated hourly charging need versus outdoor temperatures for the BASE scenario during a full year. Figure 11 illustrates an example winter week (average temperature of about - 10°C) and an example summer week (average temperature of about 20°C). Due to the temperature dependency, the charging need increases with a factor of about 1.6, assuming similar user behaviour.

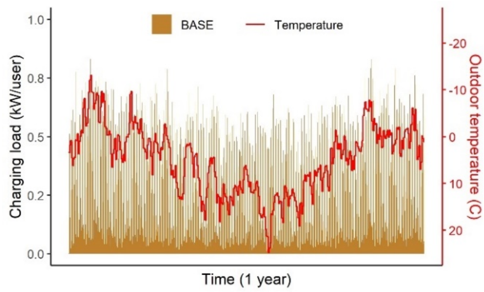

Figure 10: Hourly EV load profile per EV user for BASE scenario versus average daily outdoor temperatures.

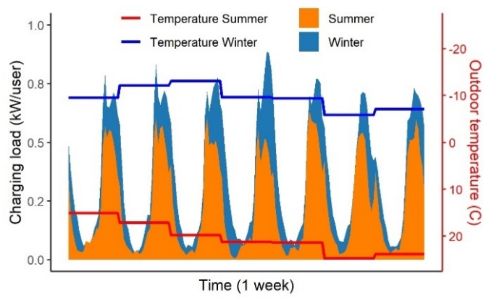

Figure 11: Example weeks Winter (January) and Summer (July): EV load profile per EV user for BASE scenario versus average daily outdoor temperatures.

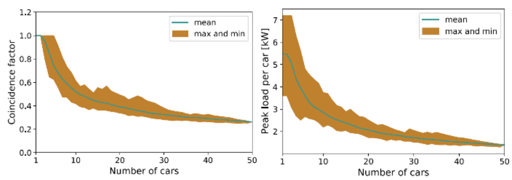

Figure 12: Coincidence factor and average peak load per EV for an increasing number of EVs. BASE scenario.

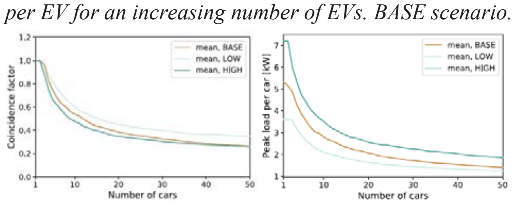

Figure 13: Mean coincidence factor and average peak load per EV. All three scenarios.

Coincidence factors

Coincidence factor and coincident peak demand are important factors in grid dimensioning (Dickert & Schegner, 2010). Figure 12 shows minimum, mean and maximum coincidence factors and peak load per EV for an increasing number of EVs in the BASE scenario. In Figure 13, mean coincidence factor and peak load values are shown for all the three scenarios. The figures show how the peak load per EV user is stabilizing with an increasing number of users. Assuming charging immediately after plug-in, the peak load per EV is descending towards 1.4 kW in BASE, 1.3 kW for "small" EVs (LOW), and 1.9 kW for "large" EVs (HIGH).

Conclusion and Further work

A stochastic bottom-up model is developed for residential EV charging, taking outdoor temperatures into account. The generator is based on data from residential charging in Norway, with 5466 charging sessions from 56 private CPs. The EV load profile generator provides hourly load profiles for any number and combination of "small" and "large" EVs, assuming immediate charging after plug-in. The data generated can be used for e.g. load and flexibility simulations for residential EV charging.

Load profiles are simulated for 1000 EVs, where the EV mix is either BASE (reflecting the dataset mix), LOW ("small" EVs only) or HIGH ("large" EVs only). For the BASE scenario, the charging need is about 2500 kWh per year, which is in the range of the original data. Comparing the LOW and HIGH scenarios, the EVs in LOW charge about 25% less energy on an annual basis. The EVs in LOW are charged more frequently than in HIGH (1.7 times), but charge less energy per session (0.5 times). The potential to move the charging in time is higher for HIGH, due to the increased charging power.

Coincident peak demand is an important factor in grid dimensioning, and is calculated for the three mixes of user types, with the number of EVs increasing from 1 to 50. Assuming EV charging immediately after plug-in, the average peak load per EV is descending towards 1.4 kW for BASE, 1.3 kW for "small" EVs, and 1.9 kW for "large" EVs.

It is found that the model generates realistic hourly load profiles for residential EV charging, reflecting today’s charging patterns. The results illustrate how charging habits and load profiles depend on the EV type, and how this affect coincidence factors and coincident peak demand.

It is our intention to further improve the EV load profile generator. Prospects for future works include:

- Creating new probability distributions based on a larger dataset, to make the model more robust and reflect a more general situation.
- Considering improvements in the EV load profile generator, e.g. to include a dependence between energy charged and type of day; to allow more than one charging session per day; to allow the connection time to be longer than 24 hours; to include a dependence between plug-in and plug-out time also for plug-ins Friday, Saturday or Sunday; to add a

minimum period between two charging sessions, e.g. based on a statistical dependence between previous plug-out time and the new plug-in time.

- Improving the temperature dependency based on real data, possibly with a difference between "small" and "large" EVs. Considering how other seasonal factors impact the scaling factor, such as season dependent tyres, driving habits, cabin and battery preheating, and user behaviour.
- Differentiate between holiday periods or special days.
- Characterizing the EV charging sessions and their energy loads as flexible or non-flexible, depending on the duration of the non-charging idle times.
- Improving the characteristics of EV types and adding hourly battery SoC to the output data, based on methods in Sørensen et al. (2022).
- Considering if hourly local traffic density should be included as a possible input from the generator user, since correlation is found between plug-in/plug-out times and local hourly traffic (Sørensen et al., 2021a).

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Sørensen, Å.L., Lindberg, K.B., Sartori, I. & Andresen, I. (2021b) Residential electric vehicle charging datasets from apartment buildings. *Data in Brief*, **36**.

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Westad, M.C. (2021) *A stochastic simulation tool for generating hourly load profiles for residential EV charging, based on real-world charging reports*. NTNU MSc thesis.

D. Data publications

Data article I

Residential electric vehicle charging datasets from apartment buildings

Åse Lekang Sørensen, Karen Byskov Lindberg, Igor Sartori, Inger Andresen

Published in *Data in Brief*, Elsevier

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Table: The paper's context in the thesis.

	Supplementary articles	Main article I	Main article II	Main article III	Main article IV	Data articles (*D* describes planned articles)*
RQ1: What are the energy profiles for household energy use and PV generation for apartment buildings, and how are the energy profiles influenced by climate variables?	S I. Electricity S II. Heat-DHW S III. DHW S IV. PV				Main IV. Energy profiles	D* IV. Data Main IV
RQ2: How does the user habits influence the electricity load profiles of residential EV charging, and how is the el. load affected by EV cabin preheating?	S V. Stochastic EV charging	Main I. EV charging	Main II. EV charging	Main III. EV cabin preheating		D I. Data Main I D* II. Data Main II D* III. Data Main I
RQ3: What is the potential for electricity flexibility from EVs, in relation to non-flexible apartment building loads and PV generation, in the Norwegian context?					Main IV. Flexibility	

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Data Article

Residential electric vehicle charging datasets from apartment buildings

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Residential electricity demand
Load profiles
End-user flexibility
Energy management

A B S T R A C T

This data article refers to the paper "Analysis of residential EV energy flexibility potential based on real-world charging reports and smart meter data" [1]. The reported datasets deal with residential electric vehicle (EV) charging in apartment buildings. Several datasets are provided, with different levels of detail, aiming to serve various needs. The paper provides real-world EV charging reports describing 6,878 charging sessions registered by 97 user IDs, from December 2018 to January 2020. The charging reports include identifiers, plug-in time, plug-out time and charged energy for the sessions. Synthetic charging loads are provided with hourly resolution, assuming charging power 3.6 kW or 7.2 kW and immediate charging after plug-in. The non-charging idle time reflects the flexibility potential for the charging session, with synthetic idle capacity as the energy which could potentially have been charged during the idle times. Synthetic hourly charging loads and idle capacity are provided both for individual users, and aggregated for users with private or shared charge points. For a main garage with 33% of the charging sessions, smart meter data and synthetic charging loads are available, with aggregated values each hour. Finally, local hourly traffic density in 5 nearby traffic locations is provided, for further work related to the correlation with

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plug-in/plug-out times. Researchers, energy analysts, charge point operators, building owners and policy makers can benefit from the datasets and analyses, serving to increase the knowledge of residential EV charging. The data provides valuable insight into residential charging, useful for e.g. forecasting energy loads and flexibility, planning and modelling activities.

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Specifications Table

Subject	Renewable Energy, Sustainability and the Environment
Specific subject area	Residential electric vehicle (EV) charging habits and energy loads
Type of data	CSV files Table Figure Map
How data were acquired	Obtained data, e.g. EV charging reports and Advanced Metering System (AMS) measurements, were processed using the statistical computing environment R [2]. Synthetic hourly charging loads and idle capacity were created, based on information in the charging reports and assumptions.
Data format	Raw Analysed Filtered
Parameters for data collection	Data from December 2018 to January 2020: • EV charging reports with individual charging sessions, listing identifiers, plug-in time, plug-out time and charged energy. • Hourly electricity data from AMS meters in one of the garages. • Local hourly traffic density in 5 nearby traffic locations.
Description of data collection	EV charging reports from charge point operator and hourly electricity data from grid company, both available with consent from the housing cooperative. Local hourly traffic data is downloaded from [3].
Data source location	Institution: Risvollan Housing Cooperative City/Town/Region: Trondheim Country: Norway Latitude and longitude for collected data: lat 63.395254, long 10.426319
Data accessibility	Repository name: Mendeley Data [4] Data identification number: 10.17632/jbks2rcwyj.1 Direct URL to data: http://dx.doi.org/10.17632/jbks2rcwyj.1
Related research article	Å.L. Sørensen, K.B. Lindberg, I. Sartori, I. Andresen, Analysis of residential EV energy flexibility potential based on real-world charging reports and smart meter data, https://doi.org/10.1016/j.enbuild.2021.110923 [1].

Value of the Data

- The datasets describe residential EV charging in apartment buildings. There is a lack of real-world data found in the literature, even though energy needs and flexibility potential are recognized.
- Researchers, energy analysts, charge point operators, building owners and policy makers can benefit from the datasets and analyses, serving to increase the knowledge of residential EV charging.
- The data provides valuable insight into residential charging, useful for e.g. forecasting energy loads and flexibility, planning and modelling activities.
- Several datasets are provided, with different levels of detail, aiming to serve various needs.

- Local traffic data is provided for further analysis, where correlation with plug-in/plug-out times can be part of new models for EV charging loads and flexibility.

1. Data Description

Data have been collected from a large housing cooperative in Norway, with 1,113 apartments and 2,321 residents. A new infrastructure for EV charging was installed from December 2018. From December 2018 to January 2020, charging sessions were registered by 97 user IDs; 82 of these IDs appeared to be still active at the end of the period. In the data provided with this article, Central European Time (CET) zone is used, which is GMT +1. Daylight saving time (DST) applies.

1.1. Dataset 1: EV charging reports

The CSV file "Dataset 1" describes 6,878 individual charging sessions, registered by 97 user IDs from December 2018 to January 2020. The charging reports include plug-in time, plug-out time and charged energy per charging session. Each charging session is connected to a user ID, charger ID and address. The charger IDs are either private or shared, since the charge points (CPs) are either located on the residents private parking spaces, or on shared parking areas available for all residents registered as users. Table 1 shows the parameters available for each of the charging sessions.

1.2. Dataset 2: Hourly EV charging loads and idle capacity, for all sessions and users individually

The CSV file "Dataset 2" describes EV charging loads and non-charging idle capacity for each user and all EV charging sessions individually. The synthetic hourly charging loads and idle capacity are created as described in [1]. Charging power 3.6 kW or 7.2 kW is assumed, with immediate charging after plug-in. The non-charging idle time reflects the flexibility potential for the charging session. Synthetic idle capacity is the energy load which could potentially have been charged during the idle times. The time period is from December 2018 to January 2020, and includes all active hours for each user (not a complete hourly time series per user, but hours with charging loads or idle capacity). Table 2 shows the parameters available.

Table 1
Description Dataset 1: EV charging reports, describing each individual EV charging session.

session_ID	Unique ID for EV charging session (N=6878)
Garage_ID	ID for garage address (N = 24)
User_ID	ID for user (N=97)
User_type	CP ownership: Private or shared CPs
Shared_ID	When shared CPs used: ID for shared CP (N=12)
Start_plugin	Plug-in date and time (format 21.12.2018 10:20)
Start_plugin_hour	Clock hour for plug-in (from 00 to 23)
End_plugout	Plug-out date and time (format 21.12.2018 10:20)
End_charging_hour	Clock hour for plug-out (from 00 to 23)
El_kWh	Charged energy (kWh)
Duration_hours	Duration of the EV connection time, per charging session (decimal hours)
month_start	Plug-in month (January-December)
weekdays_start	Plug-in weekday (Monday-Sunday)
Plugin_ category	Category for plug-in time during the day. Each category lasts three hours (early/late night, morning, afternoon, evening)
Duration_category	Category for plug-in duration (<3h, 3-6h, 6-9h, 9-12h, 12-15h, 15-18h, >18h)

Table 2
Description Dataset 2: Hourly EV charging loads and idle capacity, for all users individually.

date_from	Starting time (format 22.01.2019 19:00)
date_to	Ending time (format 22.01.2019 20:00)
User_ID	ID for user (N=97)
session_ID	Unique ID for EV charging session (N=6878)
Synthetic_3_6kW	Synthetic hourly energy load (kWh/h) assuming 3.6 kW charging power (ref. [1]), for users individually
Synthetic_7_2kW	Synthetic hourly energy load (kWh/h) assuming 7.2 kW charging power (ref. [1]), for users individually
Flex_3_6kW	Synthetic hourly idle capacity (kWh/h) assuming 3.6 kW charging power, for users individually
Flex_7_2kW	Synthetic hourly idle capacity (kWh/h) assuming 7.2 kW charging power, for users individually

Table 3
Description Dataset 3a and 3b: Hourly EV charging loads and idle capacity, aggregated for users with private (3a) or shared (3b) CPs.

date_from	Starting time (format 22.01.2019 19:00)
daily_hour	Clock hour (from 00 to 23)
weekday	Weekday (Monday-Sunday)
month	Month (January-December)
Synthetic_3_6kW	Synthetic hourly energy load (kWh/h) assuming 3.6 kW charging power, aggregated for users with private (2a) or shared (2b) CPs
Synthetic_7_2kW	Synthetic hourly energy load (kWh/h) assuming 7.2 kW charging power, aggregated for users with private (2a) or shared (2b) CPs
Flex_3_6kW	Synthetic hourly idle capacity (kWh/h) assuming 3.6 kW charging power, aggregated for users with private (2a) or shared (2b) CPs
Flex_7_2kW	Synthetic hourly idle capacity (kWh/h) assuming 7.2 kW charging power, aggregated for users with private (2a) or shared (2b) CPs
2a: n_ private	Number of registered User IDs using private CPs (increasing, 1 to 58)
2b: n_ shared	Number of registered User IDs using shared CPs (increasing, 1 to 24)

1.3. Dataset 3: Hourly EV charging loads and idle capacity, aggregated for private or shared CPs

The CSV files “Dataset 3a” and “Dataset 3b” describe EV charging loads and idle capacity, aggregated for users with private (3a) or shared (3b) CPs. Charging power 3.6 kW or 7.2 kW is assumed, with immediate charging after plug-in. The time period is from December 2018 to January 2020, with a complete hourly time series. Table 3 shows the parameters available.

1.4. Dataset 4: Average EV charging loads per user, for each daily hour during weekdays/Saturdays/Sundays

Dataset 4 in Table 4 shows average EV charging loads per user, for each daily hour during weekdays, Saturdays, and Sundays. Charging power 7.2 kW is assumed, with immediate charging after plug-in. In the table, charging loads for users with private and shared CPs are shown separately. The daily charging load profiles are based on the period with 30 to 82 users, from June 2019 to January 2020, with the number of users with private CPs increasing from 18 to 58, and users with shared CPs increasing from 12 to 24. The subset of the period is chosen, to get a more representative overview of expected power per user for aggregated loads.

1.5. Dataset 5: Hourly smart meter data from garage Bl2

The EVs were parked in 24 locations, whereof 22 locations have an AMS-meter measuring aggregated EV-charging at that location, with hourly resolution. This article includes

Table 4
Average EV charging loads per user, for each daily hour during weekdays, Saturdays, and Sundays.

CP ownership	Private CPs located on residents' private parking spaces			Shared CPs available for all residents registered as users		
Daily hour	Weekdays (kWh/h/user)	Saturdays (kWh/h/user)	Sundays (kWh/h/user)	Weekdays (kWh/h/user)	Saturdays (kWh/h/user)	Sundays (kWh/h/user)
00 - 01	0.28	0.33	0.18	0.21	0.21	0.20
01 - 02	0.17	0.18	0.14	0.16	0.15	0.18
02 - 03	0.09	0.11	0.13	0.12	0.11	0.13
03 - 04	0.06	0.09	0.10	0.08	0.09	0.10
04 - 05	0.03	0.08	0.06	0.04	0.06	0.07
05 - 06	0.02	0.04	0.03	0.02	0.04	0.06
06 - 07	0.01	0.02	0.04	0.01	0.01	0.05
07 - 08	0.02	0.01	0.03	0.01	0.00	0.04
08 - 09	0.05	0.05	0.04	0.05	0.01	0.05
09 - 10	0.06	0.07	0.04	0.07	0.04	0.05
10 - 11	0.06	0.05	0.04	0.09	0.07	0.06
11 - 12	0.06	0.08	0.03	0.11	0.07	0.11
12 - 13	0.09	0.15	0.07	0.13	0.07	0.14
13 - 14	0.10	0.19	0.17	0.13	0.12	0.17
14 - 15	0.15	0.22	0.33	0.16	0.11	0.17
15 - 16	0.27	0.35	0.46	0.18	0.13	0.23
16 - 17	0.54	0.41	0.48	0.27	0.12	0.22
17 - 18	0.60	0.49	0.52	0.24	0.17	0.25
18 - 19	0.54	0.45	0.56	0.22	0.21	0.30
19 - 20	0.51	0.44	0.66	0.24	0.24	0.35
20 - 21	0.57	0.43	0.65	0.28	0.23	0.32
21 - 22	0.54	0.27	0.63	0.27	0.26	0.27
22 - 23	0.48	0.24	0.53	0.26	0.25	0.24
23 - 24	0.40	0.18	0.41	0.24	0.21	0.23
Total	5.7	4.9	6.3	3.6	3.0	4.0

Table 5
Description Dataset 5: Hourly smart meter data from garage Bl2.

Garage_ID	ID for garage address (Bl2)
date_from	Starting time (format 22.01.2019 19:00)
date_to	Ending time (format 22.01.2019 20:00)
month	Measurement starting month
AMS_kWh	Aggregated electricity use in the garage each hour, measured by AMS meter
Synthetic_3_6kW	Synthetic hourly energy load (kWh/h) assuming 3.6 kW charging power, aggregated for users in the garage
Synthetic_7_2kW	Synthetic hourly energy load (kWh/h) assuming 7.2 kW charging power, aggregated for users in the garage
Simultaneous_if_3_6kW	Number of simultaneous charging sessions, assuming that all sessions charge with 3.6 kW charging power. NA if no charging sessions are assumed

Table 6
Description Dataset 6: Local hourly traffic density.

Date_from	Starting time (format 22.01.2019 19:00)
Date_to	Ending time (format 22.01.2019 20:00)
Location 1 to 5	Number of vehicles shorter than 5.6 meter each hour, in 5 nearby traffic locations

AMS-measurements from a main garage, where 33% of the charging sessions took place (2,243 charging sessions). The CSV file “Dataset 5” describes hourly smart meter data from garage Bl2, with aggregated electricity use each hour. The dataset also includes synthetic hourly energy loads, aggregated for the same garage. The time period for the dataset is from January 2019 to January 2020, with a complete hourly time series. Table 5 shows the parameters available.

1.6. Dataset 6: Local traffic density

The CSV file “Dataset 6” describes local hourly traffic density in 5 nearby traffic locations, downloaded from [3]. The data includes an hourly count of vehicles shorter than 5.6 meter, from December 2018 to January 2020. Table 6 shows the parameters available.

2. Experimental Design, Materials and Methods

The data are analysed using the statistical computing environment R [2].

2.1. Dataset 1: EV charging reports

EV charging reports are received from the housing cooperative’s charge point operator. Several subdivided reports are added together and organised. For each individual charging session (session_ID), plug-in time (Start_plugin), plug-out time (End_plugout) and charged energy (El_kWh) are known, as well as user ID (User_ID), CP ownership (User_type, Shared_ID) and garage location (Garage_ID). The difference between the plug-in and plug-out times of the charging sessions, provides the duration of the EV connection time (Duration_hours). Clock- and calendar data are added to the dataset (Start_plugin_hour, End_charging_hour, month_start, weekdays_start), as well as categorical values for plug-in time and plug-in duration (Plugin_ category, Duration_category).

Table 7
Method to develop synthetic hourly charging loads.

Charged energy	Method to develop synthetic hourly charging loads	Example, Session_ID 4, assuming $P_{charging}$ 3.6 kWh/h
$E_{first\ hour}$	Number of minutes after plug-in is counted. Potential energy is calculated, for a given $P_{charging}$. If $E_{charged}$ is larger than energy potential, $E_{first\ hour}$ equals energy potential. If not, $E_{first\ hour}$ is $E_{charged}$	Plug-in at 16:15: Up to 45 min charging (2.7 kWh). Since $E_{charged}$ is 15.56 kWh, $E_{first\ hour}$ is 2.7 kWh.
$E_{middle\ hours}$	Remaining energy charged is calculated, as difference between $E_{charged}$ and $E_{first\ hour}$. Remaining energy is divided on $P_{charging}$, to get number of full hours charging with $P_{charging}$.	Remaining energy: 12.86 kWh. $E_{middle\ hours}$: 3.6 kWh/h for 3 h. Remaining energy: 2.06 kWh.
$E_{last\ hour}$	Remaining energy will be charged.	$E_{last\ hour}$: 2.06 kWh (34 min). Total charging time: 4 h 19 min

The original EV charging reports have 7,245 charging sessions. The main steps of data cleaning include removing unrealistic charging sessions (1 CP with 29 charging sessions removed) and charging sessions with no energy charged (338 charging sessions removed). If the plug-out time is too early, compared to energy charged and maximum 11 kW charging power available, the plug-out time is removed (set to NA), since this indicates that the value is incorrect (relevant for 34 charging sessions). Further, there was quality assurance to assure correct data time zones/DST, before calendar data was added. The final dataset includes 6,878 individual charging sessions (95%).

2.2. Dataset 2: Hourly EV charging loads and idle capacity, for all sessions and users individually

Dataset 2 includes hourly EV charging loads and idle capacity, for all sessions and users individually. The dataset includes all active hours for each user, which are all hours the users are connected to the CP. The synthetic hourly charging loads and idle capacity are created as described in [1]. Since the actual charging time and charging power are not known, two alternative charging powers are assumed: 3.6 or 7.2 kWh/h, representing typical levels for the onboard charger capacities. The assumed charging power is the average charging power during an hour.

Synthetic hourly charging loads and idle capacity are created per charging session for all the users, assuming immediate charging after plug-in. Table 7 shows the method used to develop synthetic hourly charging loads for the charged energy (El_kWh). $P_{charging}$ is assumed charging power, $E_{Charged}$ is charged energy during the charging session (El_kWh), $E_{first\ hour}$ is energy charged during the first clock hour connected, $E_{middle\ hours}$ is energy charged during full hours charging, $E_{last\ hour}$ is energy charged during the last clock hour. The table includes an example session (Session_ID 4).

The difference (non-charging idle time) between the duration of the EV connection time and the assumed charging time, reflects the flexibility potential for the charging session. The idle capacity is the energy which could potentially have been charged during the non-charging idle times. Table 8 shows the method used to develop synthetic hourly idle capacity, multiplying idle time each hour with charging power. $Flex_{first\ hour}$ is idle capacity during the first clock hour with idle time, $Flex_{middle\ hours}$ is idle capacity during full hours with idle time, $Flex_{last\ hour}$ is idle capacity during the last clock hour with idle time. Also this table includes an example session (Session_ID 4).

For the synthetic hourly charging loads, the synthetic charging time can become equal to or even longer than the actual connection time. If so, there is no non-charging idle time included.

Table 8
Method to develop synthetic hourly idle capacity.

Flexible energy	Method to develop synthetic hourly idle capacity	Example, Session_ID 4, assuming $P_{charging}$ 3.6 kWh/h
$Flex_{first\ hour}$	Number of minutes needed to charge $E_{last\ hour}$ is calculated. If plug-out time is after needed charging time, then the charging session has idle time. $Flex_{first\ hour}$ is calculated for the available idle minutes the first hour, for a given $P_{charging}$.	Connection time: 24 h 25 min. Total charging time: 4 h 19 min. Since $E_{last\ hour}$ is 2.06 kWh, $Flex_{first\ hour}$: 1.54 kWh (26 min).
$Flex_{middle\ hours}$	Remaining idle time is calculated, as difference between session connection time, total charging time and idle time first hour. Number of full idle hours is multiplied with $P_{charging}$.	Remaining idle time: 19 h 40 min. $Flex_{middle\ hours}$: 3.6 kWh/h for 19 h. Remaining idle time: 40 min.
$Flex_{last\ hour}$	Remaining idle minutes is multiplied with $P_{charging}$.	$Flex_{last\ hour}$: 2.41 kWh (40 min). Total idle capacity: 72.35 kWh.

Also, when the plug-out time is removed in the initial data cleaning (set to NA), there is no non-charging idle time included.

2.3. Dataset 3: Hourly EV charging loads and idle capacity, aggregated for private or shared CPs

Dataset 3 describes EV charging loads and idle capacity, aggregated for users with private or shared CPs. First, Dataset 2 is divided on users classified as private or shared (User_type). Two hourly aggregated databases are then created by grouping the data per hour. Hours with no charging are added to the aggregated databases, to assure a full hourly timeseries for the period, from mid-December 2018 to end-January 2020.

Information about the number of registered users each day is added to the databases. The users are classified as active from the date of their first charging session (user has value NA before and 1 after first connection). In addition, some users become inactive, if they for example move or if a user using shared CPs becomes a user with private CP. Users with NA values towards the end of the measurement period are therefore classified as inactive and not included in the number of EV users. The change of classification takes place after their last charging session, from their first inactive date. However, during the last month (January 2020), only users not charging at all during the month were classified as inactive, to avoid wrong classification of users travelling etc.

2.4. Dataset 4: Average EV charging loads per user, for each daily hour during weekdays/Saturdays/Sundays

To create average hourly EV charging loads per user in Dataset 4, aggregated values in dataset 3 are divided on the number of users each hour. Averages for weekdays, Saturdays and Sundays are calculated for each daily hour.

The daily charging load profiles are based on the period with 30 to 82 users only, with the number of users with private CPs increasing from 18 to 58, and users with shared CPs increasing from 12 to 24. The subset of the period is chosen, to get a more representative overview of expected power per user for aggregated loads. Fig. 1 shows the monthly peak values per user, where the period June 2019 to January 2020 is included when calculating the average hourly EV charging loads. The figure shows how the peak power per user is reduced with increasing number of users, due to a lower coincidence factor.

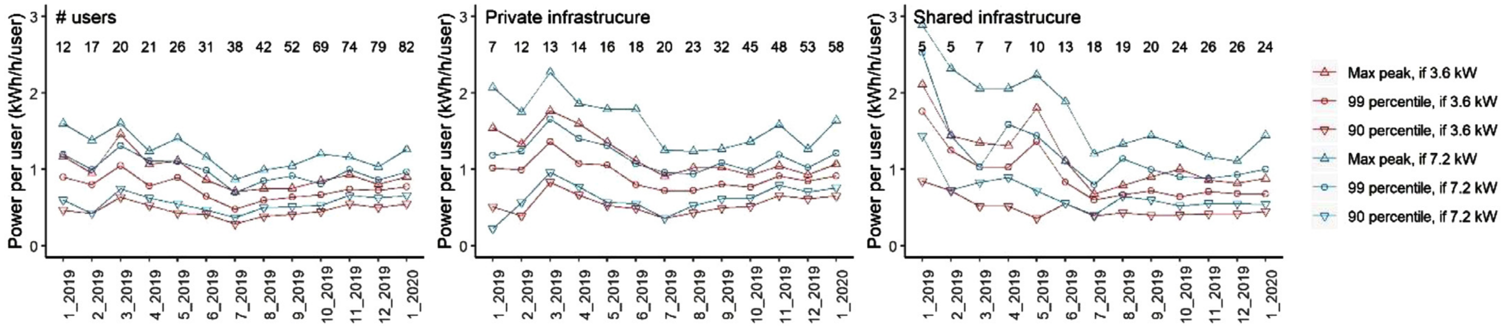

Fig. 1. Estimated aggregated power per user, with increasing number of users, assuming charging power 3.6 kW and 7.2 kW. Left: All users, Middle: Users using private CPs, Right: Users using shared CPs.

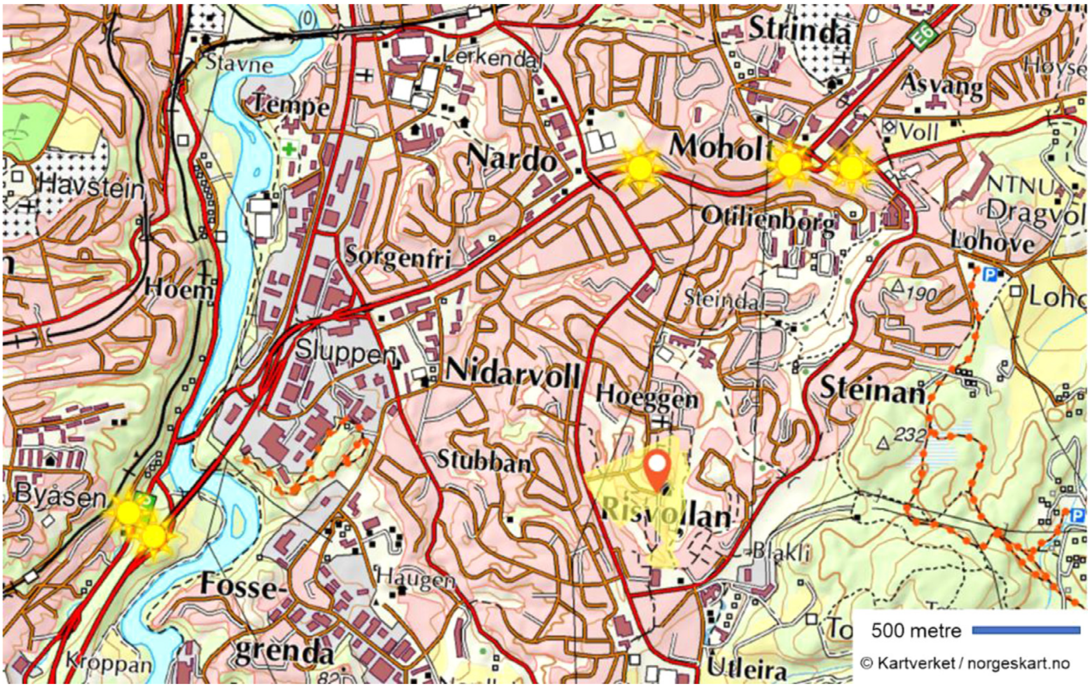

Fig. 2. Position of the 5 locations with hourly traffic data from [2] (yellow stars) and the housing cooperative (red marker). Map: © Kartverket/norgeskart.no.

2.5. Dataset 5: Hourly smart meter data from garage Bl2

Dataset 5 describes hourly AMS meter data for garage Bl2, measuring aggregated charging in the garage each hour. Hourly energy estimates provided by the DSO are removed from the data (8 values changed to NA), since inaccurate hourly values may influence the results. The time period for the dataset is from January 2019 to January 2020, with a complete hourly time series.

Synthetic hourly charging loads are also added to the dataset, aggregated for the garage. Finally, the dataset includes a count of the number of simultaneous charging sessions. The count is done when grouping the charging sessions each hour. For the count, it is assumed that all sessions charge with 3.6 kW charging power. The values in the column are NA if there are no counted charging sessions.

2.6. Dataset 6: Local traffic density

Dataset 6 describes local hourly traffic density in 5 nearby traffic locations: KROPPAN BRU, MOHOLTLIA, SELSBAKK, MOHOLT RAMPE 2, Jonsvannsveien vest for Steinanvegen. The traffic data is downloaded from [3], where traffic data is counted for vehicles with different sizes. The hourly number of small cars (less than 5.6 m) is used in the analysis, as an hourly average of the traffic measured by the five traffic stations. The geographic locations of the traffic stations and the housing cooperative are shown in the map in Fig. 2.

Ethics Statement

Data are provided with consent from the housing cooperative and charge point operator NTE Marked. EV charging reports are anonymized.

CRediT Author Statement

Åse Lekang Sørensen: Conceptualization, Methodology, Investigation, Data Curation, Writing-Original draft preparation; **Karen Byskov Lindberg**: Conceptualization, Writing - Review & Editing, Supervision; **Igor Sartori**: Conceptualization, Writing - Review & Editing, Supervision; **Inger Andresen**: Conceptualization, Writing - Review & Editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships which have or could be perceived to have influenced the work reported in this article.

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