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

Å.L. Sørensen [a,b,*], B.B. Morsund [c], I. Andresen [b], I. Sartori [a], K.B. Lindberg [c]

[a] SINTEF, Department of Architectural Engineering, P.O. Box 124 Blindern, 0314 Oslo, Norway
[b] Norwegian University of Science and Technology (NTNU), Department of Architecture and Technology, 7491 Trondheim, Norway
[c] NTNU, Department of Electric Energy, 7491 Trondheim, Norway

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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

* Corresponding author at: SINTEF, Department of Architectural Engineering, P.O. Box 124 Blindern, 0314 Oslo, Norway.
E-mail address: ase.sorensen@sintef.no (Å.L. Sørensen).

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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],

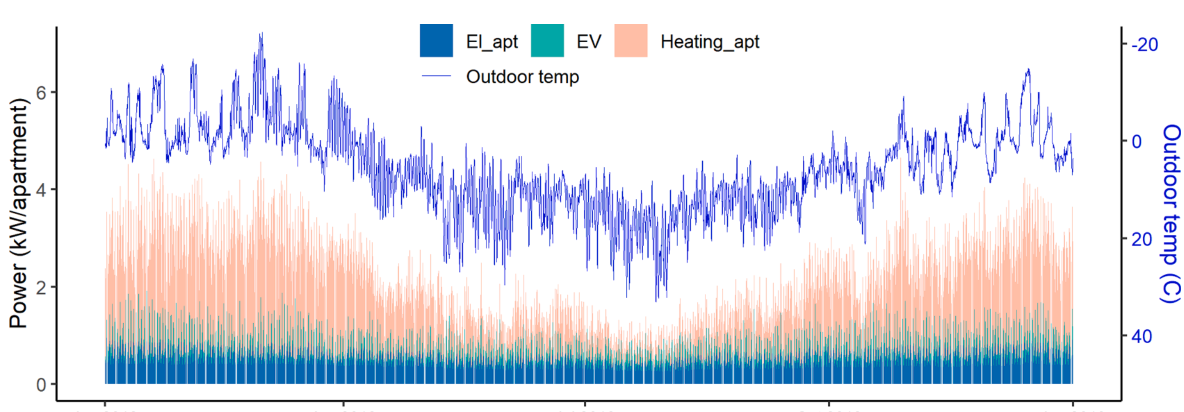


Fig. 2. Hourly energy loads in Norwegian apartment buildings during a year, with 1 EV per apartment.

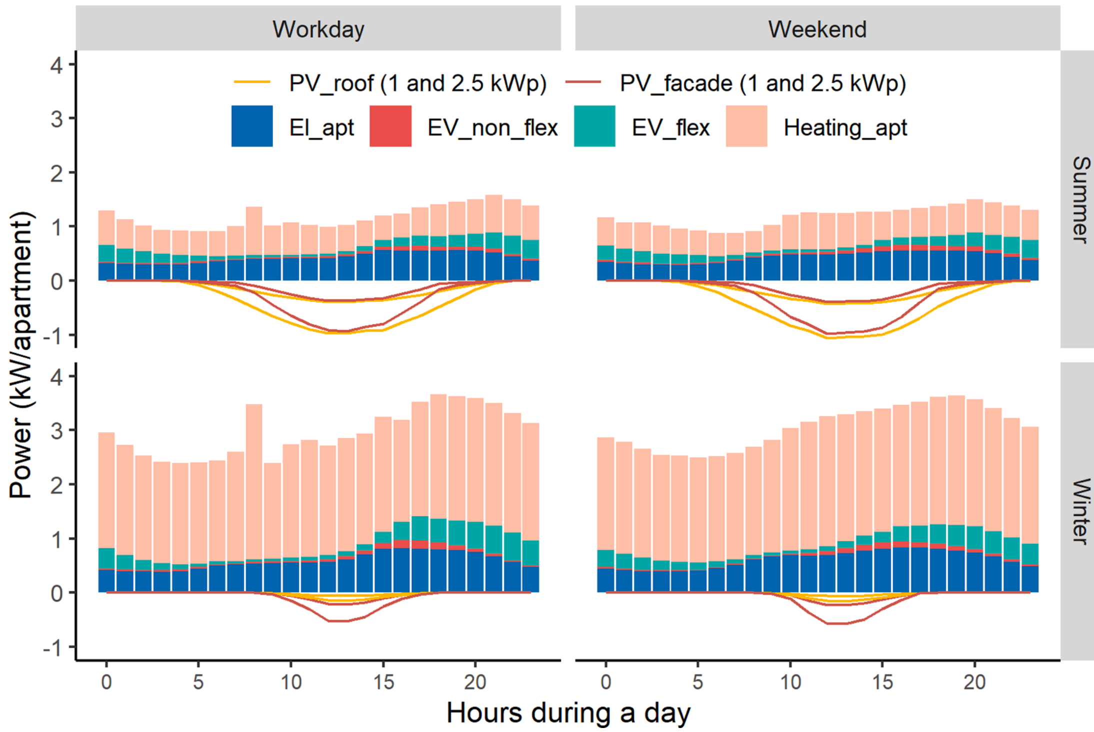


Fig. 3. Daily average energy profiles for Norwegian apartment buildings, with 1 EV per apartment.

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

	Delivered energy (kWh/apt/year)	Delivered energy (kWh/m^2/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 %)

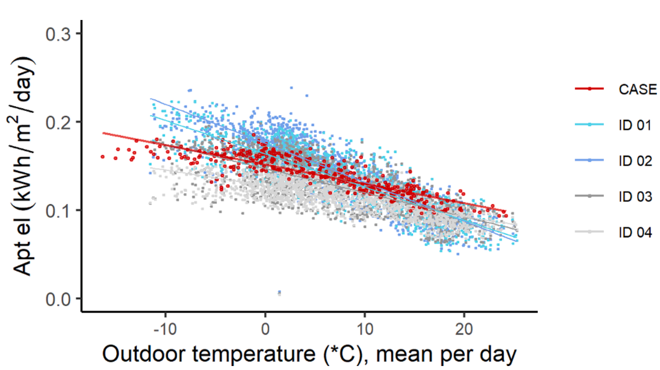


Fig. 4. Daily electricity use in 5 apartment associations, as a function of outdoor temperature.

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

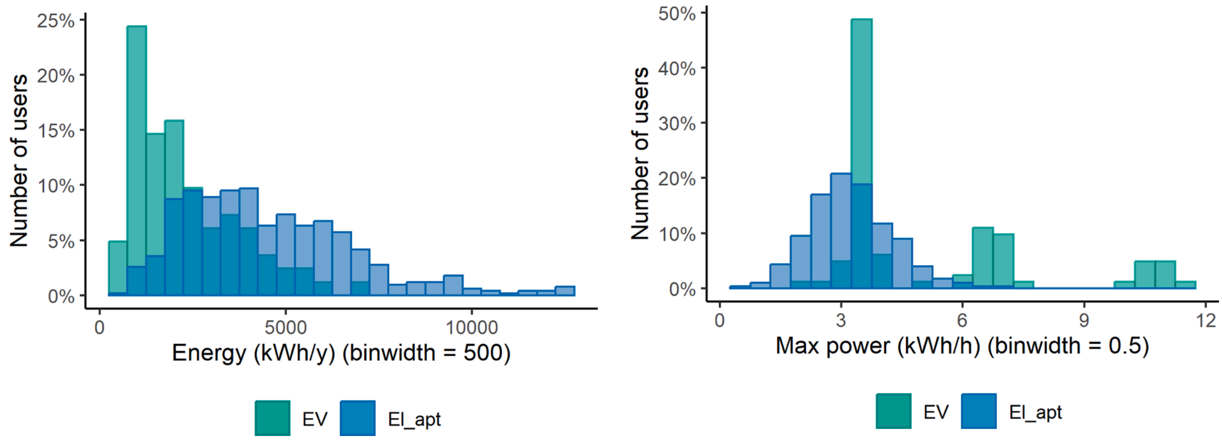


Fig. 5. Histograms with annual energy use (left) and maximum power (right) per EV and per apartment.

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.

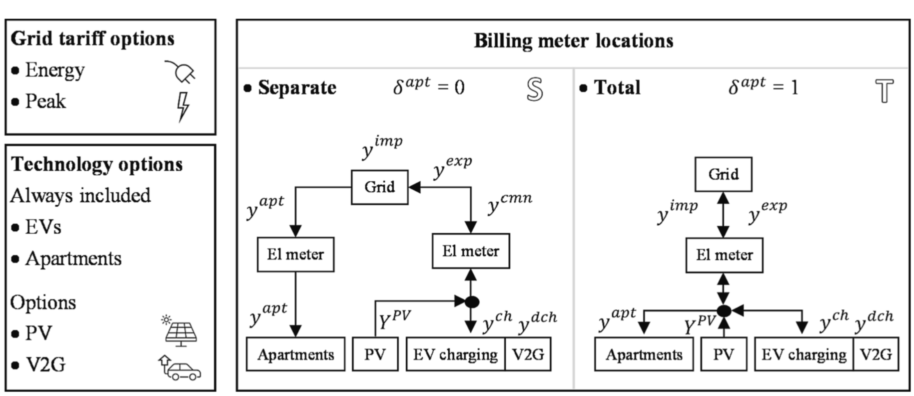


Fig. 6. Overview of the options in the optimisation scenarios.

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

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

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

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 $\delta^{apt} = 1$).

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

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

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

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.

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

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

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

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

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

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

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

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

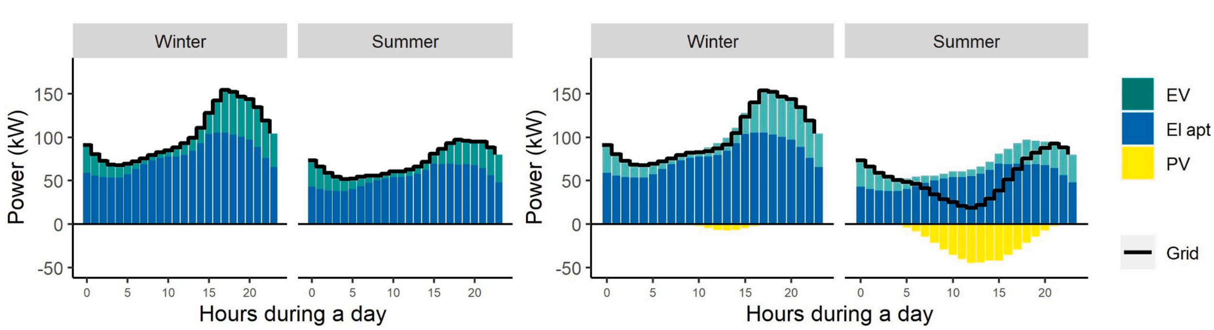


Fig. 7. Average daily profiles for uncontrolled EV-charging, without PV (left) and with PV (right).

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

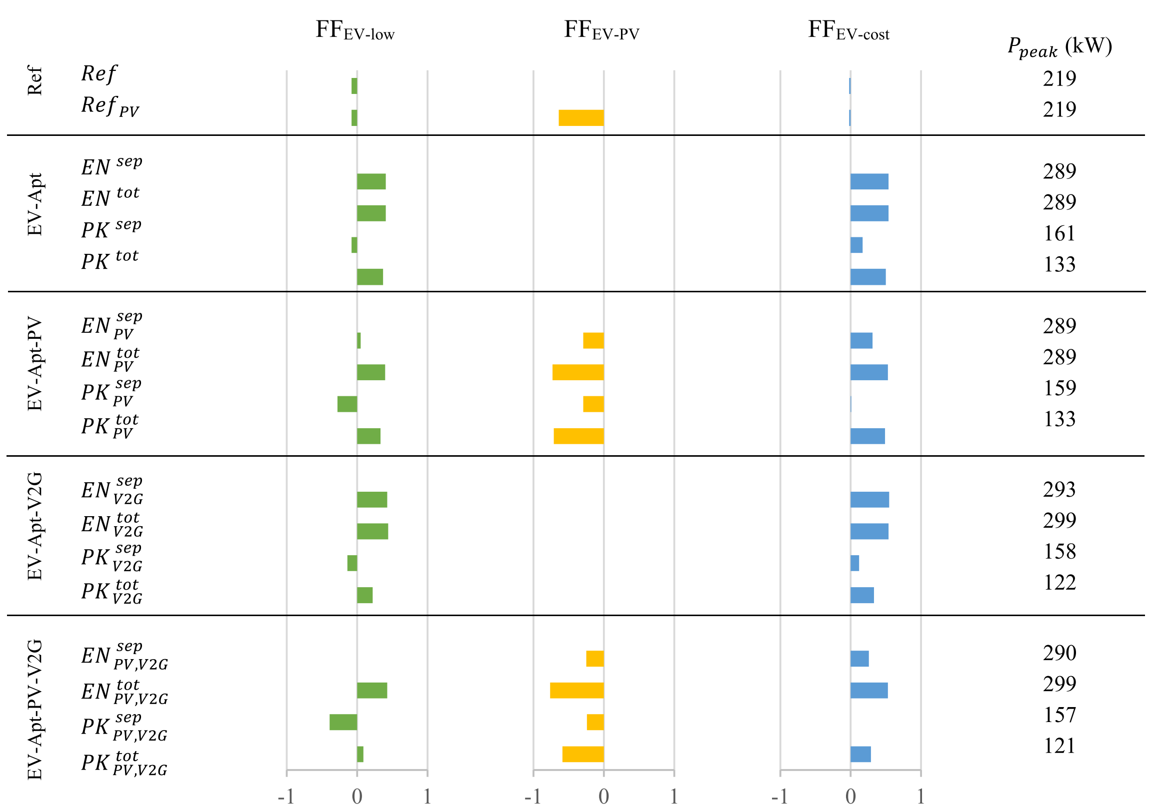


Fig. 8. Flexibility Factors and annual peak power for the scenarios.

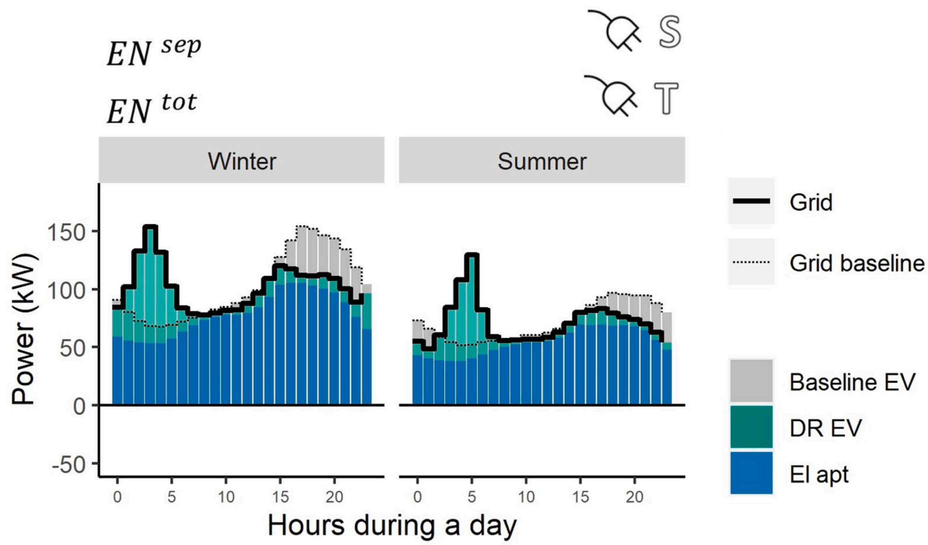


Fig. 9. Average daily profiles: "EV, Apt"-scenarios with energy tariffs.

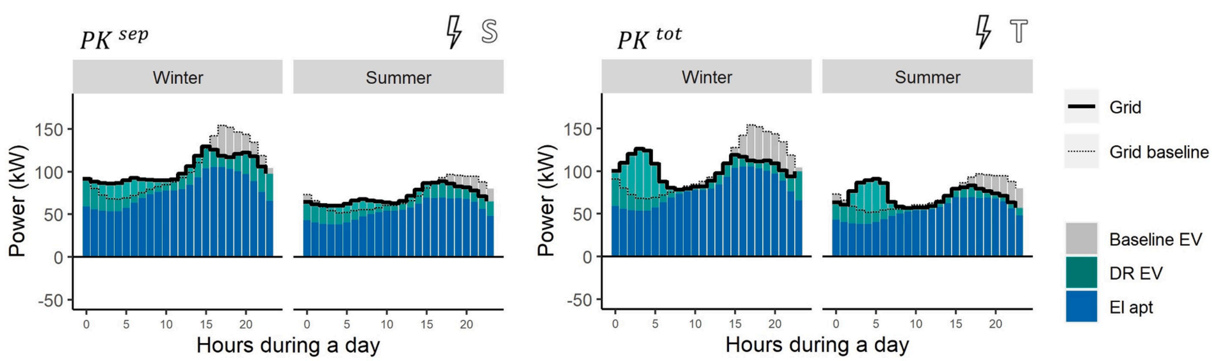


Fig. 10. Average daily profiles: "EV, Apt"-scenarios with peak tariffs.

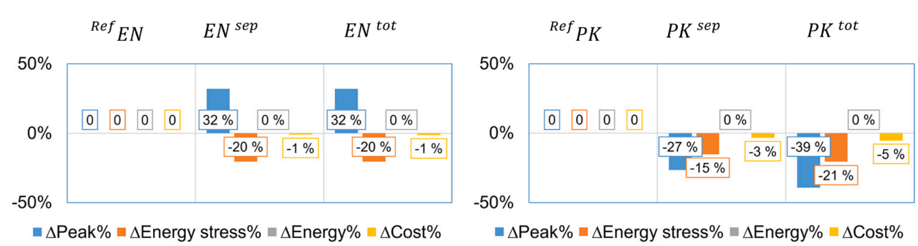


Fig. 11. Energy flexibility KPIs for the "EV, Apt"- scenarios.

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.

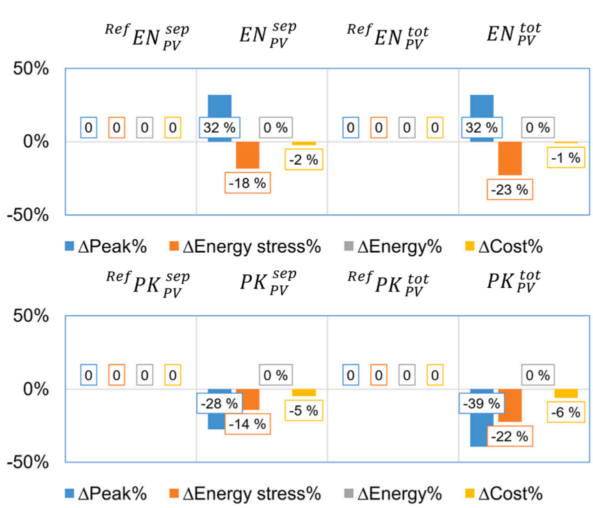
4.4. Optimised EV charging, energy loads in apartments, and V2G ("EV, Apt, V2G" scenarios)

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.

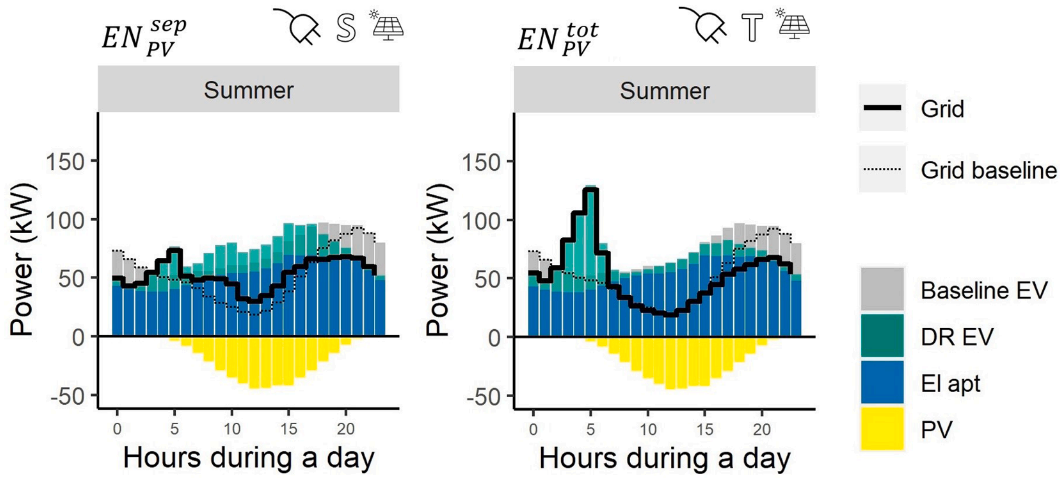


Fig. 13. Average daily profiles (summer): "EV, Apt, PV"-scenarios with energy tariffs.

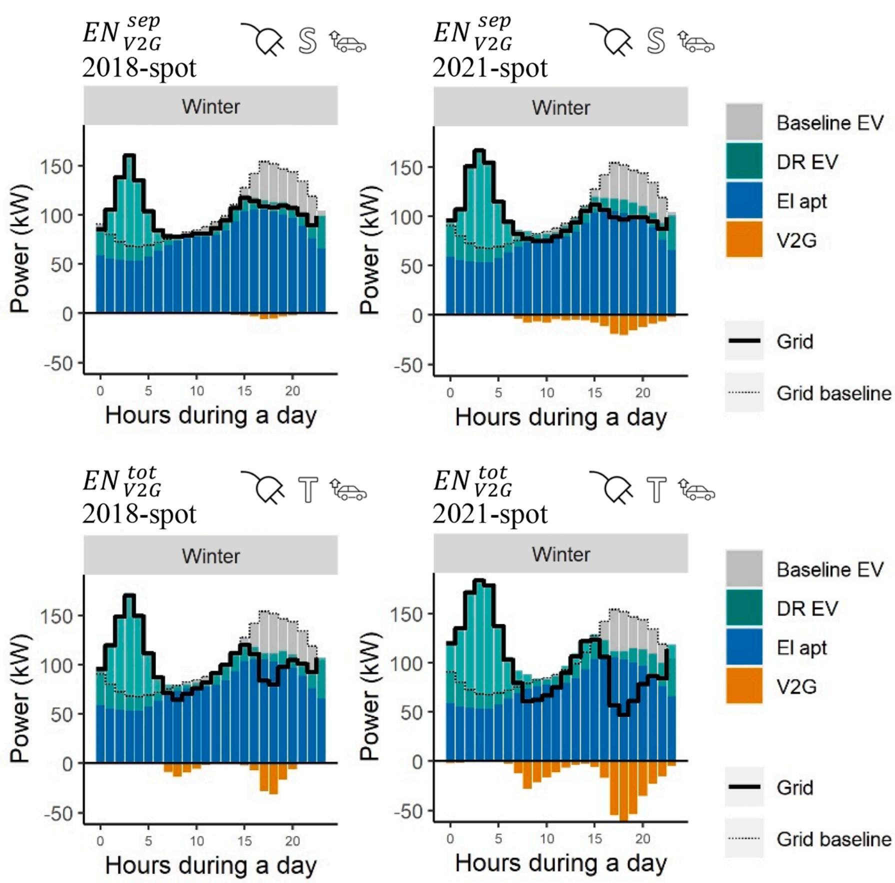


Fig. 14. Average daily profiles (winter): "EV, Apt, V2G"-scenarios with energy tariffs from 2018 and 2021.

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

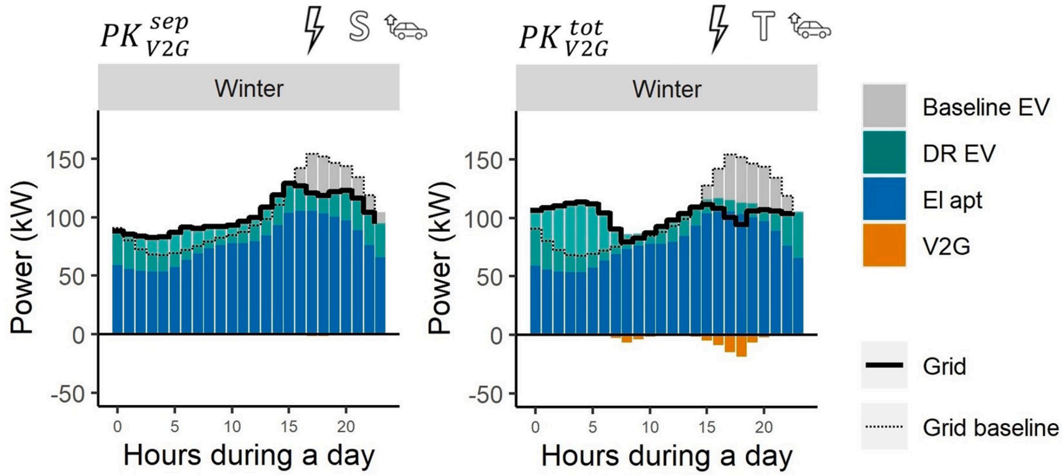


Fig. 15. Average daily profiles (winter): "EV, Apt, V2G"- scenarios with peak tariffs.

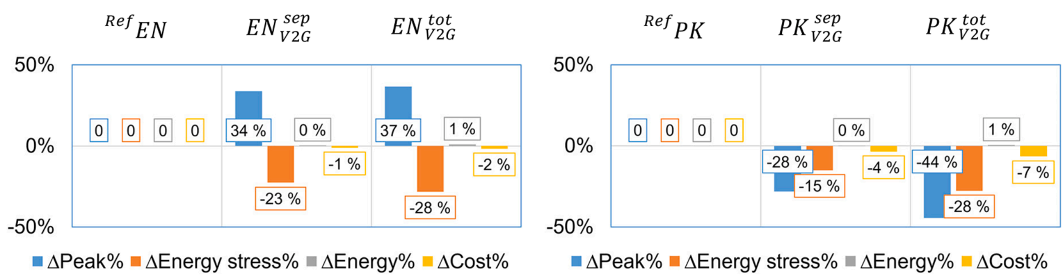


Fig. 16. Energy flexibility KPIs for the "EV, Apt, V2G"- scenarios.

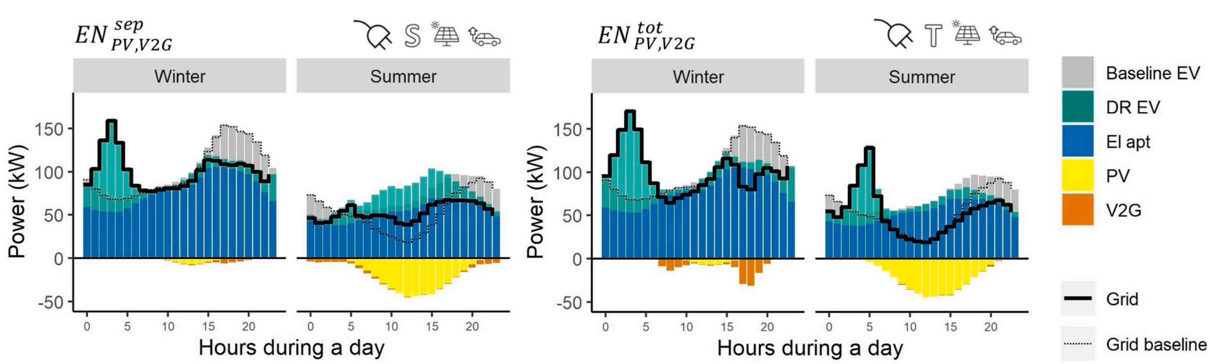


Fig. 17. Average daily profiles: "EV, Apt, PV, V2G"-scenarios with energy tariffs.

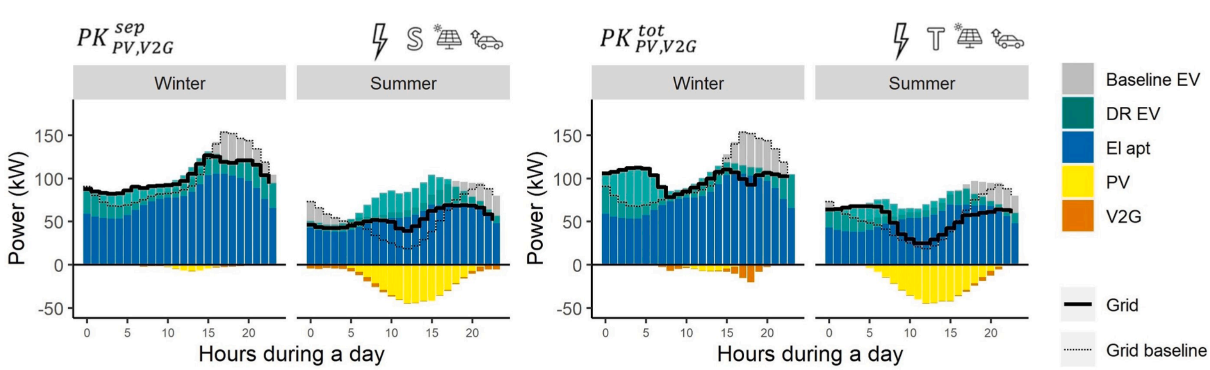
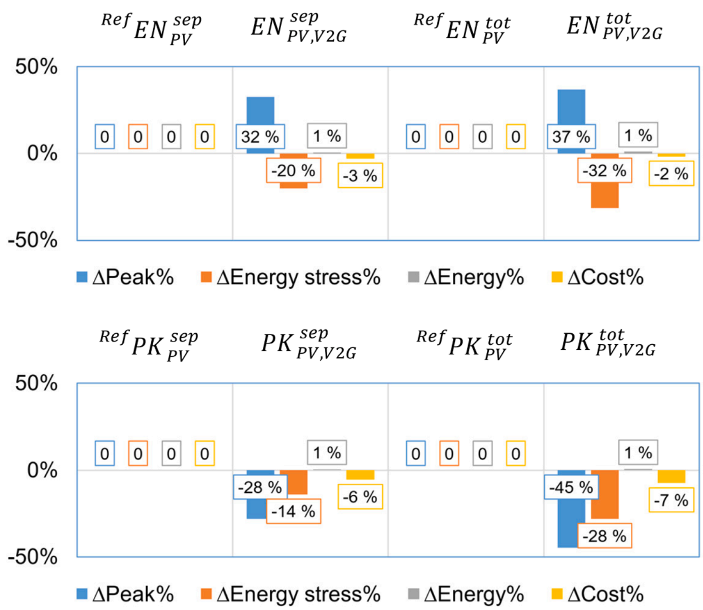


Fig. 18. Average daily profiles: "EV, Apt, PV, V2G"-scenarios with peak tariffs.



	SC (SC_{EV})	SS (SS_{EV})
Ref^{sep}_{PV}	38% (38%)	4% (18%)
Ref^{tot}_{PV}	98% (38%)	11% (18%)
$EN^{sep}_{PV,V2G}$	83% (83%)	10% (38%)
$EN^{tot}_{PV,V2G}$	100% (29%)	12% (12%)
$PK^{sep}_{PV,V2G}$	83% (83%)	10% (38%)
$PK^{tot}_{PV,V2G}$	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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