Einolander, Johannes; Kiviaho, Annamari; Lahdelma, Risto

Power outages and bidirectional electric vehicle charging : Simulation of improved household energy resilience in subarctic conditions

Published in:
Energy and Buildings

DOI:
10.1016/j.enbuild.2024.114055

Published: 15/04/2024

Document Version
Publisher's PDF, also known as Version of record

Energy & Buildings 309 (2024) 114055

Contents lists available at ScienceDirect

Energy & Buildings

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

Power outages and bidirectional electric vehicle charging: Simulation of improved household energy resilience in subarctic conditions

Johannes Einolander [a,*], Annamari Kiviaho [b,c], Risto Lahdelma [a,d]

[a] Department of Mechanical Engineering, Aalto University, School of Engineering, P.O. BOX 14100, FI-00076 Aalto, Finland
[b] Faculty of Science, University of Helsinki, P.O. BOX 4, FI-00014, Finland
[c] Ruralia Institute, University of Helsinki, Lönnrotinkatu 7, 50100, Mikkeli, Finland
[d] Department of Mathematics and Systems Analysis, Aalto University, School of Science, P.O. BOX 14100, FI-00076 Aalto, Finland

ARTICLE INFO

Keywords:
Electric vehicle
Power outage
V2H
Energy resilience
Simulation

ABSTRACT

In the highly digitalized and electrified modern world, blackouts and power outages cause significant disruptions to societies and to the normal daily life of individuals. The ongoing energy transition, climate change and energy crisis complicate grid dynamics, generate new forms of instability, and weaken the resilience of the electricity transmission grid leading to possible increases in power outages. Electric vehicles (EVs) with bidirectional charging points offer a convenient possibility for households to maintain electricity use during power outages through vehicle-to-home (V2H) operation. This study introduces a novel hybrid model that combines linear programming and deterministic approaches, considering ambient temperatures, to evaluate the efficacy of V2H for power outage prevention in subarctic detached households. The methodology includes a power outage response model that dynamically adjusts the EV's SOC based on 5-minute interval household demand during sampled outage events. Utilizing real data, we simulate the energy resilience of V2H-equipped households during power outages, focusing on how this capability influences main customer objectives such as outage avoidance, electricity cost reduction, and EV state-of-charge (SOC). The approach provides insights into the system's performance across distinct EV-utilization cases and alternative customer preference assumptions. Based on our results, an EV could be used to fully prevent up to 98 % of all outages of the year occurring during EV plug-in. The average increased electricity costs resulting from outage response are less than 0.2€ if all outage types are considered. Overall, it can be stated that EVs can be effectively used to sustain household loads during power outages with V2H given EV availability, high SOC-level when the outage begins and if the EV is not needed for its primary purpose, mobility, during the outage.

1. Introduction

In the ever more connected and electrified world, power outages cause significant disruptions to societies and the normal daily lives of individuals. Even though societies have been highly reliant on electricity for decades, the increased complexity and interconnectedness between modern power grids and infrastructure, such as ICT, has resulted in a system where power outages cause devastating impacts across the society. The ongoing energy transition including i.e., increased integration of variable renewable energy generation, electric vehicles (EVs) and the phase-out of conventional large power plants radically changes grid dynamics and weakens the security and resilience of the transmission grid through, for instance, increased variability and decreased predictability and controllability of network assets [1–3]. At the same time, the increasing frequency of extreme weather events due to climate change will strain electricity grids and heightens the risk of power outages even more in the future [4]. Additionally, the global energy crisis that began in the aftermath of the COVID-19 pandemic and was escalated due to the invasion of Ukraine pushed electricity prices to record highs and induced considerable new uncertainties to the market and power grid operation [5–7]. Particularly in the Nordic countries, these high and volatile electricity prices led customers to adopt dynamic exchange-priced electricity contracts as a means to minimize electricity bills by shifting the time of electricity use [8–10]. Further, all these uncertainties led governments and transmission system operators, for instance in Finland, to consider planned rolling blackouts, especially during cold winter peak times to ensure power grid stability [11,12].

* Corresponding author.
E-mail address: johannes.einolander@aalto.fi (J. Einolander).

https://doi.org/10.1016/j.enbuild.2024.114055
Received 3 November 2023; Received in revised form 6 February 2024; Accepted 3 March 2024
Available online 5 March 2024

Nomenclature

Abbreviations

AMR	Automatic Meter Reading
BESS	Battery Energy Storage System
CPO	Charging Point Operator
DR	Demand Response
EV	Electric Vehicle
ICT	Information and Communications Technology
LP	Linear Programming
MILP	Mixed-Integer Linear Programming
PHEV	Plug-in Hybrid Electric Vehicle
SOC	State of Charge
TSO	Transmission System Operator
V2G	Vehicle-to-Grid, bidirectional power flow
V2H	Vehicle-to-Home, bidirectional power flow
V2HG	Vehicle-to-Home and Vehicle-to-Grid case
WTP	Willingness To Pay

Indices and index sets

i	Electric vehicle charging event of a household, 1, …, I
t	Time index of the charging event (5-minute intervals), 1, …, T
b	Time index of the power outage event (1-minute intervals), 1, …, B

Symbols

Symbol	*Description* (*Unit*)
C_t^{Spot}	Electricity spot market rate (€/kWh)
C^{VAT}	Value added tax rate (1)
C^{Mar}	Margin of the electricity supplier (€/kWh)
C^{Tra}	Electricity transmission fees, tax & fee inclusive (€/kWh)
C^{Deg}	Battery degradation cost (€/kWh)
C^{Rep}	Battery replacement cost (€)
D_t, D_b	Ambient temperature power decrease factor, at time t or b (1)
E_t^{Hou}	Household electricity purchased from the grid (kWh)
E_t^{EV}	EV electricity purchased from the grid (kWh)
E_t^{V2G}	Discharged EV electricity for sale to the grid (kWh)
E_t^{V2H}	Discharged EV electricity to the household (kWh)
E_t^{Dem}	Household electricity demand (kWh)
E^{Event}	Original EV charging event electricity consumption (kWh)
E^{Bat}	EV battery capacity (kWh)
$E^{Not-Fulfilled}$	Household demand during outage, not fulfilled by EV (kWh)
$EV_b^{Plugged-in}$	EV availability during outage, at time b (bin)
L^{Cyc}	Battery lifetime in cycles (1)
P_t^{cha}	EV charge power, at timeframe t (kW)
P_t^{dis}, P_b^{dis}	EV discharge power, at timeframe t or b (kW)
$P^{max,cha}$	Maximum EV charge power (kW)
$P^{max,dis}$	Maximum EV discharge power (kW)
SOC_0	Initial SOC level for the LP-model, plug-in/after outage (1)
SOC_B	SOC level at the end of a power outage event (1)
$SOC_{Discomfort}$	Discomfort SOC level during power outages (1)
SOC_{min}	Minimum SOC level (1)
SOC_{max}	Maximum SOC level (1)
SOC_t, SOC_b	SOC at time t or b (1)
SOC_T	SOC level at the end of optimization, at plug-out time (1)
$T^{Not-fulfilled}$	Outage duration, not fulfilled by EV (h)
τ_t	Duration of EV dis-/charge, at charging event period t (h)
τ^{Dur}	Duration of the charging event at LP-model initialization (h)
τ_b^{dis}	Duration of outage EV discharge, at period b (h)
τ_b^{Outage}	Duration of outage, at period b (h)
$\tau_b^{ToPlugout}$	Time to EV plug-out, at beginning of period b (h)
η^{cha}	EV charging efficiency (1)
η^{dis}	EV discharging efficiency (1)

Power outages and blackouts can have devastating impacts on societies. First, power outages cause significant economic costs, for instance though loss of production and equipment damage [1,13]. In addition, power outages have severe social impacts. Power outages can for instance result to deaths, chaos, material losses and cause severe discomfort to households and sectors dependent on electricity [1,4,14,15]. However in the modern highly digitalized world, the major household inconveniences resulting from power outages concentrate on interruptions in ICT use, as ICT cannot easily be substituted by other technologies or appliances [16,17].

Rural and sparsely populated areas are more vulnerable to power outages than cities. Compared to cities, rural areas and communities suffer more commonly from poor infrastructure, disruptions and power outages, and from more frequent and severe natural disasters [18]. Even in otherwise highly developed countries such as in Finland, a major portion of long power outages occur outside cities [19] where overhead power lines are still in use and exposed to natural phenomena like winds and storms, snow, and ice [20,21]. Furthermore, the repair of damage to power lines in more rural locations is slowed down by long distances [22]. Rural and sparsely populated areas can also experience legislative disparities in comparison to urban areas. For instance, in Finland, the Electricity Market Act [23] proposes that by 2028, interruptions in electricity distribution should not exceed six hours in urban areas, however, in rural areas, interruptions up to 36 h are acceptable. Overall, the authors of [15] noted that power outages may be considered acceptable or even normal in rural areas, while they are not tolerated in cities. Nonetheless, the daily lives of rural residents are disrupted by outages similarly as their urban counterparts; however, they must cope with these outages on a more frequent basis.

Due to major inconveniences caused by power outages, people are willing to pay in order to avoid such events. Some previous studies have attempted to determine the willingness to pay (WTP) of households to avoid power outages. For instance, according to [4], UK households were willing to pay around 6€ to avoid having power outages during peak periods and over 35€ to avoid outages in winter, with electric heated households having higher WTP. The authors also found that the WTP to avoid an outage decreases as outage duration increases [4]. These results correspond to the results of the EU-level study [24], that is, the average hourly WTP is higher in winter than summer, and higher for short outages than longer ones. The mean WTP was generally highest for the low power system reliability countries as well as in some of the wealthiest countries in the sample (Finland, Denmark, Ireland), these countries had an average hourly WTP between 2.5 and 4€ for short winter outages and 0.3–1.1€ for medium length summer outages [24].

The rising popularity of electric vehicles and the introduction of bidirectional EV chargers to the consumer market has brought forth a novel possibility for households to avoid power outages through vehicle-to-home (V2H) utilization of EVs [25]. In V2H the EV is used as a household electricity storage that can be used to power households loads, for instance, during high electricity prices or power outages [26–28]. Utilization of EVs as a household uninterruptible power supply during power outages has been considered and validated experimentally in [29]. In some countries it is also possible to sell electricity from the EV back to the grid, this is called Vehicle-to-Grid (V2G). EVs, with and without bidirectional chargers, can also be used in different demand response (DR) schemes to minimize electricity costs or create additional revenue. EV charging can, for instance, be scheduled to low electricity price hours (implicit DR) and EV charging loads can be aggregated and offered to different marketplaces like to frequency containment reserves (explicit DR) [30,31]. During the 2022 energy crisis, there was a considerable shift towards hourly exchange-electricity contracts, particularly among Finnish households [9,10]. Such time-based electricity contracts are a prerequisite for implicit DR [9]. In addition to financial aspects, demand response behavior can also decrease CO_2 emissions from electricity use [32,33]. In this study, we concentrate on electric vehicles as a means to increase the energy resilience of households through power outage avoidance, while also considering household electricity cost minimization through implicit DR, V2H and V2G.

Contrary to typical household electricity storages, EVs are usually parked either outside or to non-heated garages and are thus more prone to outdoor temperatures. Ambient temperature has a major impact on overall EV utilization and energy efficiency. For instance, lithium-ion batteries typically used in EVs have poor low-temperature performance with power, efficiency and available capacity degrading in cold temperatures [34,35]. At freezing temperatures EV charging and discharging is further impaired as the internal resistances of the battery increase and maximum voltage is reached earlier [36,37].

In [38], the authors proposed a model that can be used to predict the EV SOC over time with different initial SOCs and under different ambient charging temperatures based on analysis of EV fast charging events of a taxi-fleet. Based on this model, when a 30-minute charging event is done in 0 °C the end SOC can be 22–36 % smaller than for events conducted in 25 °C. The authors further state that based on their dataset, the average rate of charge has an approximately linear relationship with ambient temperature and initial SOC [38]. A more up-to-date study on cold climate EV charging was conducted through laboratory measurements in [39]. Here the authors compared the cold climate charging performance of four full EVs and one plug-in hybrid vehicle in different ambient temperatures (20, 0, −10 & −20 °C). Based on the results, cold temperatures have a major impact on charging event energy transfer and charging power, reaching up to 40 % decrease in loss-inclusive charging power in the coldest temperatures [39,40].

The aim of this study is to simulate power outage prevention capabilities of rural detached households enabled by EVs and bidirectional EV charging points while considering the impact of ambient temperature in EV charging and discharging. There exist only a very limited number of previous studies that have analyzed how well EVs could be used to avoid power outages in households. In [41], the authors proposed a home resilient energy management system based on natural aggregation algorithm that coordinates different home energy resources, including appliances, a plug-in hybrid electric vehicle (PHEV) and photovoltaics (PV), to sustain the household during planned power outage periods. The authors conclude that the proposed model can significantly reduce the impact of power outages and enhance residential resilience, however the authors present only one example of the simulation results regarding outage avoidance [41]. In [42], the authors introduced an optimization model that aims to maximize backup duration provided by V2H during power outages. In this study, the authors considered a system with PV and a PHEV that can generate electricity from fuel in addition to battery capacity in outage response. The authors state that during off-peak seasons in Austin, Texas, the proposed system including a PHEV with a 10.5 kW battery and 18 kg of gasoline could support a single home for around 16 to 20 days without need for grid electricity [42]. In [43], a computational tool for household energy modelling was introduced and used to optimize an off-grid detached home energy system comprising of an EV with V2H, solar panels, battery storage, gasoline generator and different household appliances. Backup duration was calculated for every time step of the model assuming an always available EV (no mobility) and repeating load profiles and weather. The authors found that the backup durations ranged from one day to multiple weeks depending on number of appliances used, home size, configuration and season [43]. In [44], the self-sustainment duration during a blackout was modeled for a single Californian reference house with PV, battery energy storage system (BESS) and an EV. This resilience duration was found to be more than 3 h without V2H and at least 12 h with V2H, assuming an initial EV SOC of 90 %, that the EV can be fully discharged during the outage and that the EV is not needed for driving purposes [44]. Additionally, for instance battery swapping has been consider as a way to further improve outage resilience gained with V2H [45]. There also exist studies that consider residential or smart communities in outage prevention with V2H [46,47].

Most previous research on V2H outage prevention has relied on artificial data or limited samples from few case buildings or EVs, often focusing on urban environments. These studies have also ignored the influence of ambient temperature on V2H efficiency, which can have a major impact especially in colder climates during winter. This major research gap underscores the absence of comprehensive analysis on household outage avoidance through V2H, particularly in the challenging conditions of northern subarctic climate. Our study represents the first comprehensive methodology and assessment of V2H outage prevention capabilities under such extreme conditions, leveraging real 5-minute interval automatic meter reading (AMR), and real EV charging event data, thus addressing a significant gap in the existing body of research.

This study bridges the gaps of previous research by introducing a novel hybrid model that considers ambient temperatures when assessing the power outage prevention capabilities of bidirectional EV charging in subarctic detached households. Self-reliant outage prevention increases the energy resilience of households especially in rural regions where power outages are common. In this study we utilize linear programming and deterministic models to simulate how households with EVs and bidirectional chargers can survive power outages and what kind of impact this outage response has on different main objectives of customers (outage avoidance, electricity cost minimization, fully charged battery at the end of the charging event) given distinct EV-utilization cases and alternative customer preference assumptions. Further, we analyze what kind of impact ambient temperature has on customer main objectives and conduct a multi-criteria comparison of the considered alternatives. To the authors knowledge, no similar studies have been conducted previously.

2. Methodology

2.1. Model overview

The aim of this study is to assess the household power outage prevention capabilities enabled by bidirectional EV charging points while minimizing the household electricity costs considering the impact of cold temperatures. In addition to the reference case (*dumb charging*) where the EV begins charging immediately after plug-in, we consider three different EV-utilization cases: *Implicit DR*, *V2H* and combined V2H & V2G case (*V2HG*).

In the *implicit DR* case, the charging costs of the charging events are minimized through "smart charging", also known as implicit or time-based demand response. This means that EV charging is scheduled to happen during the least expensive hours of the charging event.

In the *V2H* and *V2HG* cases, we utilize a bidirectional EV charging point to minimize the overall costs of electricity purchased from the grid for household and EV during the charging events. In the *V2H* case, the EV can only discharge electricity to the household, whereas in the *V2HG* case, the discharged electricity can be used in the household and sold to the grid.

Typical behavior of different EV-utilization cases is exhibited in Fig. 1. Here we can see that *dumb charging* is conducted right after EV plug-in, whereas *implicit DR* charging is shifted to the lowest electricity price hours to minimize charging costs. In *V2H* case, the EV SOC

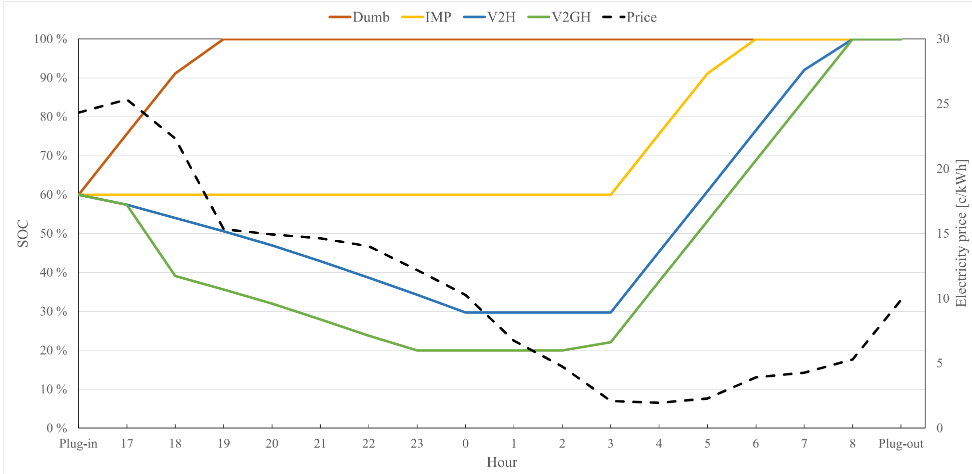

Fig. 1. Example behavior of the different EV-utilization cases, SOC as a function of time.

decreases during expensive electricity hours as the EV battery is used to power household loads, and the EV charging happens during the cheapest hours possible. The *V2HG* case behaves similarly, but in addition to powering the household, electricity from the EV is sold back to the grid during the most expensive hour of the event, 17. The SOCs at the figure represent the SOC at the start of each hour, and at plug-in and plug-out times. It should be noted that in the *V2HG* case the discharging is curtailed due to reaching of the minimum accepted SOC (20 %) in the hour 23, with lower min-SOC even more discharge would happen.

For each of these EV-utilization cases we consider two sub-cases, one where the EV is used to power the household during power outages, and the other where the EV does not react to the outage. These sub-cases are used to compare how outage response impacts the EV SOC and to calculate the extra electricity and battery degradation costs resulting from outage response. That is, in the first sub-case we assume that even in the *dumb* and *implicit* cases, which for normal operation would not require a bidirectional charging point, the EV could be discharged to power the household during outages.

In addition to the EV-utilization cases, we will compare three different customer preference assumptions: *high savings (HSavings)*, *high outage averse (OAverse)* and *high SOC discomfort (HSOC)*. These scenarios represent different main objectives of this study: to minimize household electricity costs, to minimize suffered power outage time, and to have the EV charged as full as possible at the end of the charging event. These customer preference assumptions are described further in section 2.5.

In this study, we employ a hybrid approach that combines both linear programming (LP) and deterministic models. This synergistic combination allows us to leverage the strengths of each type of model, enhancing the accuracy and efficiency of our analyses. The impact of ambient temperature on EV charging and discharging is calculated deterministically based on results of previous studies as described in section 2.2. Before and after power outages, in *implicit DR*, *V2H* and *V2HG* cases, we utilize an LP-model to optimize the household and EV system similarly as in [26,27]. The utilized LP-model is further described in section 2.3. The *dumb charging* case is calculated deterministically as no optimization is needed. For the power outage response model (section 2.4), we utilize power outage statistics and a deterministic model to calculate how well the EV can handle household demand during the outage, and how this impacts the EV SOC. Simplified version of the methodological workflow used in this study is presented in Fig. 2. All elements of the methodology are further described in the following subsections.

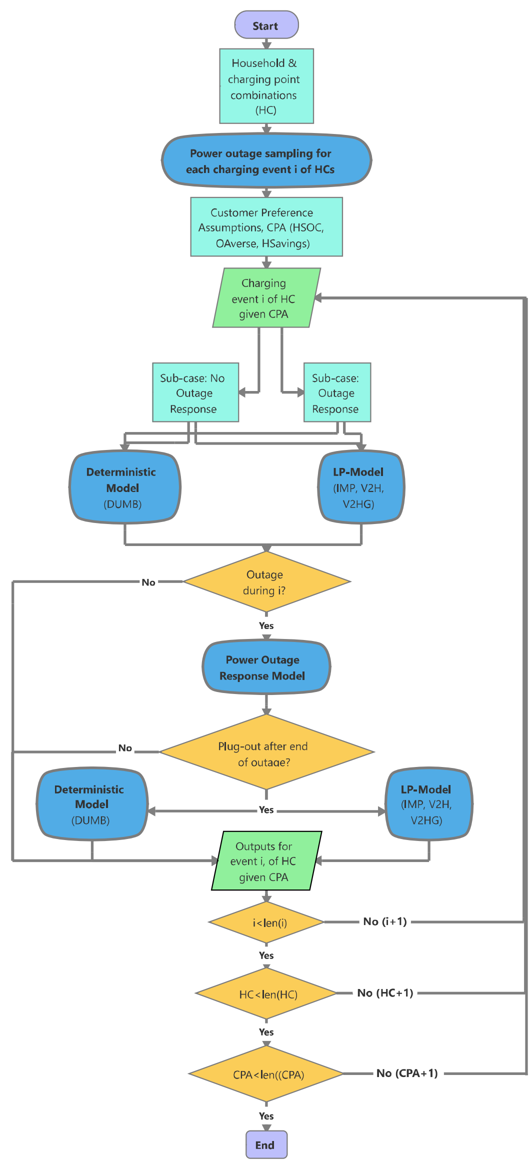

Fig. 2. Simplified workflow of the methodology.

2.2. Impact of ambient temperature on charging and discharging

Outdoor temperature has a major impact on energy transfer and charging powers during EV charging and discharging. In this study we utilize a similar approach as in [38], that is, the ambient temperature is used as a proxy for battery temperature when assessing the cold temperature impact on EV battery charging and discharging. Additionally we utilize the EV laboratory measurement data from [39,40] to quantify the diminishing energy transfer in cold temperatures.

The average charging power decreases in different temperatures, calculated based on the laboratory measurement dataset [40] and assuming linear decrease between measurements, are presented in Fig. 3. It should be noted that these average powers are calculated based on total energy transfers of charging events, and thus include charging efficiencies as the authors utilized SOC-levels reported by the vehicles. It should also be noted that in Volkswagen ID.3 the charging power was not heavily impacted by ambient temperature, due to larger preheating load before the dynamometer drive sequence, which resulted in higher battery temperature during the charging sequence [39].

As discussed before, there exist very few studies that investigate the dependence of V2G discharge power and ambient temperature. However, we can assume this dependence is similar to the dependence between EV charging power and ambient temperature, that is, the average discharging power decreases in cold temperatures. Additionally we assume that the available maximum capacity of the battery does not significantly diminish in cold temperatures, and that during EV charging the battery SOC increases linearly under a constant charging power, as for instance in [27,48,49], and vice versa during EV discharging. As the aim of the EV selection for the laboratory measurements conducted in [39,40] was to represent the car pool of the Nordic countries as close as possible, we utilize the results of this study and the average power transfer decrease curve presented in Fig. 3 to represent a power decrease factor in both EV charging and discharging.

These assumptions and simplifications were made to minimize computational time and complexity, and to enable the LP-model to efficiently solve the problem. Especially the impact of cold temperatures on battery performance contains multiple non-linear factors that an LP-model is unable to consider without similar simplifications. The limitations of this approach are further discussed in the Discussion section.

2.3. LP-model

The linear programming (LP) model used in this study is based on a mixed-integer linear programming (MILP) model utilized in [26,27]. This MILP-model was simplified to an LP-model to minimize computational time and complexity of the model. In [26,27], the use of the more complex MILP-model was justified as to ensure that no simultaneous EV charging and discharging occurs due to the binary variables, even during negative electricity price hours. In this study, we found that the charging/discharging efficiencies and other losses are able to keep simultaneous charging/discharging from happening at any time of the year.

The LP model is used for the *implicit DR, V2H* and *V2HG* cases, whereas the *dumb charging* case is calculated deterministically as no optimization is needed. The LP-model aims to minimize the electricity costs of a system comprising of a detached house and an EV during each EV charging event. As discussed in 2.1 the LP-model is first used to optimize the system without knowledge of the outage events to calculate parameters needed for the power outage model (SOC at outage occurrence time etc.), this is referred to as the "*initial run*" of the model. The same LP-model is further used to optimize the system after an outage event if the EV is still plugged-in after the outage ends, referred to as the "*second run*" of the model.

The linear programming model is formulated by equations (1) through (9). For each charging event, the objective function (1) minimizes the total cost of electricity purchased from the grid during the EV plug-in period. In (1), E_t^{Hou} and E_t^{EV} denote the house and EV charging electricity purchased from the grid, and $E_t^{V2G}\eta^{dis}D_t$ is the V2G sales to the grid, at event period t, where event periods are 5-minute intervals, or less, so as to be consistent with household automatic meter reading (AMR) data. The ambient temperature power decrease factor, at event period t, is denoted with D_t, and differs between ambient temperatures as discussed in section 2.2. The addition of this power decrease factor improves the MILP models of [26,27] by enabling the model to consider the fact that it takes more energy to reach the same resulting energy transfer in cold than warm temperatures. The addition of this factor significantly reduces the profitability of V2H and V2G operation in cold temperatures due to increased losses in both discharging and charging.

The hourly electricity spot market rate is denoted with C_t^{Spot}, while C_t^{VAT} covers the value added taxes (24 %) and C^{Mar} the margin of the electricity supplier. Differing from [27], value added tax is calculated also for negative values to correspond with up-to-date energy company billing practices where VAT is added after calculating the cost of monthly electricity purchases. Electricity taxes, security of supply payments and transmission fees are charged by the DSO based on transferred energy, these, including VAT, and denoted here by C^{Tra}. The battery degradation costs from additional battery utilization due to V2H and V2G are assumed small based on [27] and are not used in the LP-model, but are calculated after the optimization based on increased battery cycling. The values of the previous parameters are reported in Table 3. Depending on the considered EV-utilization case, the decision variables of the LP-model can include: E_t^{Hou}, E_t^{EV}, E_t^{V2H} and E_t^{V2G}. When using the LP-model in *V2H*-only and *implicit DR* cases, E_t^{V2G} is disregarded, and in implicit DR case E_t^{Hou} is not a variable as all household

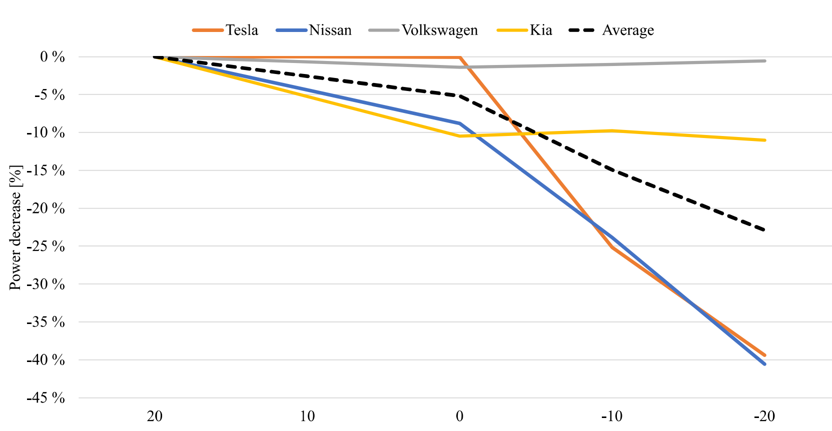

Fig. 3. Average charging power decrease in different ambient temperatures, based on [39,40].

electricity is purchased from the grid.

$$\mathrm{Min}\sum_{t=1}^{T}\left(\left(E_t^{Hou}+E_t^{EV}\right)\left(C_t^{Spot}+C_t^{Spot}C^{VAT}+C^{Mar}+C^{Tra}\right)-E_t^{V2G}\eta^{dis}D_tC_t^{Spot}\right) \tag{1}$$

subject to

$$E_t^{V2H}\eta^{dis}\leq E_t^{Dem} \tag{2}$$

$$E_t^{EV}\leq P_t^{cha}\tau_tD_t \tag{3}$$

$$E_t^{V2H}+E_t^{V2G}\leq P_t^{dis}\tau_t \tag{4}$$

$$SOC_{min}\leq SOC_t\leq SOC_{max} \tag{5}$$

$$SOC_t=SOC_{t-1}+\frac{E_{t-1}^{EV}\eta^{cha}-E_{t-1}^{V2H}-E_{t-1}^{V2G}}{E^{Bat}} \tag{6}$$

$$SOC_T=SOC_{Plug-out} \tag{7}$$

$$E_t^{Dem}=E_t^{Hou}+E_t^{V2H}\eta^{dis}D_t \tag{8}$$

$$E_t^{EV},E_t^{V2H},E_t^{Hou},E_t^{V2G}\geq 0 \tag{9}$$

$$t=1,\ldots,T$$

Here, constraint (2) represents that the discharged energy transferred to the household $E_t^{V2H}\eta^{dis}$ cannot be larger than the household demand E_t^{Dem}. Constraint (3) ensures that thecharged energy E_t^{EV} cannot be larger than the energy transferred in the timeframe τ_t with charging power P_t^{cha} given temperature decrease factor D_t. Constraint (4) ensures that the discharged energies or their sum cannot be larger than the energy discharged in the timeframe while assuming it is possible to simultaneously use discharged energy in the house and sell it to the grid.

The EV SOC at any given time-period t of the charging event, calculated with (6), should also stay between the minimum and maximum SOCs as noted in constraint (5). As will be discussed in section 2.5, we consider three customer preference assumptions cases each with different SOC_{min} to consider different customers priorities. The SOC after the optimization SOC_T should be equal to plug-out SOC $SOC_{Plug-out}$ as indicated by constraint (7). The next constraint (8) represents balance, that is the discharged electricity from the EV plus household electricity purchased from the grid should equal the original household electricity demand in the addressed time-period.

Equations (10)–(12) are used to pre-compute the initial SOC level SOC_0 at the beginning of the optimization, and the plug-out SOC level $SOC_{Plug-out}$ used as a target in (7). As noted in (10), for the *initial run* of the LP model, we use the SOC level at EV plug-in time $SOC_{Plug-in}$ as the initial SOC of the optimization. If a power outage happens during the charging event, and if the outage ends before the EV plug-out, we utilize the same LP-model to optimize the system for the rest of the charging event period. In this *second run* of the model, we use the SOC after the outage/blackout event, SOC_B, as the initial SOC of the optimization.

However, as the EV charging event dataset lacks explicit SOC information, we estimate the plug-in SOC with (11). If the potential energy that could be charged during the charging event duration τ^{Dur} with maximum charging power $P^{max,cha}$ exceeds the actual energy charged E^{event}, we conclude that the battery reaches a predefined SOC_{max} during the event. Under this condition, the plug-in SOC is calculated with the first part of (11), a method consistent with [26,27]. In cases where the EV does not reach SOC_{max} during the charging event, a less common scenario, the plug-in SOC is inferred, similarly as in [50], by sampling from an empirical EV plug-in SOC distribution documented in [51]. This alternate method of plug-in SOC estimation is adopted only when estimation based on E^{event} is not possible as reflected by the 'otherwise' clause of equation (11).

The SOC at the end of the charging event $SOC_{Plug-out}$ should be as high as possible to avoid compromising the EV's driving range unless required by outage response. This plug-out SOC is calculated with (12) by taking the minimum between SOC_{max} and the SOC that would be reached if the EV would charge with maximum power $P^{max,cha}$ for the whole event duration (calculated through summation over each 5-min period to ensure ambient temperature power decrease factor of each t is considered).

$$SOC_0=\begin{cases}SOC_{Plug-in}\ \textit{if initial run}\\ SOC_B\ \textit{if second run}\end{cases} \tag{10}$$

$$SOC_{Plug-in}=\begin{cases}SOC_{max}-\dfrac{E^{Event}\eta^{cha}}{E^{Bat}}\ \ \textit{if}\ P^{max,cha}\tau^{Dur}\geq E^{event}\\ \textit{Sampled from distribution otherwise}\end{cases} \tag{11}$$

$$SOC_{Plug-out}=\min\left(SOC_0+\sum_{t=1}^{T}\frac{\tau_tP^{max,cha}\eta^{cha}D_t}{E^{Bat}},SOC_{max}\right) \tag{12}$$

When considering the implicit DR case, all constraints with E_t^{V2H}, E_t^{V2G} are redundant. In V2H-only case E_t^{V2G} can be regarded always zero. In all of the aforementioned cases, the total yearly electricity costs are calculated by considering the household electricity costs from non-EV plug-in times in addition to the costs from charging event timeframes calculated with the previous equations. The energy flows of the LP model are further showcased in Fig. 4.

The battery degradation cost C^{Deg} is calculated with (13) based on [52,53]. Here C^{Rep} is the battery replacement cost and L^{Cyc} the battery lifetime in cycles. In this study, battery degradation is only considered for the extra degradation due to additional battery cycling due to V2H and V2HG operation. This cycling degradation cost could also be regarded zero if the battery's lifetime in years is reached before lifetime in cycles [53].

$$C^{Deg}=\frac{C^{Rep}}{L^{Cyc}E^{Bat}} \tag{13}$$

2.4. Power outage response model

The power outage model is called for each charging event after conducting the initial LP-optimization. Here, we utilize the most up-to-date power outage statistics from Finnish Energy [19] to sample power outage events to the charging events based on their typical occurrence and distribution. To ensure comparability of the results, identical power outages are used across all different customer preference assumption and EV-utilization cases. The utilized power outage statistics offer the best available open information about power outage occurrences in Finland. As most long power outages happen outside urban areas in regions without underground cabling, we utilize the outage statistics for regions outside urban area development plans. Households in these areas will benefit the most from increased outage resilience and the households of these areas without underground cabling are more generalizable to other countries with lower level of underground cabling. A summary of the outage statistics used for power outage sampling is presented in Table 1. Here the "technical, weather & other" and

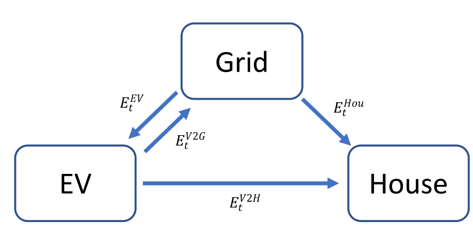

Fig. 4. Energy flows of the LP model.

Table 1
Summary of the outage statistics, based on Finnish Energy statistics [19].

Outage category	Avg. count	Avg. duration
Technical, weather & other	6.38	0.96 h
Snow and ice load	4.42	1.03 h
Fast reconnection	15.95	1.56 min
Automatic reconnection	8.48	1 s

"snow and ice load" outages are long outages that typically require some repairs to power lines, whereas the short outages (fast and automatic reconnection) can be handled automatically off-site.

The outage statistics are utilized to sample power outages for charging events, considering the probabilities of outage occurrences and the time of year (for snow and ice load outages). It is assumed that the outage has an equal probability to happen at any minute. The durations for long outages are estimated with log-normal distribution, as seen best for instance in [54].

If a power outage is sampled to a charging event, we select the EV SOC of the outage occurrence time from the *initial run* of the LP-model. As the LP-model iterates time on 5-minute intervals (household smart meter interval), SOCs for outages starting at non-5-minute divisible times are interpolated based on 5-minute interval SOCs. The outage model iterates the minutes of the outage event and calculates for every time-step whether the EV can fulfill the household energy demand and reduces the EV SOC accordingly. It should be noted that identical outage events sampled to a charging event of a charging point/household combination are used across different EV-utilization cases and customer preference assumptions to ensure comparability of the results.

The equations used in the power outage model are presented below. Here the first two equations (14 & 15) are used to calculate the power outage duration and energy demand not fulfilled by the EV. The equation (16) is used to estimate the discharge power in cases when the whole demand can be filled and otherwise. Equation (17) is used to calculate the possible time the EV can discharge during the outage/blackout event period/minute b, given SOC constraint and EV availability ($EV_{plugged-in}$).

$$E^{Not-Fulfilled} = \sum\nolimits_{b=1}^{B} E_b^{Dem} - P_b^{dis}\tau_b^{dis}\eta^{dis}D_b \tag{14}$$

$$T^{Not-Fulfilled} = \sum\nolimits_{b=1}^{B} \tau_b^{Outage} - \tau_b^{dis} \tag{15}$$

$$P_b^{dis} = \begin{cases} \dfrac{E_b^{Dem}}{\tau_b^{dis}} \; if \; \dfrac{E_b^{Dem}}{\tau_b^{dis}} \leq P^{max,dis}\eta^{dis}D_b \\ P^{max,dis}\eta^{dis}D_b \; otherwise \end{cases} \tag{16}$$

$$\tau_b^{dis} = \begin{cases} \tau_b^{Outage} \; if \; SOC_b - \dfrac{P_b^{dis}\tau_b^{Outage}}{E^{Bat}} \geq SOC_{Discomfort} \; and \; EV_b^{Plugged-in} \\ \dfrac{\left(SOC_b - SOC_{Discomfort}\right)E^{Bat}}{P_b^{dis}} \; if \; SOC_b - \dfrac{P_b^{dis}\tau_b^{Outage}}{E^{Bat}} \geq SOC_{Discomfort} \; and \; EV_b^{Plugged-in} \\ 0 \; otherwise \end{cases} \tag{17}$$

$$SOC_{Discomfort} = \begin{cases} SOC_{min} \; if \; \tau_b^{ToPlugout} \geq 3h \\ -0.1\tau_b^{ToPlugout} + 0.9 \; if \; \tau_b^{ToPlugout} < 3h \end{cases} \tag{18}$$

$$SOC_b = SOC_{b-1} - \frac{P_b^{dis}\tau_b^{dis}}{E^{Bat}} \tag{19}$$

In the equation (18), $SOC_{Discomfort}$ is used to denote the willingness to discharge the EV to power the household during power outages. The equation (18) is used only in the *high plug-out SOC* customer preference assumption presented in the following section 2.5. In all other customer preference assumptions, we utilize a stationary value for $SOC_{Discomfort}$ as will be described in the next section.

The final equation (19) is used to keep track of the EV SOC during the outage event, as the discharge time τ_b^{dis} is zero after EV plug-out, SOC_B represents the EV SOC either at plug-out time (if the outage continues after EV plug-out time) or at the end of the outage event (if outage ends before plug-out). If the outage ends before EV plug-out, this SOC_B is used as the initial SOC level for the *second run* of the model, as noted in Eq. (10).

The presented power outage model outputs information of how well the EV can be used to take care of the outage event (fulfilled outage time and household energy), whether the EV plug-out happens during the outage and about reasons for the EV not being able to handle the whole outage (min-SOC reached, unable to meet household power demand).

2.5. Customer preference assumptions

In this study we consider three alternative customer preference assumptions that prioritize different main objectives during EV plug-in. The *high savings* (*HSavings*) assumption represents customers that have high motivation towards financial savings and experience only a little discomfort from power outages or low SOC at plug-out. This is represented by SOC_{min} = 20 % in the LP model, and by a stationary $SOC_{Discomfort}$ = 20 % in the power outage model.

The *high plug-out SOC* (*HSOC*) customer preference assumption represents customers that prioritize a high SOC at plug-out time. In the LP-model this is represented by SOC_{min} = 60 % and by $SOC_{Discomfort}$ that starts to increase linearly near plug-out time according to Eq. (18) in the power outage model. This equation (18) represents the decreasing willingness to continue discharging the EV during outages that continue near the time when EV is needed for driving purposes.

The *high outage response* or "*outage averse*" (*OAverse*) assumption represents those customers that prioritize good power outage response possibilities over monetary savings and high SOC-level at plug-out time. This is represented by SOC_{min} = 60 % in the LP-model and a constant $SOC_{Discomfort}$ = 20 % in the outage model.

It is possible that the initial SOC_0 used in the model is lower than SOC_{min}, making the LP model infeasible, especially in customer assumptions with SOC_{min} = 60 %. In such cases, we utilize "dumb" charging until SOC_{min}-level is reached and solve the LP-model for the remaining part of the charging event. If the power outage ends before plug-out, we solve the LP-model again with SOC_B , SOC after the outage, for the remaining part of the charging event as noted in Eq. (10).

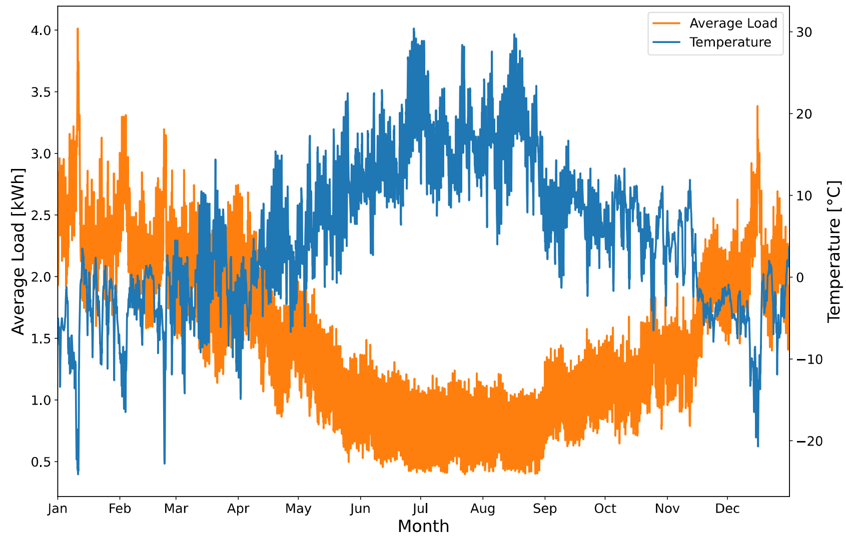

Fig. 5. Average hourly household load and ambient temperature.

2.6. Data Description

In this study we utilized a household an automatic meter reading (AMR) dataset that covered all detached households from municipality of Orivesi in central Finland. Orivesi is a detached household-centric municipality with around 9,000 residents located within commuting distance to the third largest city in Finland, Tampere. This municipality appropriately represents the share of detached/semi-detached houses of Finnish semi-urban and rural municipalities based on Statistics Finland [55]. In 2022, half of all Finnish detached/semi-detached houses were located in semi-urban or rural municipalities [55], with a significant share of these households located outside urban area development plans that are more prone to power outages based on outage statistics [19].

During AMR data cleaning we removed clearly erroneous measurements, households with yearly consumption less than 2 MWh or more than 40 MWh, households with multiple long gaps, missing values or errors in the measurements, and households that transferred electricity back to the grid. In the end the AMR dataset consisted of the 5-minute interval electricity usage data for nearly 400 detached households in 2022. The average yearly electricity consumption for these households was 12.1 MWh, with a median of 11.2 MWh and a standard deviation of 6.3 MWh indicating a range of different primary heating types. Fig. 5 depicts the average load curve of the households, highlighting significantly higher electricity consumption during the dark, cold winter months due to increased need for e.g., heating and lighting. Furthermore, the reduced variability in the load profile during summer months can be attributed to warmer temperatures, extended periods of daylight, and summer vacations.

The EV charging event dataset was procured from a Finnish EV charging point operator. However, none of the contacted Finnish charging point operators (CPOs) had enough detached households from Orivesi utilizing their services to offer charging event data from this municipality without compromising customer privacy. In Finland, most of the EV home charging is conducted from standard household sockets or from charging points not connected to any CPO service. Due to these restrictions, in this study we utilize a dataset that covers all charging events conducted in 2022 on private EV charging points installed to household customers in Helsinki. The initial data processing and cleaning of the dataset was conducted similarly as, for instance, in [26,30,31,56]. That is, during data cleaning, the clearly erroneous charging events (events with NULL values, zero energy transfer and impossible charged energies), test events, and events lasting either less than 5 min or longer than a week were discarded from the dataset. After initial data cleaning, charging points not in active use for the whole year, points with utilization by multiple EVs and slow charging points were also discarded leading to over ten actively used charging points with maximum charging powers of 11 kW or more. Based on initial analysis, the events from these charging points reflect the typical charging behavior of electric vehicle owners of Finnish household customers who frequently utilize home charging. On average, these charging points had around 220 acceptable charging events in 2022. The main features of the charging event data are; plug-in time, plug-out time, duration, and energy charged during the event. Table 2 presents a statistical overview of the key features for an average charging point. The limitations that arise from this and the other datasets are discussed further in the Discussions section.

The final pairing of household electricity consumption and EV charging events on different charging points was done by generating all possible combinations of these customers leading to around 4,000 unique combinations of detached households with EV charging points. When considering the three alternative customer preference assumptions and the four different EV-utilization cases, this leads to around 48,000 different yearly household cases, and to over 10 million different charging event and household load combinations without considering cases without outage response or various runs with different power outage samples.

Table 2
Statistical overview of charging event features for an average charging point.

Feature	Mean	Std Dev	Median
Charged energy, E^{Event} [kWh]	20.1	11.5	19.7
Event duration, τ^{Dur} [h]	14.6	13.5	12.6
Plug-in time of the EV [hh:mm]	16:51	4:11	17:55

Table 3
Technical specifications and assumptions.

Specification	Value
Battery capacity, E^{Bat} [kWh]	60
Max. Charging power, $P^{max,cha}$ [kWh]	11
Max. Discharging power, $P^{max,dis}$ [kWh]	11
Charging efficiency, η^{cha} [%]	85
Discharging efficiency, η^{dis} [%]	70
Battery lifetime cycles,L^{Cyc}	1,500
Battery replacement cost, C^{Rep} [€]	10,000
Electricity supplier margin, C^{Mar} [c/kWh]	0.38
Transfer fees incl. VAT, C^{Tra} [c/kWh]	8.00
Value added tax rate, C^{VAT} [%]	24

The temperature data used to calculate the ambient temperature power decrease factors was downloaded from the open data portal of the Finnish Meteorological Institute [57], and the hourly electricity spot price data for the Finnish market zone in 2022 was downloaded from the ENTSO-E Transparency portal [58]. Hourly ambient temperature and the average household hourly load are further presented in Fig. 5. It is evident from the figure that lower temperatures are associated with a subsequent rise in average hourly electricity usage, and that electricity consumption in the summer is considerably lower than during cold winter months.

Technical specifications and other assumptions used in the study are compiled to Table 3. In the model we assume a bidirectional EV charging point with 11 kW power rating similarly as in [27]. Charging and discharging efficiencies were assumed 85 % and 70 % respectively based on [59–61]. The presented battery capacity assumption was adjusted for charging points with events non-viable with the initial assumption. The battery replacement cost was estimated to be 10,000 € considering decreasing battery costs and a modest second life value for the old battery similarly as in [27].

3. Results

Power outage handling statistics for all different customer preference assumption and EV-utilization cases are presented in Table 4. This table contains the average percentages of fully handled power outages in total and during the EV plug-in period, separated further for long outages. Additionally, percentage of outage events where outage response was stopped due to reaching of the preference-specific discomfort-SOC are presented. In all cases, EV plug-out happens in the middle of an outage in 2.3 % of charging events with outages (7.1 % for events with long outages). From the table it can be noted that the *outage averse* (*OAverse*) customer preference assumption leads to best performance with regards to fully handled outages regardless of the EV-utilization case, with 97.8 % of all outages fully handled during plug-in. The outage response of *OAverse*-cases almost never terminates due to the $SOC_{Discomfort}$ constraint, and the main reason for non-perfect outage response during EV plug-in results from discharge powers smaller than the household demand. The *high end-SOC* (*HSOC*) preference assumption leads to worst outage handling performance, with on average only around 80 % of long outages fully handled. Overall, it is easier to fully handle short outages than long ones, however it might differ between customers which outages cause more inconvenience.

The average suffered power outage times and not-fulfilled household demand during EV plug-in are presented in Table 5. The table also covers the average total handled outage duration during the year. Here again it can be noted that the *outage averse* customer preference assumption leads to best performance with regards to outage handling, with on average only seconds of suffered outage during EV plug-in regardless of the EV-utilization case. Overall worst performer is the *high end-SOC* preference assumption with *V2HG*, which on average leads to almost 31 min of outage time and cannot cover over 17 % of the household outage electricity demand during yearly EV plug-in.

Table 4
Power outage handling statistics for the customer preference assumption and EV-utilization cases.

Case	Fully handled outages [%]		Fully handled outages during plug-in period [%]		Response stopped; Discomfort-SOC reached [%]	
	All	Long	All	Long	All	Long
HSOC_Dumb	94.5	87.3	96.7	94.4	1.1	1.5
OAverse_Dumb	95.5	88.6	97.8	95.7	0.0	0.0
HSavings_Dumb	95.5	88.6	97.8	95.7	0.0	0.0
HSOC_Implicit	92.9	82.5	95.2	89.6	2.8	6.8
OAverse_Implicit	95.5	88.6	97.8	95.7	0.0	0.0
HSavings_Implicit	95.5	88.6	97.8	95.7	0.0	0.0
HSOC_V2H	86.4	76.4	88.7	83.5	9.6	13.4
OAverse_V2H	95.5	88.6	97.8	95.7	0.0	0.0
HSavings_V2H	94.4	87.2	96.7	94.3	1.2	1.6
HSOC_V2HG	82.9	73.9	85.2	81.0	13.1	15.9
OAverse_V2HG	95.5	88.6	97.8	95.7	0.0	0.0
HSavings_V2HG	93.6	86.5	95.9	93.5	2.0	2.4

Table 5
Average suffered outage time, total handled outage time and not-fulfilled household demand during EV plug-in.

Case	Suffered power outage time during plug-in [min]	Suffered power outage time during plug-in [%]	Total handled outage time during the year [h]	Not fulfilled energy demand during plug-in [%]
HSOC_Dumb	2.6	1.30	3.15	2.00
OAverse_Dumb	0.1	0.01	3.19	0.77
HSavings_Dumb	0.1	0.01	3.19	0.77
HSOC_Implicit	11.8	6.36	3.00	7.47
OAverse_Implicit	0.1	0.01	3.19	0.77
HSavings_Implicit	0.1	0.03	3.19	0.79
HSOC_V2H	26.0	14.66	2.76	15.86
OAverse_V2H	0.2	0.01	3.19	0.78
HSavings_V2H	3.6	1.76	3.13	2.70
HSOC_V2HG	30.8	16.96	2.68	17.44
OAverse_V2HG	0.2	0.01	3.19	0.78
HSavings_V2HG	5.0	2.54	3.11	3.34

Table 6
Average and maximum increased electricity costs and differences in end-SOC due to outage response per charging events with outages.

Case	Avg. Increased cost per outage [€]		Max. Increased cost per outage [€]	Avg. Difference in end-SOC per outage [%]	
	All	Long		All	Long
HSOC_Dumb	0.14	0.42	22.68	0.06	0.18
OAverse_Dumb	0.14	0.43	22.68	0.06	0.19
HSavings_Dumb	0.14	0.43	22.68	0.06	0.19
HSOC_Implicit	0.10	0.30	18.37	0.06	0.19
OAverse_Implicit	0.12	0.36	18.37	0.07	0.23
HSavings_Implicit	0.11	0.34	18.37	0.07	0.23
HSOC_V2H	0.09	0.29	18.37	0.06	0.20
OAverse_V2H	0.13	0.38	23.19	0.07	0.23
HSavings_V2H	0.11	0.34	18.37	0.08	0.24
HSOC_V2HG	0.09	0.29	18.37	0.06	0.20
OAverse_V2HG	0.13	0.39	23.19	0.07	0.23
HSavings_V2HG	0.11	0.34	18.37	0.08	0.24

Table 7
Average yearly total electricity costs with and without outage response and average battery degradation costs from increased battery cycling.

Case	Avg. Total yearly costs, With Resilience [€]	Avg. Total yearly costs, No Resilience [€]	W.Avg. Increased yearly costs [€]	Avg. Yearly battery degradation costs from increased cycling [€]
HSOC_Dumb	4203.4	4201.9	1.92	0.49
OAverse_Dumb	4203.4	4201.9	1.94	0.49
HSavings_Dumb	4203.4	4201.9	1.94	0.49
HSOC_Implicit	3959.0	3958.0	1.44	0.45
OAverse_Implicit	3959.2	3958.0	1.56	0.49
HSavings_Implicit	3883.0	3881.9	1.52	0.49
HSOC_V2H	3911.9	3910.8	1.38	0.38
OAverse_V2H	3919.5	3918.1	1.71	0.46
HSavings_V2H	3834.0	3832.8	1.54	0.44
HSOC_V2HG	3880.1	3879.0	1.37	0.37
OAverse_V2HG	3900.4	3899.0	1.73	0.46
HSavings_V2HG	3796.0	3794.8	1.54	0.43

Average and maximum increased electricity costs and the average differences in end-SOC due to outage response are presented in Table 6 for all preference and EV-utilization case combinations. The average increased and average differences in end-SOC are presented for all outage events and separately for long outages. Overall, the increased electricity costs resulting from additional charging need due to outage response are on average very low, less than 0.42€ in all cases. However, the maximum increased costs can be over 23€ if the outage response leads to "mandatory" extra charging during expensive electricity hours to reach as high as possible SOC before plug-out.

The average total yearly household electricity costs for different cases with and without outage response are presented in Table 7. Additionally, here we present the weighted average increased yearly costs for charging events with outages, and average yearly battery degradation costs resulting from increased cycling due to outage response. Overall, it can be noted that on average the yearly electricity costs of the households do not increase significantly due to outage response, with less than 1.5€ increase in every case. Additionally, the average degradation costs from increased cycling are very small, less than 0.5€ in all cases. The lowest yearly costs are reached with the *high savings* preference assumption and *V2HG* EV-utilization, with on average around 10 % savings compared to *dumb charging*. It should be noted that around 75–81 % of the yearly savings of the *V2HG* cases, compared to *dumb charging*, result from conventional implicit demand response, i.e., from shifting of EV charging during normal/non-outage operation.

To further analyze the customer preference main objectives (*high end-SOC, high outage handling, high savings*) we present the applicable criteria values with confidence levels in the following figures. The average end-SOC differences and confidence levels (95 %) for all combinations of customer preferences and EV-utilization cases are presented in Fig. 6.

The similar scale of average end-SOC differences is due to the fact that most power outages can be fully handled, and the EV usually has time to recover from the outage event in all customer preference assumption and EV-utilization cases. It's important to highlight that the average differences in end-SOC are computed considering all types of power outages. Consequently, the short, automatically reconnected outages result in very small average end-SOC differences. If only the longer fault outages are considered, the averages are around four times higher as presented in Table 6. Even though the average differences in end-SOC do not have major disparities, in the worst-case scenarios, customer preferences and EV-utilization cases can have a significant impact on the EV SOC at plug-out. These maximum end-SOC differences due to outage response are presented in Table 8. It should be noted that all of these maximums happen due to the same snow load induced power outage event, with a duration of 6.3 h, sampled to January. As can be seen, under the *outage averse* and *high savings* assumptions the plug-out SOC is almost 40 % lower than without outage response. However, under the *high plug-out SOC* preference assumption, the SOC difference is smaller (around 29 %) as the $SOC_{Discomfort}$ constraint is reached. It should be noted that these maximum SOC differences are highly affected by the occurrence time and length of outages, with long and rare system-wide blackouts, the maximum differences in end-SOC can be even higher. In our case, these large maximum SOC differences result from mobility need, as EV plug-out happens before the outage ends and the EV has no time to charge after the end of the outage.

Table 8
Maximum differences in end-SOC due to outage response.

	Dumb	Implicit	V2H	V2HG
HSOC	29.2 %	29.2 %	29.2 %	29.2 %
OAverse	39.4 %	39.4 %	39.4 %	39.4 %
HSavings	39.4 %	39.4 %	39.4 %	39.4 %

The average yearly suffered power outage times and confidence levels (95 %) for all combinations of customer preferences and EV-utilization cases are presented in Fig. 7.

Similarly, to the average difference in end-SOC case, the maximum suffered power outage times are considerably larger than the average values of Fig. 7. Based on regression analysis to assess the sensitivity of suffered outage time, we identified a minor inverse correlation between EV plug-in SOC and suffered power outage durations, indicating that higher initial SOC levels slightly reduce suffered outage time. However, this sensitivity was found to be quite marginal considering all outage types. The maximum durations across all households when the household electricity demand could not be filled with the EV during a power outage are presented in Table 9. The maximum suffered outage durations all result from the same power outage, specifically a snow load-induced outage, which lasted nearly 27 h and occurred in February. The values of *outage averse* and *high savings* scenarios are identical as these assumptions share a similar $SOC_{Discomfort}$ constraint. Overall, in the worst-cases the *HSOC* preference assumption leads to over 24-hour outages due to the higher discomfort SOC constraint and V2H/V2G operation prior to the outage. Even though similar extreme events are rare (as can be seen from the yearly averages in Fig. 7), these very long outages can be huge inconveniences for households.

The average yearly total electricity costs and confidence levels (95 %) for all combinations of customer preferences and EV-utilization cases are presented in Fig. 8. Here it can be noted that with *dumb* EV-utilization, the costs are similar between customer preference assumptions, whereas the *high savings* customer preference leads to lowest

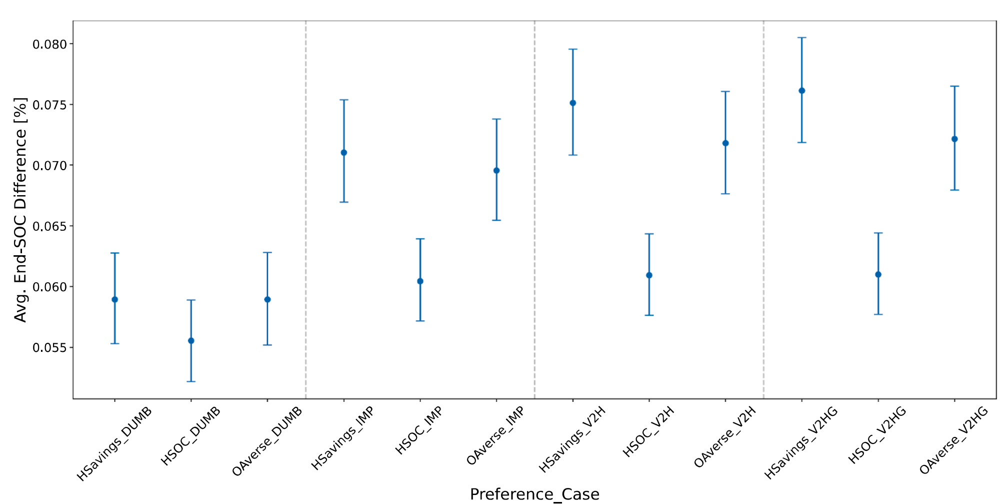

Fig. 6. Average difference in end-SOC for customer preference/EV-utilization cases.

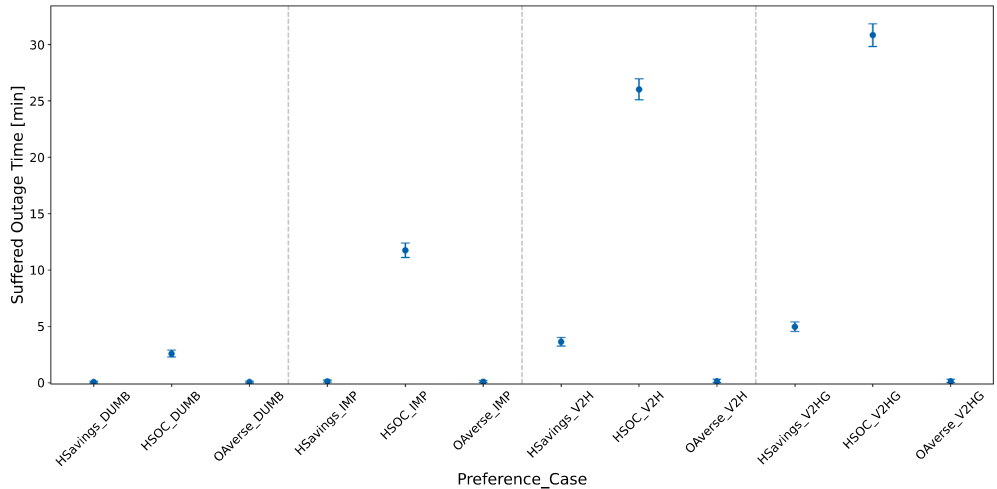

Fig. 7. Average yearly suffered power outage time for customer preference/EV-utilization cases.

Table 9
Maximum suffered outage time during a power outage [h].

	Dumb	Implicit	V2H	V2HG
HSOC	17.4	18.1	24.3	24.3
OAverse	6.6	7.5	15.0	15.0
HSavings	6.6	7.5	15.0	15.0

average total yearly electricity costs in all other EV-utilization cases with around 3 % savings compared to the other preference assumptions.

3.1. Impact of ambient temperature on the results

As ambient temperature has a major impact on energy transfer of EV charging and discharging, we have further analyzed the customer objectives with charging events conducted in three different average ambient temperature intervals (over 0 °C, between 0 °C and −10 °C, and below −10 °C). Here we only consider the difference in end-SOC and suffered power outage time due to outage response, as consideration of the total yearly electricity costs is impossible for temperature intervals that only contain a portion of all charging events conducted during the year.

In Fig. 9, we present the average end-SOC differences with 95 % confidence levels for charging events of the different ambient temperature intervals. It can be seen that the average end-SOC differences are largest and have most variance in charging events conducted in very cold (below −10 °C) temperatures, whereas in positive centigrade temperatures the average end-SOC differences are significantly smaller. Comparison of this figure with Fig. 6, implies that the large overall average end-SOC difference of, for instance, the *HSavings_V2HG* case compared to *HSavings_Dumb* might result mostly from poor performance under cold temperatures. It should however be noted that over 53 % of the analyzed charging events were conducted under positive average temperatures, whereas only 5.1 % of the charging events had an average temperature below −10 °C.

In Fig. 10, we present similar temperature grouping for average suffered power outage times during EV plug-in. Here the suffered outage time is presented in percentages (not in minutes as in Fig. 7) to consider the differing total outage time in different temperature categories. Here it can be noted that colder temperatures do not always result to longer suffered outage times, as is the case with *HSOC_V2HG*. This can result from differing total outage and EV plug-in times in different temperature categories, from differences in hourly electricity prices or demand leading to different initial charging/discharging behavior and from the probabilistic nature of the power outage sampling. In 2022, the Finnish hourly electricity spot-prices were highest and had most variance in August [58] (temperature over 0 °C) which can explain the differences between *HSOC V2H* and *V2HG* behavior, as it might have been very profitable to sell electricity back to the grid during these peak hours, which in turn leads to poorer outage response. Overall, in regard to

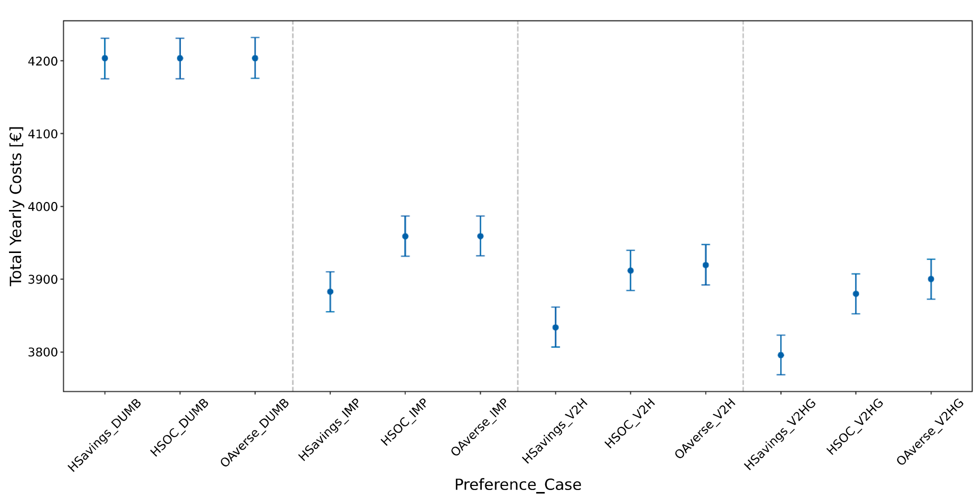

Fig. 8. Average yearly electricity costs for customer preference/EV-utilization cases.

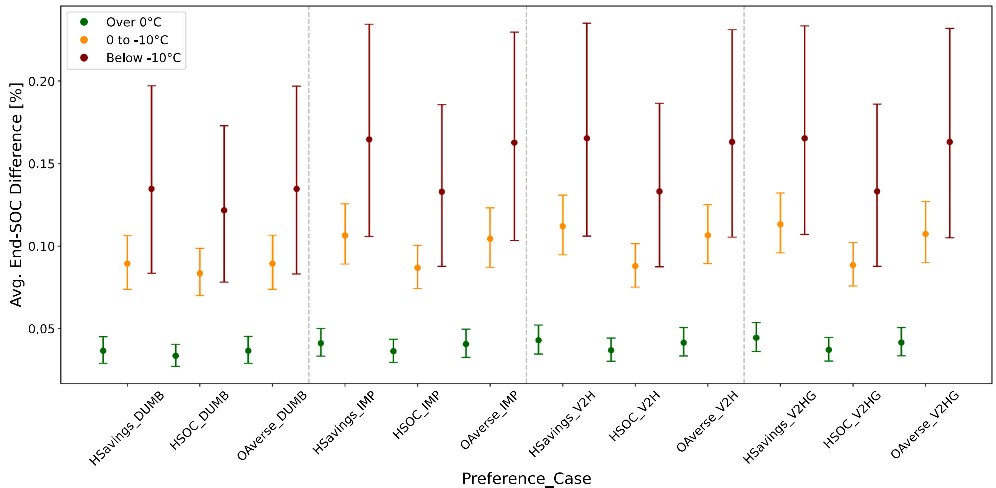

Fig. 9. Average difference in end-SOC for customer preference/EV-utilization cases for charging events conducted under different ambient temperatures.

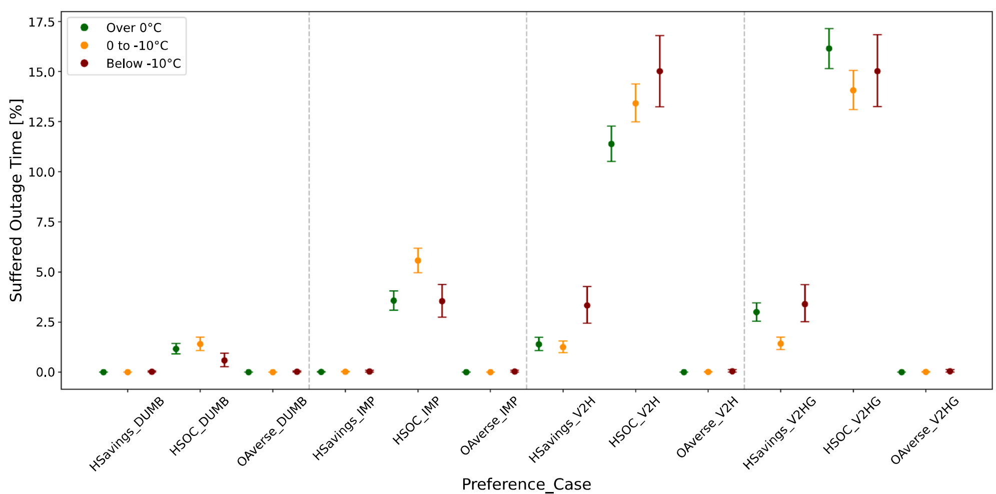

Fig. 10. Average suffered power outage time during charging events under different ambient temperatures for customer preference/EV-utilization cases.

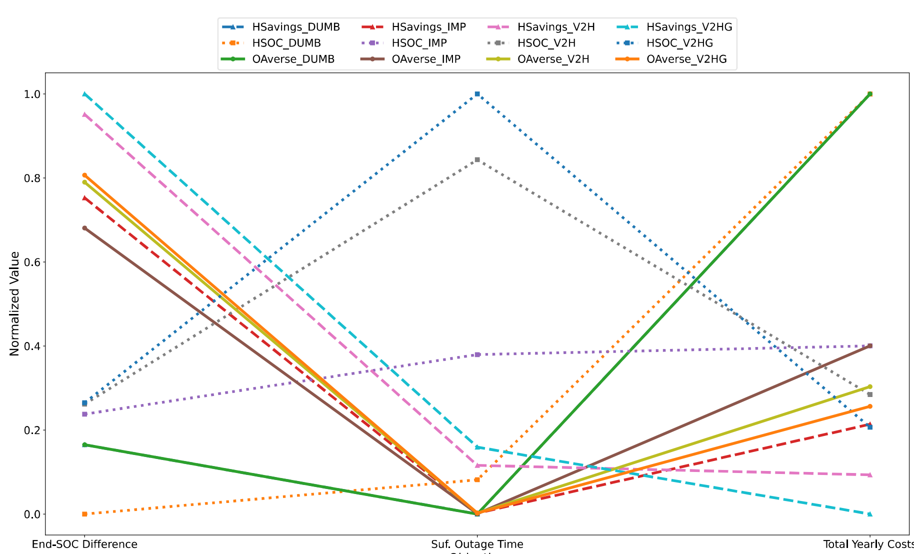

Fig. 11. Normalized customer main objectives under different customer preference/EV-utilization cases.

suffered outage time, the *outage averse* preference assumption dominates other preference assumptions in all temperature groups and EV-utilization cases with even the upper 95 % confidence level being always very close to 0 %.

3.2. Multi-Criteria comparison of the cases

Comparison of the different customer preference/EV-utilization cases in terms of the three main objectives can be seen as a typical multi-criteria decision problem, where no alternative is optimal with respect to all criteria/objectives. The most preferred alternative is normally a compromise between different criteria depending on how the decision-maker sees the relative importance of the criteria. In any case, only Pareto efficient (non-dominated) solutions need to be considered [62]. A solution is non-dominated if no other solution is strictly better with respect to one objective and at least as good with respect to the others.

Fig. 11 shows the different customer preference/EV-utilization case alternatives with average main objective values normalized to the range [0,1]. Here the *high plug-out SOC* objective is represented by the average difference in end-SOC, the *high outage handling* objective by average yearly outage time suffered, and *high savings* by total yearly costs. Thus, for all objectives, a smaller value implies better performance with regards to the customer objective. The normalized objective values of the *HSavings_Dumb* case are identical to *OAverse_Dumb*, thus overlapping in the figure.

It should be noted that none of the cases is dominated by the others, which means that (subject to suitable preferences) any of the alternatives may be regarded optimal (most preferred). If in the different customer preference assumptions only the main objective is of importance, the *V2HG*-case would be the best choice for the *high savings* preference assumption, and "*dumb charging*"-case would be the best choice for both *high plug-out SOC* and *outage averse* preference assumptions.

4. Discussion and conclusions

This study introduced a novel hybrid model to assess the power outage self-sustainment capabilities of households with bidirectional EV charging, while considering different main objectives of the households regarding EV-utilization. The main objectives considered were; outage prevention, household electricity cost minimization and a high EV state-of-charge at the end of the charging event. The optimization was conducted with real AMR and EV charging event data from Finland given four distinct EV-utilization cases and three alternative customer preference assumptions. The study represents the first comprehensive methodology and assessment of V2H outage prevention capabilities under challenging conditions of the northern subarctic climate.

Based on our results, bidirectional EV charging provides an excellent opportunity for households in mitigation of power outages. On average, an EV can be used to handle over 95 % of all outages occurring during EV plug-in. With the *outage averse* preference assumption, almost 98 % of all outages can be fully averted during EV plug-in.

The main reasons for the EV not being able to fully prevent an outage were due to a) reaching of the minimum discomfort SOC-level under which the EV could not discharge its battery, b) higher household power demand than the EV could supply or c) EV plug-out during the outage. Of these reasons a) was almost fully mitigated with the *outage averse* customer preference assumption, where the EV retained a SOC-level of at least 60 % during normal non-outage operation. The reason b) could be mitigated either by lowering the household electricity consumption during power outages (e.g., reducing non-essential appliance use) or by installing a bidirectional charging unit with a higher discharge-power rating. The reason c) could be mitigated by leaving the EV connected to the charger until the outage has passed. In our study, we however assume that the primary use of an EV is mobility, and that outages happening when the EV is not plugged-in do not cause as much discomfort to the household, as at least the EV driver is elsewhere during this time.

There exist major differences between the assessed EV-utilization and customer preference assumptions cases when considering customer main objectives. In outage prevention, the *dumb charging* cases led to lowest suffered outage duration (0.1–2.6 min) during the year, with the overall worst performer being *V2HG* with *high plug-out SOC* preference (30.8 min). The maximum suffered outage time during a single event was also highest with *high plug-out SOC* preference assumption, with variation between 17 and 24 h across EV-utilization cases. In electricity cost minimization, the *dumb charging* cases led to highest total yearly costs, whereas the *V2HG* case with *high savings* assumptions led to highest monetary savings, 10 % reduction in yearly electricity bill compared to *dumb charging*. It should be noted that around 75–81 % of these savings result from conventional implicit demand response, i.e., from shifting of EV charging to cheap electricity hours during normal/non-outage operation. When considering the impact of outage response on the EV SOC at plug-out time, the *dumb charging* cases performed best with smallest deviations in end-SOC, with *V2HG* under *high savings* assumption leading to the worst average results. The differences between these yearly averaged differences in end-SOC were however quite small. The maximum differences in end-SOC due to outage response (~40 %) were noted in *outage averse* and *high savings* preferences, whereas with the *high plug-out SOC* preference this maximum difference was only around 29 % due to higher discomfort SOC constraint. Based on the multi-criteria comparison of different customer preference/EV-utilization cases, none of the cases is dominated by the others, thus the optimal way of utilizing bidirectional charging is heavily influenced by customer inclinations.

Average increased electricity costs resulting from outage response are less than 0.2€ if all outages are considered, and less than 0.5€ for long fault outage events. Based on [24], the average hourly willingness to pay (WTP) to avoid shorter and medium outages (1 h & 4 h) in Finland were 3.2€ & 0.5€ respectively for winter and summer, and 2.2€ & 1.2€ for longer winter and summer outages (24 h & 12 h). Based on these values, it seems that customers would be willing to use bidirectional charging to avoid outages, as the increased costs are on average smaller than the WTP. The maximum increased costs per an outage in our study vary between 18.4€ and 23.2€ for different cases and preference assumptions, with all these worst-case events occurring in the winter. The costs per outage hour in these cases with outage durations between 5 and 7 h ranged from 2.7€ to 4.1€ thus being slightly higher than the estimated customer WTP. It should be noted that these increased costs result from "mandatory" charging during more expensive electricity hours to meet as high as possible SOC before plug-out.

Additionally, the average yearly degradation costs from increased cycling due to bidirectional operation are very small, less than 0.5€ in all cases. As the bidirectional operation does not lead to significant increase in cycling, the EV battery would not reach its estimated lifetime of 1500 cycles until around 25 years with similar utilization. That is, if the battery's lifetime due to calendar aging would be less than 25 years, the cost of cycling degradation could be regarded zero as the lifetime in years is reached before lifetime in cycles [53].

Overall, based on our results it can be stated that EVs can be effectively used to sustain household loads over power outages with V2H given EV availability, high SOC-level when the outage begins and if the EV is not needed for its primary purpose, driving, during the outage. These findings are consistent with previous research [41,42,44]. Our research however showed that V2H (with assumed discharging power of 11 kW) cannot always supply enough power to cover the whole household load during power outages, and that different customer preferences and EV-utilization methods have a significant impact on overall outage response capability as well as to other important customer objectives. In summary, the outage prevention capabilities of EVs via bidirectional charging can serve as an important non-monetary incentive for EV and bidirectional charger adoption, especially as based on our results, and based on [26,27], V2H/V2HG does not offer considerable financial savings compared with conventional implicit DR. It should be noted that, for instance, self-generation and explicit DR programmes can considerably increase the financial profitability of domestic bidirectional EV chargers.

In analyzing the strengths and weaknesses of our proposed approach, it is crucial to acknowledge that while it provides a robust framework for assessing the typical efficacy of V2H in power outage prevention, there are several factors that could lead to its underperformance. A primary limitation lies in the model's reliance on mainly deterministic inputs, which, although grounded in real data, may not fully capture the dynamic and unpredictable nature of household energy consumption, EV usage patterns and power outage occurrence. The reliance on real data, especially of detached household consumer EV charging events and of 5-minute interval AMR consumption data might also pose challenges in replicating similar analyses in regions where such detailed data is not readily available. As the study utilized data from Finland, generalization of results to apply to other locations, especially to non-subarctic regions, can be difficult. However, as the building stock and climate in other Nordic countries is very similar to that of Finland, and as the Nordic countries share a common electricity market, the results can be seen as the best available reference point for Nordic household V2H operation in outage prevention. Nevertheless, bidirectional EV charging can significantly bolster power outage prevention capabilities in all areas, irrespective of climate conditions, with greatest potential in regions characterized by unreliable power grids and frequent outages. Additionally, as in this study we assumed a single EV per household and 11 kW bidirectional chargers, the results are applicable only to comparable systems. It can be speculated that in households with higher power chargers or multiple EVs (or in community scale systems) the outage prevention capabilities and other benefits would be even greater. Another limitation of this study arises from the utilized ambient temperature model, in future research the methodology could be complemented with a dedicated battery model that considers actual battery temperature including possible need for battery heating in the optimization. Inclusion of an accurate battery model would however significantly increase the complexity and computational time needed in the simulation.

As our model employs a primarily deterministic approach due to utilization of real data, with stochastic elements introduced mainly through outage sampling, it is important to acknowledge the inherent uncertainties present in real-life use cases that could influence the predictive accuracy of the model. Factors such as fluctuating electricity prices, variable household demand, changes in ambient temperature, and the availability and initial SOC of the EV can significantly influence the utility of V2H in outage prevention. Applying the model in real-time scenarios would necessitate prediction of household demand, additional data of EV use, and for best performance, information about possible planned power outages, local distribution grid, and of weather events that might cause disruptions in power supply. In future study, integration of these factors could enhance the model's practical utility for V2H households.

To sum up, electric vehicles and bidirectional charging offers multiple benefits to households ranging from financial savings to self-sustainment during power outages. Overall, EVs and V2H significantly improve the energy resilience of households, which is especially important for rural households that are more prone to suffer from blackouts and power outages. Further, outage prevention capabilities enabled through EVs and bidirectional charging serve as an important non-monetary incentive for EV and bidirectional charger adoption.

CRediT authorship contribution statement

Johannes Einolander: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Annamari Kiviaho:** Conceptualization, Validation, Writing – review & editing. **Risto Lahdelma:** Conceptualization, Funding acquisition, Project administration, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

References

[1] F. Capitanescu, Are we prepared against blackouts during the energy transition?: probabilistic risk-based decision making encompassing jointly security and resilience, IEEE Power Energy Mag. 21 (2023) 77–86, https://doi.org/10.1109/MPE.2023.3247053.

[2] S.R. Sinsel, R.L. Riemke, V.H. Hoffmann, Challenges and solution technologies for the integration of variable renewable energy sources—a review, Renew. Energy. 145 (2020) 2271–2285, https://doi.org/10.1016/j.renene.2019.06.147.

[3] A. Marot, A. Kelly, M. Naglic, V. Barbesant, J. Cremer, A. Stefanov, J. Viebahn, Perspectives on future power system control centers for energy transition, J. Mod. Power Syst. Clean Energy. 10 (2022) 328–344, https://doi.org/10.35833/MPCE.2021.000673.

[4] K. Morrissey, A. Plater, M. Dean, The cost of electric power outages in the residential sector: a willingness to pay approach, Appl. Energy. 212 (2018) 141–150, https://doi.org/10.1016/j.apenergy.2017.12.007.

[5] IEA, Global Energy Crisis, (2022). https://www.iea.org/topics/global-energy-crisis (accessed September 1, 2023).

[6] Eurostat, Electricity & gas hit record prices in 2022, (2023). https://ec.europa.eu/eurostat/web/products-eurostat-news/w/DDN-20230426-2 (accessed September 1, 2023).

[7] Finnish Energy, Energy Year 2022 Electricity, (2023). https://energia.fi/wp-content/uploads/2023/08/Electricity_Year_2022.pdf (accessed September 9, 2023).

[8] M. Hofmann, K.B. Lindberg, Residential demand response and dynamic electricity contracts with hourly prices: a study of Norwegian households during the 2021/22 energy crisis, Smart Energy. 13 (2024) 100126, https://doi.org/10.1016/j.segy.2023.100126.

[9] J. Einolander, A. Kiviaho, R. Lahdelma, Detecting changes in price-sensitivity of household electricity consumption: the impact of the global energy crisis on implicit demand response behavior of Finnish detached households, Energy Build. 306 (2024) 113941, https://doi.org/10.1016/j.enbuild.2024.113941.

[10] Finnish Energy Authority, Pörssihintaisten sähkösopimusten osuus nousi lähes 14 prosenttiin vuonna 2022 [The share of exchange-priced electricity contracts rose to almost 14 percent in 2022], (2023). https://energiavirasto.fi/-/porssihintaisten-sahkosopimusten-osuus-nousi-lahes-14-prosenttiin-vuonna-2022 (accessed October 5, 2023).

[11] S. Hautanen, Talvella voi olla edessä kiertäviä sähkö--katkoja – näihin asioihin jokaisen pitää nyt varautua [In the winter, there may be rolling power outages - everyone must now prepare for these things], IS. (2022). https://www.is.fi/politiikka/art-2000009216690.html (accessed September 18, 2023).

[12] S. Noponen, Hallitus valmistelee etäohjattuja katkoksia sähkölämmitteisiin taloihin, mutta kuka vastaa kustannuksista [The government is preparing remotely controlled interruptions for electrically heated houses, but who is responsible for the costs], Taloussanomat. (2023). https://www.is.fi/taloussanomat/art-2000009843208.html (accessed September 18, 2023).

[13] M. Macmillan, K. Wilson, S. Baik, J.P. Carvallo, A. Dubey, C.A. Holland, Shedding light on the economic costs of long-duration power outages: a review of resilience assessment methods and strategies, Energy Res. Soc. Sci. 99 (2023) 103055, https://doi.org/10.1016/j.erss.2023.103055.

[14] D.A. Hensher, N. Shore, K. Train, Willingness to pay for residential electricity supply quality and reliability, Appl. Energy. 115 (2014) 280–292, https://doi.org/10.1016/j.apenergy.2013.11.007.

[15] C. Mazur, Y. Hoegerle, M. Brucoli, K. van Dam, M. Guo, C.N. Markides, N. Shah, A holistic resilience framework development for rural power systems in emerging economies, Appl. Energy. 235 (2019) 219–232, https://doi.org/10.1016/j.apenergy.2018.10.129.

[16] U. Wethal, Practices, provision and protest: power outages in rural Norwegian households, in, Consum. Sustain. Everyday Life, Springer (2023) 135–170, https://doi.org/10.1007/978-3-031-11069-6_6.

[17] A. Kiviaho, J. Einolander, Digital transformation, well-being and shrinking communities: narrowing the divides between urban and rural, Heliyon 9 (2023), https://doi.org/10.1016/j.heliyon.2023.e18801.

[18] J. Freeman, L. Hancock, Energy and communication infrastructure for disaster resilience in rural and regional Australia, Reg. Stud. 51 (2017) 933–944, https://doi.org/10.1080/00343404.2016.1146403.

[19] Energiateollisuus, Keskeytystilasto 2019 [Interruption statistics 2019], Helsinki, 2020. https://energia.fi/files/4972/Sahkon_keskeytystilasto_2019.pdf.
[20] R. Otto, S. Susanne, H. Jouni, L. Jukka, Crown snow load outage risk model for overhead lines, Appl. Energy. 343 (2023) 121183, https://doi.org/10.1016/j.apenergy.2023.121183.
[21] M. Lehtonen, Fault rates of different types of medium voltage power lines in different environments, in: Proc. Electr. Power Qual. Supply Reliab. Conf., IEEE, 2010, https://doi.org/10.1109/PQ.2010.5549998.
[22] J. Lepistö, J. Joentakanen, H. Laurikainen, T. Kekki, Harvaan asuttujen alueiden turvallisuus 2020: tilanneraportti turvallisuudesta harvaan asutuilla seuduilla [safety in sparsely populated areas 2020: situation report on safety in sparsely populated regions.], Ministry of the Interior Finland, 2020. http://urn.fi/URN:ISBN:978-952-324-622-5.
[23] Sähkömarkkinalaki, 588/2013 [Electricity Market Act], Ministry of Trade and Industry, Finland, 2013. https://www.finlex.fi/fi/laki/ajantasa/2013/20130588.
[24] J.J. Cohen, K. Moeltner, J. Reichl, M. Schmidthaler, Linking the value of energy reliability to the acceptance of energy infrastructure: evidence from the EU, Resour. Energy Econ. 45 (2016) 124–143, https://doi.org/10.1016/j.reseneeco.2016.06.003.
[25] A. Hussain, P. Musilek, Resilience enhancement strategies for and through electric vehicles, Sustain. Cities Soc. 80 (2022) 103788, https://doi.org/10.1016/j.scs.2022.103788.
[26] J. Einolander, A. Kiviaho, R. Lahdelma, Household Electricity Cost Optimization with Vehicle-to-Home Technology and Mixed-Integer Linear Programming, in: 2023 Int. Conf. Futur. Energy Solut., IEEE, 2023, https://doi.org/10.1109/FES57669.2023.10182713.
[27] J. Einolander, A. Kiviaho, R. Lahdelma, Impact of V2G, V2H and FCR to Electricity Costs of Households with Varying Primary Heating Sources, in: 26th IEEE Int. Intell. Transp. Syst. Conf., IEEE, 2023, https://doi.org/10.1109/ITSC57777.2023.10422255.
[28] M. Alirezaei, M. Noori, O. Tatari, Getting to net zero energy building: investigating the role of vehicle to home technology, Energy Build. 130 (2016) 465–476, https://doi.org/10.1016/j.enbuild.2016.08.044.
[29] V. Monteiro, B. Exposto, J.C. Ferreira, J.L. Afonso, Improved vehicle-to-home (iV2H) operation mode: experimental analysis of the electric vehicle as off-line UPS, IEEE Trans. Smart Grid. 8 (2017) 2702–2711, https://doi.org/10.1109/TSG.2016.2535337.
[30] J. Einolander, R. Lahdelma, Explicit demand response potential in electric vehicle charging networks: event-based simulation based on the multivariate copula procedure, Energy. 256 (2022) 124656, https://doi.org/10.1016/j.energy.2022.124656.
[31] J. Einolander, R. Lahdelma, Multivariate copula procedure for electric vehicle charging event simulation, Energy. (2021) 121718, https://doi.org/10.1016/j.energy.2021.121718.
[32] G. Chantzis, E. Giama, S. Nižetić, A.M. Papadopoulos, The potential of demand response as a tool for decarbonization in the energy transition, Energy Build. 296 (2023) 113255, https://doi.org/10.1016/j.enbuild.2023.113255.
[33] A. Dik, C. Kutlu, S. Omer, R. Boukhanouf, Y. Su, S. Riffat, An approach for energy management of renewable energy sources using electric vehicles and heat pumps in an integrated electricity grid system, Energy Build. 294 (2023) 113261, https://doi.org/10.1016/j.enbuild.2023.113261.
[34] S. Ma, M. Jiang, P. Tao, C. Song, J. Wu, J. Wang, T. Deng, W. Shang, Temperature effect and thermal impact in lithium-ion batteries: a review, Prog. Nat. Sci. Mater. Int. 28 (2018) 653–666, https://doi.org/10.1016/j.pnsc.2018.11.002.
[35] J. Jaguemont, L. Boulon, Y. Dubé, A comprehensive review of lithium-ion batteries used in hybrid and electric vehicles at cold temperatures, Appl. Energy. 164 (2016) 99–114, https://doi.org/10.1016/j.apenergy.2015.11.034.
[36] W. Wu, R. Ma, J. Liu, M. Liu, W. Wang, Q. Wang, Impact of low temperature and charge profile on the aging of lithium-ion battery: non-invasive and post-mortem analysis, Int. J. Heat Mass Transf. 170 (2021) 121024, https://doi.org/10.1016/j.ijheatmasstransfer.2021.121024.
[37] J. Lindgren, P.D. Lund, Effect of extreme temperatures on battery charging and performance of electric vehicles, J. Power Sources. 328 (2016) 37–45, https://doi.org/10.1016/j.jpowsour.2016.07.038.
[38] Y. Motoaki, W. Yi, S. Salisbury, Empirical analysis of electric vehicle fast charging under cold temperatures, Energy Policy. 122 (2018) 162–168, https://doi.org/10.1016/j.enpol.2018.07.036.
[39] V. Tikka, J. Lassila, T. Laine. Technical report: measurements of cold climate EV charging, LUT University, Lappeenranta, 2021.
[40] V. Tikka, T. Laine. Measurements of cold climate EV charging, LUT University, Lappeenranta, 2021. http://urn.fi/urn:nbn:fi:att:1ac935ce-fbb9-422e-9081-9a8db3c53399.
[41] Y. Yang, S. Wang, Resilient residential energy management with vehicle-to-home and photovoltaic uncertainty, Int. J. Electr. Power Energy Syst. 132 (2021) 107206, https://doi.org/10.1016/j.ijepes.2021.107206.
[42] H. Shin, R. Baldick, Plug-in electric vehicle to home (V2H) operation under a grid outage, IEEE Trans. Smart Grid. 8 (2017) 2032–2041, https://doi.org/10.1109/TSG.2016.2603502.
[43] L.J. Daniel, C.W. King, D.P. Tuttle, W.A. Paxton, Computational tool for analysis of vehicle-to-home as home backup solution during power outages, Energy Reports. 11 (2024) 1472–1486, https://doi.org/10.1016/j.egyr.2024.01.015.
[44] H. Gong, D.M. Ionel, Combined Use of EV Batteries and PV Systems for Improving Building Resilience to Blackouts, in: 2021 IEEE Transp. Electrif. Conf. Expo, 2021, pp. 584–587, https://doi.org/10.1109/ITEC51675.2021.9490056.
[45] H. Mehrjerdi, Resilience oriented vehicle-to-home operation based on battery swapping mechanism, Energy. 218 (2021) 119528, https://doi.org/10.1016/j.energy.2020.119528.
[46] Z. Dong, X. Zhang, N. Zhang, C. Kang, G. Strbac, A distributed robust control strategy for electric vehicles to enhance resilience in urban energy systems, Adv. Appl. Energy. 9 (2023) 100115, https://doi.org/10.1016/j.adapen.2022.100115.
[47] Y. Deng, Y. Mu, X. Wang, S. Jin, K. He, H. Jia, S. Li, J. Zhang, Two-stage residential community energy management utilizing EVs and household load flexibility under grid outage event, Energy Reports. 9 (2023) 337–344, https://doi.org/10.1016/j.egyr.2022.10.414.
[48] C. Xu, P. Behrens, P. Gasper, K. Smith, M. Hu, A. Tukker, B. Steubing, Electric vehicle batteries alone could satisfy short-term grid storage demand by as early as 2030, Nat. Commun. 14 (2023) 119, https://doi.org/10.1038/s41467-022-35393-0.
[49] A. Mansour-Saatloo, A. Moradzadeh, B. Mohammadi-Ivatloo, A. Ahmadian, A. Elkamel, Machine learning based PEVs load extraction and analysis, Electronics. 9 (2020) 1150, https://doi.org/10.3390/electronics9071150.
[50] M. Akil, E. Kilic, R. Bayindir, A. Sebati, R. Malek, Uncoordinated charging of EVs based on an actual charging session data, in: 2021 10th Int. Conf. Renew. Energy Res. Appl., 2021, pp. 459–462, https://doi.org/10.1109/ICRERA52334.2021.9598554.
[51] J. Dunckley, Electric vehicle driving, charging, and load shape analysis: a deep dive into where, when, and how much Salt River project (SRP) Electric Vehicle Customers Charge, EPRI (2018) 3002013754.
[52] A.C. Duman, H.S. Erden, Ö. Gönül, Ö. Güler, A home energy management system with an integrated smart thermostat for demand response in smart grids, Sustain. Cities Soc. 65 (2021) 102639, https://doi.org/10.1016/j.scs.2020.102639.
[53] W. Kempton, J. Tomić, Vehicle-to-grid power fundamentals: calculating capacity and net revenue, J. Power Sources. 144 (2005) 268–279, https://doi.org/10.1016/j.jpowsour.2004.12.025.
[54] M.S.S. Fogliatto, H.O. Caetano, L.N. Desuó, J.A.D. Massignan, R.Z. Fanucchi, J.B. A. London, B.R. Pereira, M. Bessani, C.D. Maciel, Power distribution system interruption duration model using reliability analysis regression, Electr. Power Syst. Res. 211 (2022) 108193, https://doi.org/10.1016/j.epsr.2022.108193.
[55] Statistics Finland, Official Statistics of Finland (OSF): Number of buildings by intended use and heating fuel, 2022, (2023). https://pxdata.stat.fi/PxWeb/pxweb/en/StatFin/StatFin__rakke/statfin_rakke_pxt_116h.px/ (accessed October 14, 2023).
[56] A. Lucas, R. Barranco, N. Refa, EV Idle time estimation on charging infrastructure, comparing supervised machine learning regressions, Energies. 12 (2019) 269, https://doi.org/10.3390/en12020269.
[57] Finnish Meteorological Institute, Download observations, (2023). https://en.ilmatieteenlaitos.fi/download-observations (accessed June 15, 2023).
[58] ENTSO-E, Transparency platform, (2023). https://transparency.entsoe.eu (accessed May 1, 2023).
[59] E. Apostolaki-Iosifidou, P. Codani, W. Kempton, Measurement of power loss during electric vehicle charging and discharging, Energy 127 (2017) 730–742, https://doi.org/10.1016/j.energy.2017.03.015.
[60] Y.A. Shirazi, D.L. Sachs, Comments on "measurement of power loss during electric vehicle charging and discharging" – notable findings for V2G economics, Energy 142 (2018) 1139–1141, https://doi.org/10.1016/j.energy.2017.10.081.
[61] G.M. Freeman, T.E. Drennen, A.D. White, Can parked cars and carbon taxes create a profit? The economics of vehicle-to-grid energy storage for peak reduction, Energy Policy 106 (2017) 183–190, https://doi.org/10.1016/j.enpol.2017.03.052.
[62] R.L. Keeney, H. Raiffa, Decisions with Multiple Objectives: Preferences And Value Trade-Offs, Cambridge University Press, 1993.