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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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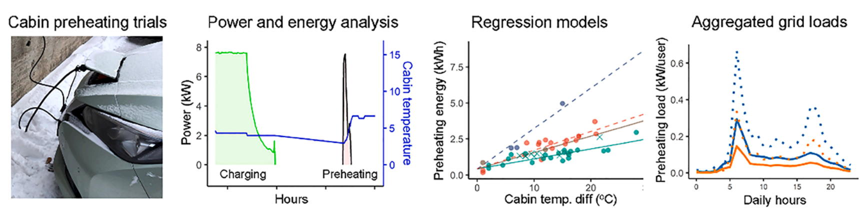
HIGHLIGHTS

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

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 %

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.

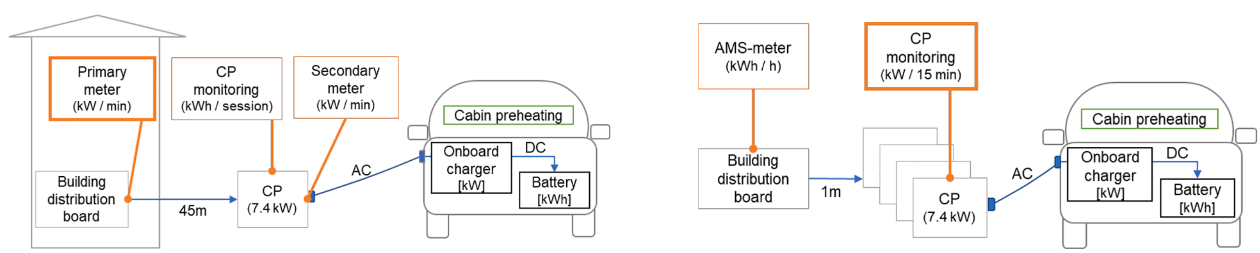

Fig. 1. System overview of test site 1 (left) and test site 2 (right), with metering locations.

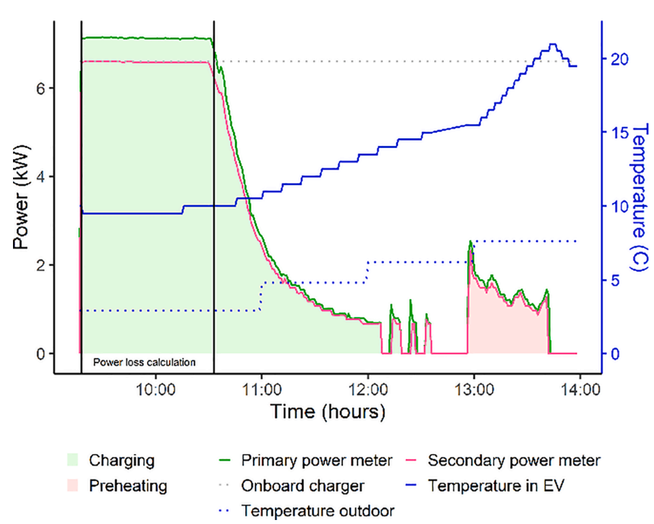

Fig. 2. Example session (ID 73) with EV charging and preheating of Nissan Leaf (MY2018) at site 1, metered at two locations.

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

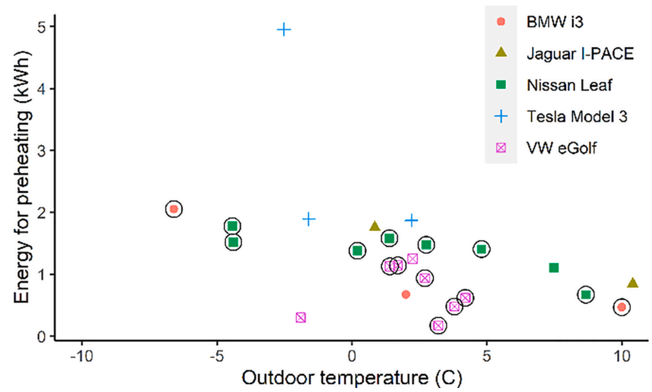

Fig. 3. Energy-Temperature diagram for preheating sessions at site 1. The circled sessions are ended by the EV thermal management system, while det remaining sessions were stopped by disconnecting the EV from the CP.

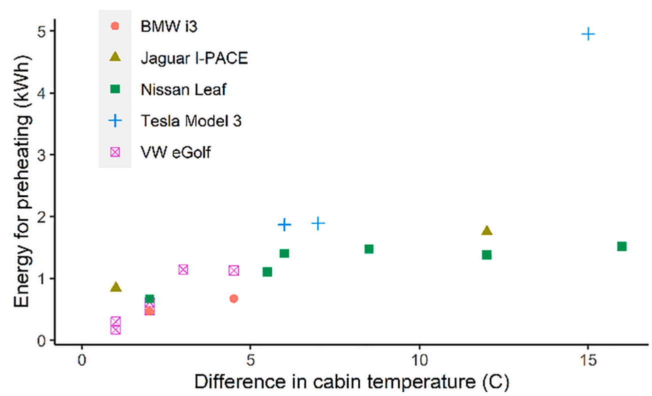

Fig. 4. Energy-Temperature diagram for preheating sessions with difference in cabin temperatures (site 1).

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.

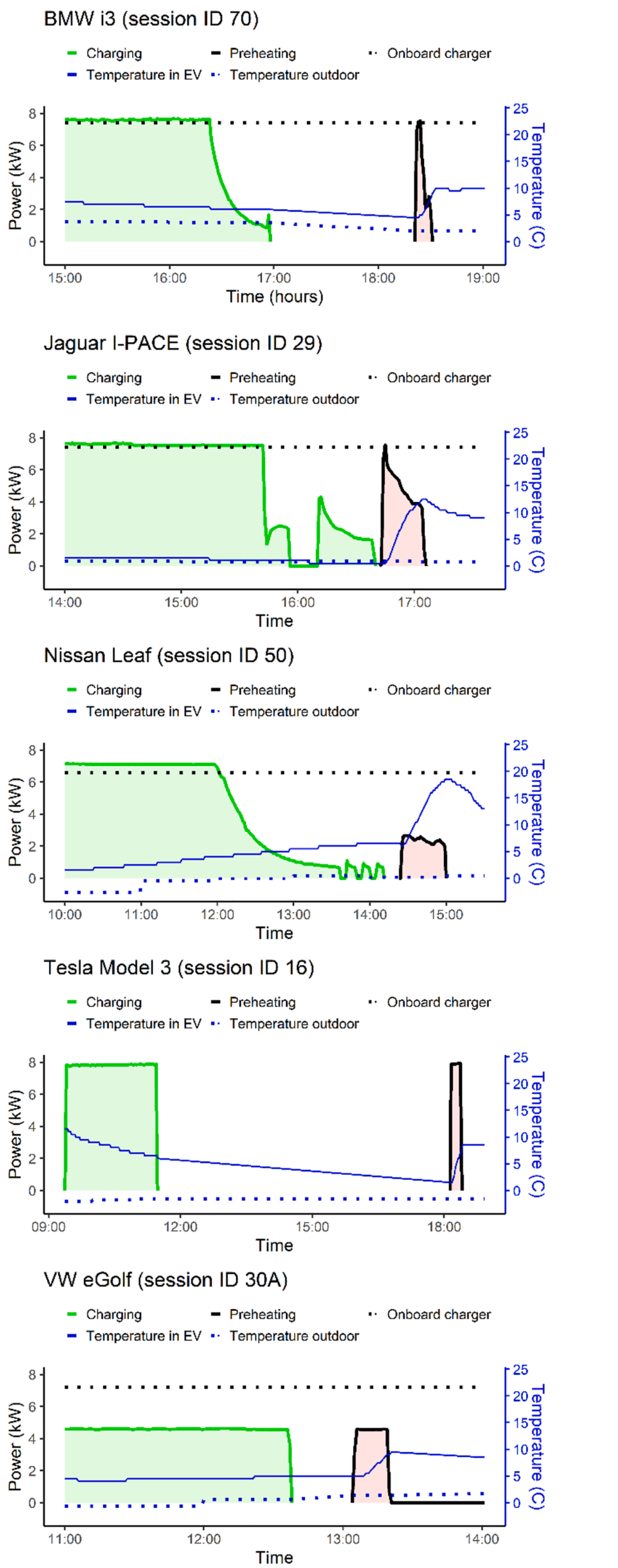

Fig. 5. Site 1 example trial sessions for each EV model, showing charging and preheating power for the EVs.

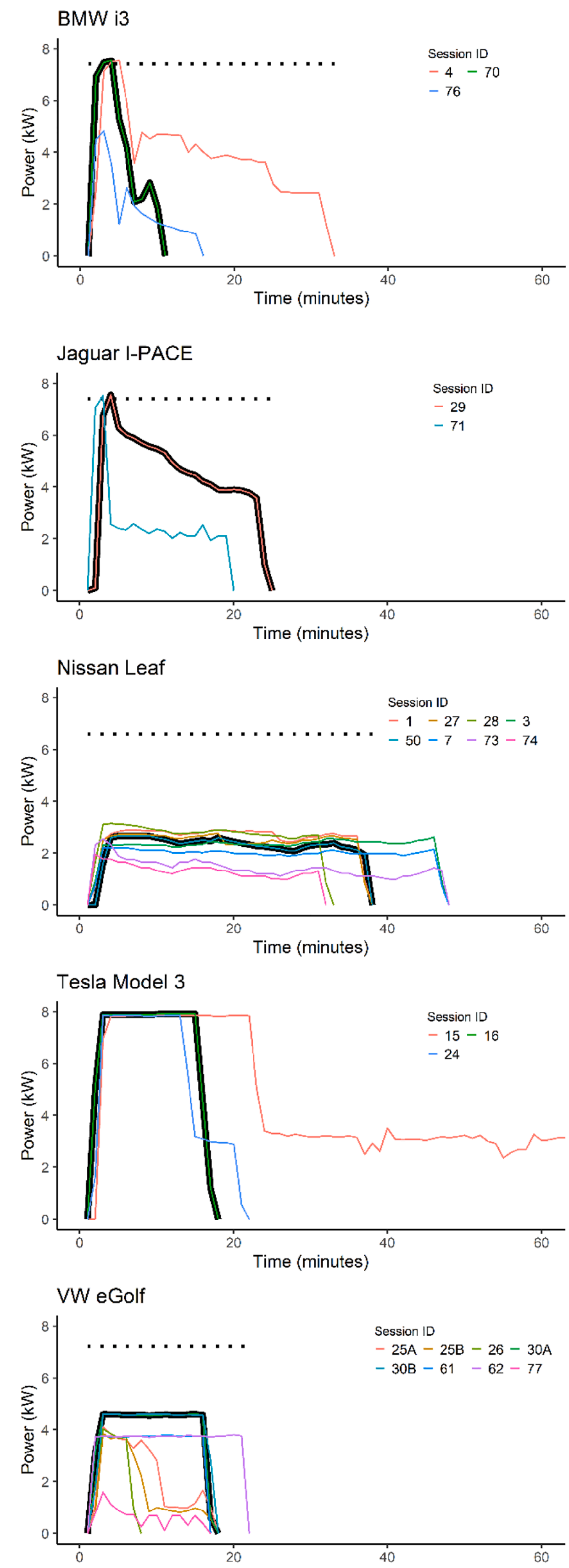

Fig. 6. Site 1 sessions for each EV model, showing preheating power. Example sessions from Fig. 5 are emphasized in black. Dotted lines: onboard charger capacity for the EVs.

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

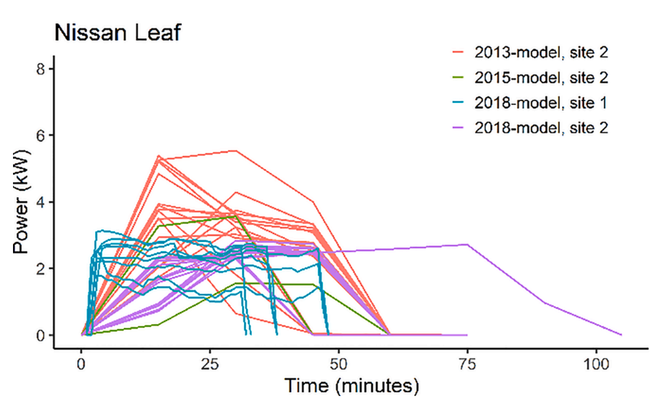

Fig. 7. Preheating power for Nissan Leaf models in the trial.

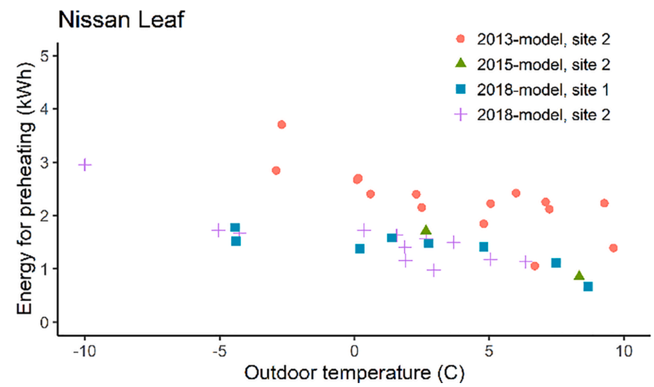

Fig. 8. Energy-Temperature diagram for Nissan Leaf models in the trial.

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_LH_{HP} and S_LH_{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.

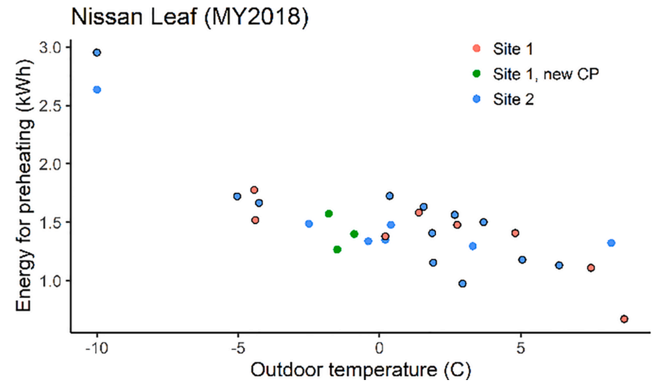

Fig. 9. Energy-Temperature diagram for preheating sessions with Nissan Leaf MY2018, using three different CPs. The figure includes trial sessions used for model training (black circles) and validation sessions.

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 · T + 0.049860 · (D: S_L: H_{HP}) + 0.023514 · (D: S_{SM}: H_{HP}) + 0.065395 · (D: S_L: H_{PTC}) + 0.046261 · (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 · (C: S_L: H_{HP}) + 0.06961 · (C: S_{SM}: H_{HP}) + 0.28108 · (C: S_L: H_{PTC}) + 0.12975 · (C: S_{SM}: H_{PTC})	0.860	0.845	0.27	0.11	0.33	23%	0.752	0.30	0.35

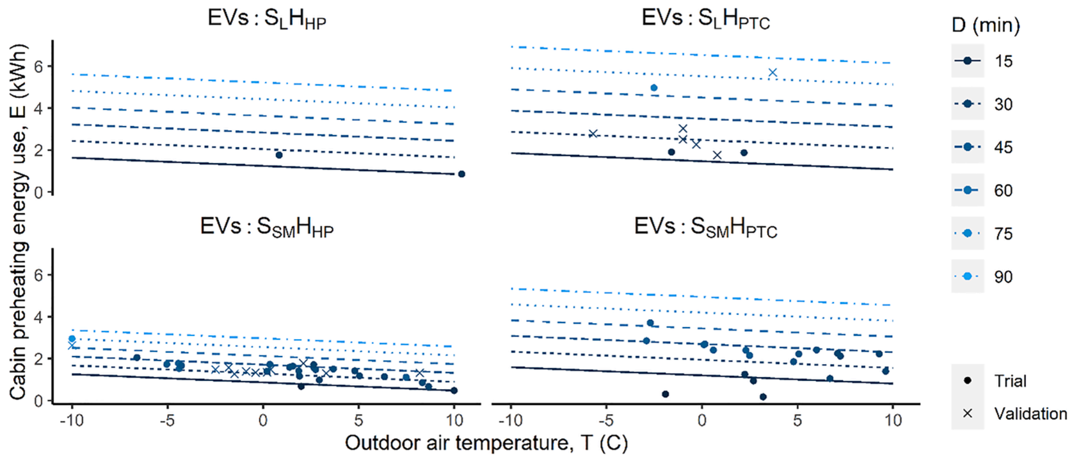

Fig. 10. The relationship between E and T, with different Ds, EV sizes (SM or L) and heating systems (HP or PTC only). Model TDSH* predictions (lines), trial data (dots), and validation data (crosses).

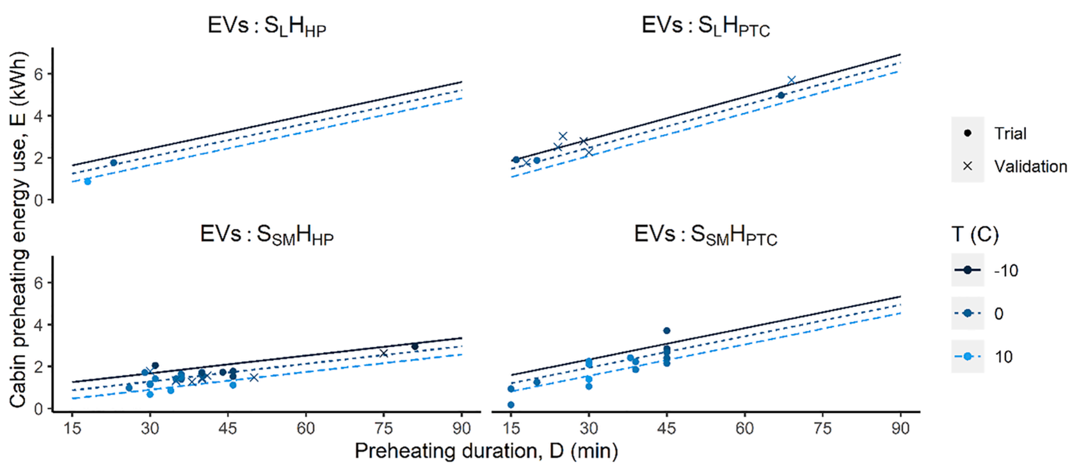

Fig. 11. The relationship between E and D, with different Ts, EV sizes (SM or L) and heating systems (HP or PTC only). Model TDSH* predictions (lines), trial data (dots), and validation data (crosses).

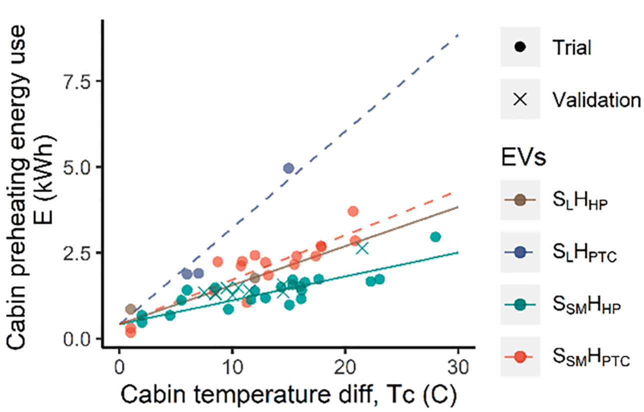

Fig. 12. Model CSH* predictions (lines), trial data (dots), and validation data (crosses) for E as a function of T_C. The EVs have different sizes (SM and L) and heating systems (HP or PTC only).

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

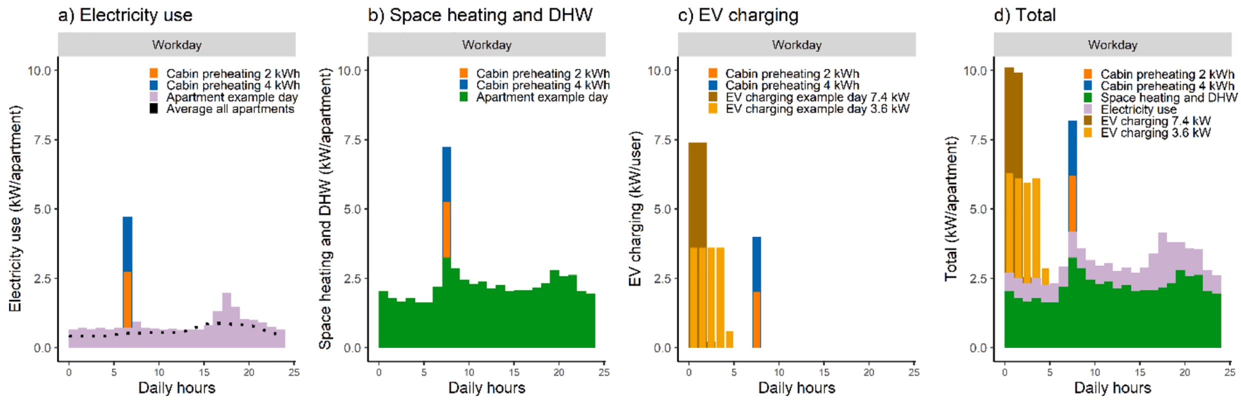

Fig. 13. Example day January 9th 2018, for an apartment with one EV, showing energy for space heating and DHW, energy for EV charging (3.6 og 7.4 kW) and cabin preheating (2 or 4 kWh), and other electricity use in the apartment.

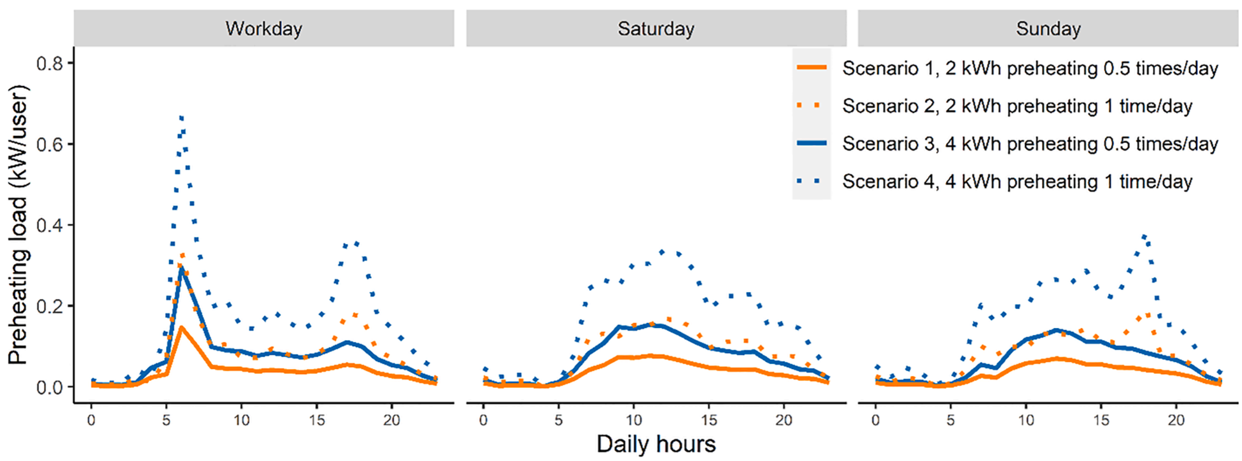

Fig. 14. Average daily profiles for cold days: Aggregated EV cabin preheating loads per EV user.

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

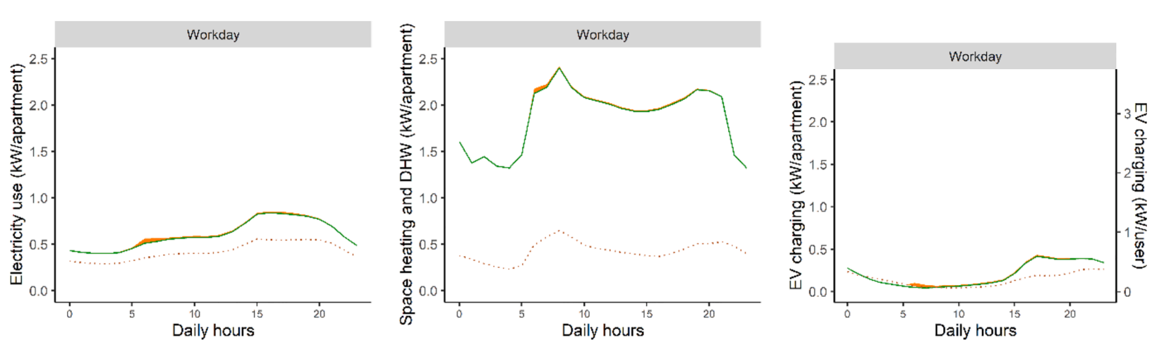

Fig. 15. Average daily profiles summer/winter: EV charging, apartment electricity use, and apartment space heating and DHW.

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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