Einolander, Johannes; Kiviaho, Annamari; Lahdelma, Risto

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Valuing the household power outage self-sustainment capabilities of bidirectional electric vehicle charging

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 University of Helsinki, 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

HIGHLIGHTS

- Assessment of EV bidirectionality enabled power outage self-sustainment
- Value of household self-sustainment estimated with both WTP and VOLL
- Methodology considers different household heating types and customer preferences
- Up to 99.7% of outages occurring during EV plug-in can be fully self-sustained
- Yearly value of self-sustained outages relatively low, but can reach up to 330€
- Highest yearly benefits from bidirectional charging in electric-heated households

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ABSTRACT

In an increasingly digitalized and electrified world, our dependence on reliable electricity has become more critical than ever. This reliance means that even brief power outages can cause significant discomfort, highlighting a major weakness in our interconnected lives. Bidirectional electric vehicle (EV) charging provides a possible solution for self-sustainment during power outages. In this study, we present the first available assessment of the value of power outage self-sustainment with bidirectional electric vehicle charging for household consumers. The study builds on an LP model used to optimize system electricity costs, on a deterministic power outage response model, and on real data of household electricity use and electric vehicle charging behavior. Further, we utilize k-means clustering to group households into different primary heating types based on system operator load curves. Two of the most popular valuation metrics, value of lost load (VOLL) and willingness to pay (WTP) are used to assess the value of annual outage self-sustainment with bidirectional EV charging. Based on our results, up to 99.7% of outages occurring during EV plug-in can be fully self-sustained. However, the average total annual value of self-sustained outages is relatively low (<24€) regardless of the valuation metric, with VOLL giving considerably higher values, reaching up to 330€ in maximum cases. Overall, the highest average total yearly benefits from bidirectional charging are gained by electric-heated households.

1. Introduction

In an increasingly electrified world, our dependence on reliable electricity has become more critical than ever. From the smart cities to remote rural communities, the seamless flow of electricity underpins not just our day-to-day convenience, but also our safety, economic stability, and technological progress. However, this reliance reveals a glaring vulnerability: power outages. Even brief disruptions in the electricity supply can cause significant discomfort and inconvenience, highlighting a crucial weakness in our modern, interconnected lives. Additionally, the energy transition including i.a. increased variable renewable energy integration, electric vehicles (EVs), and the retirement of traditional power plants, is altering power grid dynamics, reducing the security and resilience of the transmission grid through increased variability and decreased predictability [1]. Climate change-induced extreme weather

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

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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
PHEV	Plug-in Hybrid Electric Vehicle
PV	Photovoltaics
SOC	State of Charge
TSO	Transmission System Operator
V2G	Vehicle-to-Grid
V2H	Vehicle-to-Home
VOLL	Value of Lost Load
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-min intervals), 1, …, T
b	Time index of the power outage event (1-min 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 impact 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]
EC_h	Annual electricity consumption of detached household [kWh]
$EV_b^{Plugged-out}$	EV unavailability during outage, at time b [bin]
f_{sub}	Substitutability factor [1]
L^{Cyc}	Battery lifetime in cycles [1]
N_{emp}	Average number of employed persons [1]
$N_{non-emp}$	Average number of non-employed persons [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_{Disc}	Discomfort SOC level during power outages [1]
SOC_t, SOC_b	SOC at time t or b [1]
SOC_{min}	Minimum SOC level [1]
SOC_{max}	Maximum SOC level [1]
$SOC_{Plug-in}$	Plug-in SOC level [1]
$SOC_{Plug-out}$	Plug-out SOC level [1]
SOC_T	SOC at the end of optimization, at plug-out [1]
SOC_B	SOC at the end of a power outage event [1]
$T^{Not-fulfilled}$	Outage duration, not fulfilled by EV [h]
$T_{leisure}$	Annual average leisure time of an employed person [h]
t_{outage}	Outage duration, in WTP calculation [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 discharge, at time period b [h]
τ_b^{Outage}	Duration of outage, at time period b [h]
$\tau_b^{ToPlugout}$	Time to EV plug-out, at start of time period b [h]
η^{cha}	EV charging efficiency [1]
η^{dis}	EV discharging efficiency [1]
$VOLL_h$	VOLL for household h [€/kWh]
w_{avg}	Average hourly wage [€/h]

events further strain grids, heightening the risk of power outages [2]. As dependence on electricity in our daily lives is constantly rising, understanding, and mitigating the impacts of power outages becomes ever more important. Emerging technologies such as bidirectional electric vehicle charging offer potential solutions for boosting energy resilience and enabling households to self-sustain during power outages [3].

Power outages can have devastating consequences across the whole society. However, in today's highly digitalized world, the primary inconveniences caused by power outages for households are increasingly concentrated on interruptions in Information and Communication Technology (ICT) use, as ICT is not easily replaceable by other technologies or appliances [4]. Direct costs of power outages for residential customers are typically defined as the economic consequences, that is lack of consumption, arising from the disturbance in electricity access [5]. Furthermore, power outages can cause direct disruptions to ICT-dependent remote work, leading to immediate effects on productivity. There are also significant indirect and intangible costs resulting from power outages, such as inconvenience, lack of comfort, lost leisure and fear [2]. There exist different ways to estimate overall costs and values resulting from power outages. The most often used metrics meant to encapsulate outages in monetary terms are willingness to pay (WTP) and value of lost load (VOLL). While in some studies, VOLL is regarded as the broader term encompassing both metrics, it is more specifically used in this analysis to denote the statistics-based economic value of electricity not supplied due to outages. On the other hand, WTP represents the more subjective amount households are prepared to spend to avert power interruptions. Despite their inherent limitations, both metrics are employed in this study to conduct a comprehensive evaluation of bidirectional EV charging's potential in power outage self-sustainment.

Stated preference surveys are often used to capture the monetary and non-monetary costs resulting from interruptions in electricity supply and thus assess the willingness to pay (WTP) of individuals to avoid a power outage [6]. Major concerns in this approach are the subjective nature of perceived discomfort from outages and hypothetical bias, as in surveys' respondents might not answer accurately compared with actual behavior and attitudes in real outage scenarios [7]. The results of WTP studies are typically presented as payment per an hour of outage [8], or as payment per an outage of duration t [2].

Value of lost load (VOLL) describes the estimated value of electric load lost due to an interruption in power supply and is typically expressed as payment per kWh [7,9]. Most previous VOLL studies present and utilize fixed point estimates and population averages for VOLL

[9,10]. However, as in reality VOLL varies by each end-user, use-case, location, and the occurrence time of the outage, using these point estimates poses significant challenges and simplifies the complexity of electricity consumption [11]. Moreover, the growing prevalence of remote work in contemporary societies – heavily reliant on ICT and reliable electricity supply – means household outages can significantly interrupt remote working [4]. Since household VOLL is typically derived only from leisure time, the current VOLL estimates cannot be used to quantify the value of lost loads during remote working periods.

Bidirectional EV utilization can bring financial benefits to households, for instance, through utilization of the EV battery as an electricity storage to store cheap, or self-generated, electricity and from participation to different explicit demand response marketplaces, such as to frequency containment reserves [12,13]. In this context, vehicle-to-grid (V2G) can be regarded as 'arbitrage trading', where the EV owner charges the EV battery during cheap electricity hours and discharges/sells the electricity back to the grid during expensive hours to achieve profit similarly as with traditional battery storage systems [14]. Even though bidirectional charging can enable multiple substantial benefits, based on [15], there exists some skepticism among industry experts of the benefits and necessity of bidirectional charging in the Nordic countries. In [15], the top barriers for bidirectional charging were seen to be preference for other technologies, and customer resistance. There also exists a lack of awareness of V2G and its benefits, particularly among individuals who are not experts in the field, like household consumers [16,17]. However, these studies did not consider the added benefit of outage self-sustainment enabled by bidirectional charging, which is not possible with most alternative technologies, and which might be one of the keys to reducing customer resistance and increasing awareness of the benefits of bidirectional charging. During power outages, EVs with bidirectional chargers and suitable power electronics can be used to power household electricity demand akin to an uninterruptible power supply (UPS) [18]. UPS operation of EVs has been experimentally validated, for instance, in [19]. In this study, we aim to assess the value of bidirectional electric vehicle charging in enabling households with various primary heating sources to self-sustain power during outages.

Power outage self-sustainment in household systems containing i.a. battery energy storage systems (BESS) and photovoltaics (PV), but without EVs, has been covered in some previous studies. For instance in [20], the authors found that a combination of PV and 10 kWh BESS can meet limited critical loads in most United States counties throughout the year, with worst performance during winter months. Additionally, based on [21], rooftop photovoltaics could be used by over two million European detached households to become fully energy self-sufficient by 2050, implying zero risk of outages due to power grid disturbances for these households. However, contrary to permanent, property-specific solutions such as PV and BESS, EVs might provide a more cost-efficient and flexible solution to outage self-sustainment. This is particularly relevant in rural areas which are more prone to power outages [22] and where real estate prices are low and declining [23].

There exist only a limited number of previous studies that consider the outage self-sustainment potential with bidirectional vehicle-to-home (V2H) EV operation. For instance, in [24], the authors conducted a simulation with a load curve from an urban housing complex in India, and found that V2H can maintain uninterrupted power to critical loads during short power outages. In [25] the authors proposed an optimization model with a plug-in hybrid electric vehicle (PHEV) and photovoltaics to maximize V2H backup power duration during outages. Here the gasoline engine of the PHEV was used alongside the vehicles battery to provide electricity to the households during outages, leading to self-sustainment periods of three to five days during on-peak season, depending highly on the amount of gasoline in the car [25]. In [26], the authors considered both PHEVs and non-hybrid EVs in supporting household demand during outages. Here the EV outage backup duration with EVs was estimated to be somewhere between 10 and 50 h, depending on the month of the outage and battery size [26]. It should be noted that in these previous studies, the battery state-of-charge (SOC) was assumed to be full at the beginning of the outage, and it was assumed that the vehicles were not needed for mobility during or immediately after the outages, so the values can be thought as the maximum self-sustainment potentials with EV batteries, however disregarding the impact of the primary purpose of EVs, mobility. Furthermore, there exists no previous studies that consider the value of outages self-sustained with bidirectional EV operation implying a significant research gap.

This study builds on and utilizes similar models for system optimization and power outage response as in [27]. The study [27] proposed a novel methodology considering the impact of ambient temperature for estimating power outage self-sustainment capabilities with V2H, and found that bidirectional charging can fully sustain household loads during majority of outages. Contrary to [27], this research introduces novel elements, such as the consideration of various primary heating sources of Finnish detached households through load curve clustering. Most significantly, we assess the value of bidirectionality-enabled outage self-sustainment in monetary terms through VOLL and WTP. By integrating these new dimensions atop the existing models, we aim to provide a more comprehensive understanding of the potential benefits and economic implications of bidirectional electric vehicle charging for enhancing energy resilience and outage self-sustainment in detached households especially in rural regions of highly electricity dependent and digitalized societies.

As a Nordic country with a subarctic climate, Finland experiences long, dark, and cold winters, making households particularly vulnerable to winter-time power outages compared to those in more temperate regions. This is especially critical for electrically heated households, where prolonged outages can lead to life-threatening cooling. In Finland, winter is the longest season of the year, lasting 100 to 200 days depending on the latitude [28], with average temperature of January being below −7 °C in central Finland [29]. Additionally, 37.3% of all permanently occupied buildings in Finland are detached houses [30], which are particularly prevalent in rural, sparsely populated regions. These factors make Finland an especially interesting location for analyzing EV bidirectionality-enabled power outage self-sustainment.

Overall, this study contributes to the understanding of bidirectional EV charging's potential and value in enhancing energy resilience in detached households. Our analysis of bidirectional charging under different customer preference assumptions, alongside the application of standard metrics like VOLL and WTP, offers a practical, yet novel, approach to the assessment of the value of power outage self-sustainment with V2H. To the authors' knowledge, this paper presents the first assessment of the value of outage self-sustainment enabled by bidirectional EV charging. Furthermore, our consideration of different primary heating sources adds depth to the study, providing valuable and novel insights to researchers, industry professionals, and consumers alike.

2. Methodology

The aim of this study is to assess the value of power outage self-sustainment capabilities of bidirectional EV charging for subarctic detached households with different primary heating sources. This section begins with description of the different EV utilization and customer preference scenarios assessed in the study. The remainder of the methodological framework is presented in the simplified flowchart of Fig. 1.

The workflow starts with the clustering of households by heating source (HS) using the automatic meter reading (AMR) dataset, as described in Section 2.2. Following this, we sample power outages for each charging event of each household-charging point (HC) combination, as outlined in Section 2.4. Next, we iterate through the charging events of each HC, given different customer preference assumptions (CPA), and optimize the household system during the event using the LP

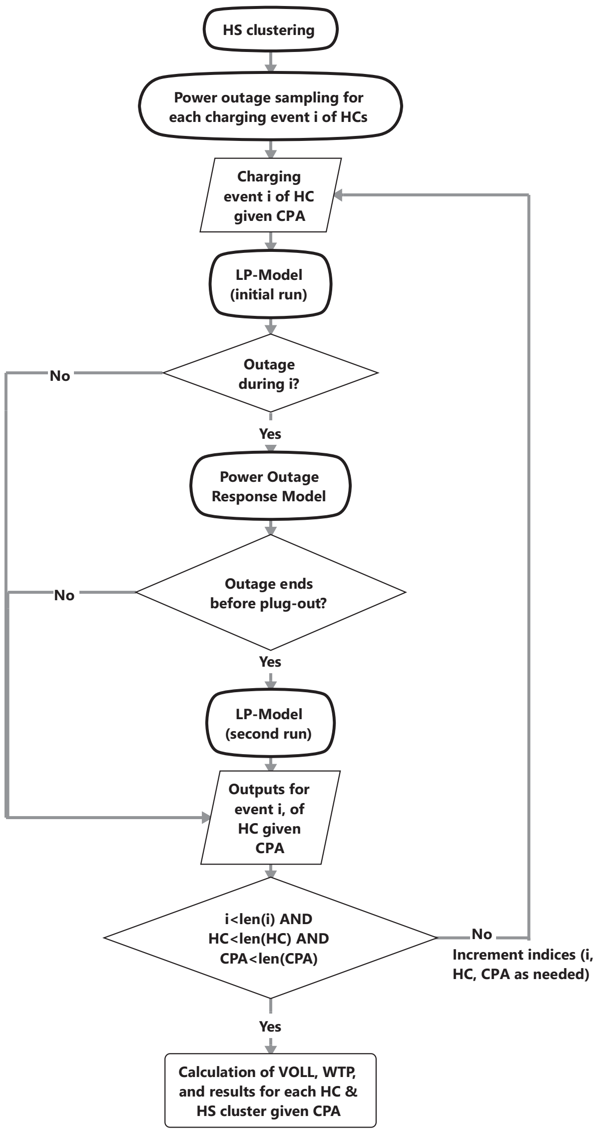

Fig. 1. Simplified workflow.

model, presented in Section 2.3. After the *initial run* of the LP model, if a power outage has been sampled for the charging event, the power outage response model (Section 2.4) is invoked. Afterwards, if the outage ends before EV plug-out, the LP model is called again to optimize the system for the remaining plug-in period. The LP model and the power outage response model are adapted from related models described in [27]. It should be noted that in the *implicit DR* case, described in the following subsection, the power outage response model is not utilized as outage self-sustainment is not possible.

Finally, we estimate the value of outage aversion and calculate different outage self-sustainment statistics for each HC and, subsequently, for each HS cluster, given the different CPA. The valuation approaches used to estimate the value of power outage aversion are introduced in section 2.5. Here we consider outage valuation with the two most popular outage valuation metrics: value of lost load (VOLL) and willingness to pay (WTP). The section ends with description of the datasets, assumptions, and computational resources used in the study.

2.1. Scenario descriptions

Regarding EV utilization in the households two different cases are considered: *Implicit demand response (DR)* and *bidirectional charging*. In *implicit DR*, EV charging is scheduled to the least expensive hours of the charging event to minimize charging costs, this is also known as smart charging. In this case outage prevention is not possible as electricity from the EV battery cannot be discharged to the household. In the *bidirectional charging* case, a bidirectional EV charging point is considered with the possibility to use electricity from the EV both in the household (V2H) and sell it back to the grid (V2G), and thus benefit from 'arbitrage trading'.

In this study, we primarily focus on *implicit DR* as our main reference point, diverging from the common approach of using *dumb charging* as the reference as in most previous studies. This choice is based on the "built-in" *implicit DR* functionality in most newer EV models, which allows the control of charging times directly through the EV itself, even without a dedicated smart charging point. Consequently, utilization of *dumb charging* as the reference point can easily lead to overestimation of the direct monetary benefits from *bidirectional charging*. However, in our study, we employ *dumb charging* as an additional reference to demonstrate that a significant portion of the value generated from *bidirectional charging*, if *dumb charging* is used as the reference point, is attributable to conventional smart charging (*implicit DR*).

In addition to the EV-utilization cases, this study considers three different customer preference assumptions summarized in Table 1. The customer preference assumptions (*high savings (HSavings)*, *high outage averse (OAverse)* and *high SOC discomfort (HSOC)*) prioritize different main objectives during EV plug-in; minimizing household electricity costs, reducing the impact of power outages, and ensuring the EV has a high state-of-charge especially when nearing the plug-out time. These assumptions are similar to Ref. [27] which can be reviewed for more detailed description. Table 1 summarizes the assumptions made under different customer preference assumptions. Here SOC_{min} refers to the minimum SOC level the EV can be discharged to during normal non-outage operation, and SOC_{Disc} refers to the minimum SOC level constraint during a power outage. By having these separate minimum SOCs for outage and non-outage operation, we can consider the discomfort resulting from possible low plug-out SOC levels due to outage response in the model. SOC_{Disc} is used in the power outage response model introduced in section 2.4, and SOC_{min} in both the LP model and the outage response model.

2.2. Heating source clustering

In this study we utilize an automatic meter reading (AMR) dataset that covers electricity consumption readings of Finnish detached households. Detailed dataset description is covered in Section 2.6. As AMR datasets do not contain information about the primary heating sources of the buildings, we utilized clustering to estimate the heating types of the analyzed households. For this purpose, we employed the k-means clustering algorithm, a widely acknowledged method in machine learning for pattern recognition, previously utilized also in heating type clustering with AMR data [31]. Utilizing the most recent available load curves for Finnish detached households, developed in [32,33] based on 2016–2018 AMR data from all detached households in Helsinki, the algorithm was fitted to discern distinct patterns in electricity consumption of households with different primary heating sources (district heating, ground source heat pump, oil heating, and heating types based on electricity; direct electric, storage heaters, night-time water heating).

Load curves represent the average hourly electricity consumption profiles for various customer categories and are routinely utilized by

Table 1
Assumptions under different customer preference assumptions.

Customer preference assumption	Main objective	SOC_{min}	SOC_{Disc}
HSavings	High savings	20%	20%
OAverse	High outage response	60%	20%
HSOC	High plug-out SOC	60%	Eq. (18)

distribution system operators in system management and load forecasting. In our study, the detached household load curves by primary heating type provided a robust foundation for the clustering of households in our AMR dataset. After fitting the k-means algorithm to the processed load curve data, we used the algorithm to predict the primary heating sources of the households in our dataset. This effectively categorized the households into the six heating type clusters based on electricity usage patterns. After the clustering, electricity-based heating type clusters were merged into a single cluster "electric heating" due to a relatively small number of households in clusters "storage heaters" and "night-time water heating". This consolidation into one "electric heating" group ensures a more robust and statistically significant grouping, enhancing the reliability and interpretability of the results. That is, the resulting household primary heating sources analyzed in this study are: district heating (DH), ground source heat pump (GSH), oil heating (Oil), and electric heating (Elec).

2.3. LP model

In this study we utilized a similar linear programming (LP) approach as in [27,34] to optimize the household electricity usage in *implicit DR*, and *bidirectional charging* cases. Additionally, we computed deterministically a *dumb charging* case, where the EV begins charging immediately after plug-in. The adapted LP model is employed to optimize the household and EV system aiming to minimize the electricity costs of a system comprising of a detached house and an EV during each EV charging event. The LP model is used before outages to estimate parameters needed for the power outage model (SOC at outage occurrence time etc.), this is referred to as the *initial run* of the model. If the EV remains plugged in after the end of an outage, the same LP model is used again to optimize the system for the rest of the plug-in period, this is referred to as the *second run* of the model.

In Eq. (1), the objective function aims to minimize the overall cost of electricity purchased from the grid during EV plug-in. E_t^{Hou} is designated as electricity purchased from the grid for use in the household, and E_t^{EV} denotes electricity purchased from the grid for EV charging, $E_t^{V2G}\eta^{dis}D_t$ is the V2G sales to the grid, at event period t, where event periods are 5-min intervals, or less, in order to match the household AMR data. The LP model also considers the impact of outdoor temperature on EV charging and discharging, as losses are higher in cold temperatures than in warm temperatures, leading to reduced profitability of V2H and V2G operations. Thus, during the event period t, D_t represents the ambient temperature impact factor. This factor is based on laboratory measurement data from [35,36], which has been utilized previously in similar use cases, for instance in [27].

Other variables in Eq. (1) are defined as follows; C_t^{Spot} denotes the hourly electricity spot market rate, C^{VAT} covers the value added taxes (24%), C^{Mar} refers the margin of the electricity supplier while, C^{Tra} includes charges based on transferred energy, such as transmission fees, security of supply payments, and electricity taxes, including VAT. It should be noted that in *implicit DR* cases, E_t^{V2G} is disregarded, and E_t^{Hou} is not a variable as all household electricity is purchased from the grid. That is, 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}.

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

subject to

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

$$E_t^{EV} \le P_t^{cha}\tau_t \tag{3}$$

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

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

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

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

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

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

$$t = 1, \dots, T$$

As the discharged energy transferred to the household $E_t^{V2H}\eta^{dis}D_t$ cannot be larger than the household demand E_t^{Dem}, it is constrained by Eq. (2). Because the energy charged in an EV cannot exceed the energy transferred in the timeframe τ_t with maximum power, this is constrained by Eq. (3). Constraint (4) ensures that the discharged energies or their sum cannot be larger than the energy discharged in the timeframe with maximum power. It is assumed that the discharged energy can be used simultaneously in the house and sold to the grid during normal non-outage operation.

Constraint (5) establishes the minimum and maximum SOC for EVs, where SOC_{min} is based on three customer preference assumptions discussed in Section 2.1. The EV SOC at time-period t of the event is calculated with (6). Eq. (7) ensures that the battery is full, or as full as possible, at the end of the charging event. Constraint (8) ensures that the original household electricity demand in the addressed time-period is equal to the discharged electricity from the EV plus household electricity purchased from the grid. The energy flows and losses in the LP model are further illustrated in Fig. 2 to clarify the process.

The following Eqs. (10)–(12) are used to calculate the initial SOC level SOC_0 at the start of the optimization, and the plug-out SOC level $SOC_{Plug-out}$ used in Eq. (7). As noted in Eq. (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. In the possible *second run* of the model, when utilizing the same LP model to optimize the system for the remaining plug-in period after an outage, we use the SOC after the outage/blackout event, SOC_B, as the initial SOC of the optimization.

As the EV charging event data does not include information of the EV SOC levels at plug-in, these levels are estimated with Eq. (11). In most cases the EV reaches a maximum SOC level during the event (more electricity could be transferred during the event with full power) and the plug-in SOC can be calculated with the first part of Eq. (11). However, in rare cases, where we cannot estimate that the EV is fully charged by the end of the event, the EV plug-in SOC distribution based on Ref [37] is used in plug-in SOC sampling. Lastly, Eq. (12) is used to calculate the SOC at the end of the charging event $SOC_{Plug-out}$, which should be as high as possible to avoid compromising the EV's driving range unless required by outage response. That is, the plug-out SOC should be either the maximum SOC or the highest possible SOC level that can be reached if charged with full power for the modelled event duration.

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

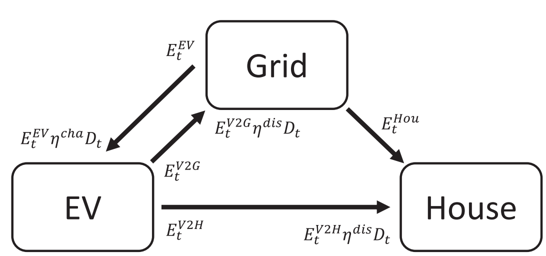

Fig. 2. Energy flows in the LP model.

$$SOC_{Plug-in} = \begin{cases} SOC_{max} - \frac{E^{Event}\eta^{cha}}{E^{Bat}} \text{ if } P^{max,cha}\tau^{Dur} \geq E^{event} \\ \text{Sampled from distribution otherwise} \end{cases} \quad (11)$$

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

The battery degradation costs for the extra cycling from bidirectional operation are estimated similarly as in [34,38,39] with Eq. (13). These battery degradation costs from cycling C^{Deg} are not incorporated into the LP model as they can be regarded zero if the battery's lifetime in years is reached before the battery's lifetime in cycles [39]. Based on [34], bidirectional operation in typically operated consumer EVs does not increase cycling so much that the lifetime in cycles would be reached before battery lifetime in years. In Eq. (13), C^{Rep} denotes battery replacement cost while L^{Cyc} denotes the battery lifetime in cycles. It should be noted that the cycling degradation costs should be incorporated into the objective function if the EVs would be under heavy utilization, e.g., used as taxis, as then it is more probable that the battery lifetime in cycles is reached before lifetime in years.

$$C^{Deg} = \frac{C^{Rep}}{L^{Cyc}E^{Bat}} \quad (13)$$

2.4. Power outage sampling and outage response model

Power outages are sampled separately for each charging event of each considered household-charging point combination. That is, the outages differ between considered households, but are consistent between different customer preference assumptions and EV-utilization cases (*bidirectional/implicit DR*). We utilize power outage statistics from Finnish Energy [40] to sample power outage events according to their distribution and typical occurrence. Table 2 provides a summary of the outage statistics for regions outside urban area development plans for the four outage types used in the power outage sampling. These statistics are utilized to sample power outages for each charging event, considering the probabilities of outage occurrences and season (for snow and ice load outages occurring only in the winter months). It is assumed that there is an equal probability of an unplanned outage occurring at any given minute of the season (winter, non-winter) due to lack of information about specific reasons for outages in the statistics of [40]. Similarly, as in the study by [41], the model uses a log-normal distribution to estimate the durations of long outages. Long outages ("technical, weather & other" and "snow and ice load") generally require onsite repairs, whereas short outages (fast and automatic reconnection) can be handled automatically offsite. The durations of short outages are assumed as presented in Table 2. As stated, to ensure comparability between households under different assumptions, identical power outages are used between EV-utilization cases and customer preference assumptions.

When the *initial run* of the LP optimization is completed for a charging event, the following power outage response model is called for the charging event. In those cases where a power outage has been sampled for the charging event, EV SOC of the outage occurrence time is selected from the *initial run* of the LP model. The LP model functions with 5-min interval timeframes, aligning with the interval duration of the household smart meters. Consequently, the SOCs for outages commencing at times not divisible by 5 min are determined through interpolation, using the SOC values from the nearest 5-min intervals. The power outage response model iterates through the minutes of the outage event, calculating whether the EV is capable of meeting household energy needs and reduces the SOC accordingly to the fulfilled demand.

Table 2
Summary of the outage statistics, based on Finnish Energy statistics [40].

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

The Eqs. (14–18) of the power outage model are listed below. Eqs. (14) and (15) are employed to calculate the household energy $E^{Not-Fulfilled}$ and duration $T^{Not-Fulfilled}$ not fulfilled by the EV during the outage. The Eq. (16) allows to estimate the V2H discharge power P_b^{dis} in cases when the whole household demand of the current period b can be filled and otherwise. Eq. (17) is used to calculate the EV discharge time during the outage event period b.

$$E^{Not-Fulfilled} = \sum_{b=1}^{B} E_b^{Dem} - P_b^{dis}\tau_b^{dis}\eta^{dis}D_b \quad (14)$$

$$T^{Not-Fulfilled} = \sum_{b=1}^{B} \tau_b^{Outage} - \tau_b^{dis} \quad (15)$$

$$P_b^{dis} = \begin{cases} \frac{E_b^{Dem}}{\tau_b^{dis}\eta^{dis}D_b} \text{ if } \frac{E_b^{Dem}}{\tau_b^{dis}\eta^{dis}D_b} \leq P^{max,dis} \\ P^{max,dis} \text{ otherwise} \end{cases} \quad (16)$$

$$\tau_b^{dis} = \begin{cases} 0 \text{ if } EV_b^{Plugged-out} \\ \tau_b^{Outage} \text{ else if } SOC_b - \frac{P_b^{dis}\tau_b^{Outage}}{E^{Bat}} \geq SOC_{Disc} \\ \frac{(SOC_b - SOC_{Disc})E^{Bat}}{P_b^{dis}} \text{ else if } SOC_b - \frac{P_b^{dis}\tau_b^{Outage}}{E^{Bat}} < SOC_{Disc} \end{cases} \quad (17)$$

$$SOC_{Disc} = \begin{cases} SOC_{min} \text{ if } \tau_b^{ToPlugout} \geq 3h \\ -0.1\tau_b^{ToPlugout} + 0.9 \text{ if } \tau_b^{ToPlugout} < 3h \end{cases} \quad (18)$$

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

$b = 1, \dots, B$

Eq. (18) is used only in the *high plug-out SOC* (*HSOC*) customer preference assumption, while for other customer preference assumptions a constant value for SOC_{Disc} is utilized. SOC_{Disc} denotes the discomfort-SOC level to which a household is willing to discharge the EV in order to power the household during a power outage, that is, the minimum SOC left to the EV even if an outage continues. This Eq. (18) represents the decreasing willingness to continue discharging the EV during outages that continue near the time when EV is needed for driving purposes. Eq. (19) keeps track of the EV SOC during each b of 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 (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 an input for the *second run* of the LP model, as noted in Eq. (10).

2.5. Valuation of power outage self-sustainment

2.5.1. Value of lost load

A typical way of estimating VOLL of households is based on the proxy method or production-function approach where for instance lost leisure time due to power outages is connected to hourly wages to calculate the annual value of lost convenience, which is then divided by yearly electricity consumption to estimate VOLL [11,42]. These methods assume that an hour of leisure time can be valued equal to an hour of income from work, and that the main impact of an power outage for households is the interruption in electricity based leisure activities

[9,43]. Different substitutability factors are used to represent the decrease in the utility of leisure activities due to an outage, for instance a factor of 50% is used in [9,44,45] implying that during a power outage half of the leisure utility is lost as most electricity based leisure is not possible.

In this study we utilize a similar approach for estimating the value of lost load (VOLL) during power outages as in [9,42]. That is, we calculate VOLL based on the estimated value of electricity-based leisure activities and electricity consumption. However differing from [9] that calculated national average VOLLs based on total population and household electricity consumption, we calculate the VOLL for each household separately similarly as was done in [42] for individuals.

Overall, the VOLL for a household h is calculated as,

$$VOLL_h = \frac{LV}{EC_h} = \frac{f_{sub} T_{leisure} w_{avg} \left(N_{emp} + 0.5 N_{non-emp}\right)}{EC_h} \tag{20}$$

Where EC_h is the annual electricity consumption of the detached household h, and LV is the annual electricity-based leisure value of an average detached household from the case municipality. Further, f_{sub} is the substitutability factor for electricity-based leisure activities, this is assumed 50% as in [9,44,45]. $T_{leisure}$ is the annual average leisure time of an employed person, calculated assuming average daily work hours in Finland and assuming (similarly as in [9,44]) that on average 11 h of each day is spent on non-electric personal care (sleeping, washing etc.). The average hourly wage is denoted with w_{avg}, this is calculated for the case municipality with data from Statistics Finland [46,47]. The final terms N_{emp} and $N_{non-emp}$ denote the average number of employed and non-employed (unemployed or not in workforce) persons per detached household in the case municipality. These values were calculated based on labor force, population and average detached household size statistics [47–49]. The value of leisure time of non-employed persons is assumed to be half of the employed person value as in [9,44,50].

As we have no information about the actual household features for our case households, the LV in Eq. (20) remains constant and the differences in household specific VOLLs result from differing annual electricity consumption. That is, the VOLL (€/kWh) is lower for households with large annual electricity consumption and vice versa.

It should be noted that this utilized VOLL remains constant for specific households regardless of the season. If seasonal or monthly VOLLs were to be used, the value of lost load would be significantly lower in cold and dark winter months than in the summer which would be contradictory to previous studies [2]. Now the utilized VOLL is on average 6.36 €/kWh, which is similar to the national average VOLL for Finland presented in [9], if the value of [9] is adjusted for inflation and purchasing power parity adjustment is removed (6.58 €/kWh). It should be noted that there were some discrepancies in the methodology of [9], and the VOLL values might not be reliable. However, the average VOLL value calculated from Eq. (20) is still considerably lower than for instance the average VOLL for German households in 2011 (15.70 €/kWh) [42], highlighting the variance in VOLL values of previous research. To evaluate the impacts of different input factors on the yearly average total VOLL of households calculated with our methodology, we conducted a sensitivity analysis, the results of which are presented in section 3.3.

2.5.2. Willingness to pay

In addition to VOLL, we calculate the value of power outages based on willingness to pay (WTP). As there exists no recent studies with WTP values for Finland, these must be estimated based on previous research. Given the lack of recent studies with WTP values specific to Finnish detached households, our WTP estimation relies on extrapolation from earlier research, which might lead to relatively coarse estimations. To evaluate this potential limitation, a sensitivity analysis is conducted to assess the impact of variations in different input factors on the yearly average total WTPs of the households.

We utilized data from the EU-level SESAME study [51] to calculate the initial one-hour WTP values for Finnish households for outages where leisure time is affected. The WTP was calculated for both winter and summer seasons and were then inflation-adjusted. Additionally, as the SESAME study was conducted in 2012/2013, the WTP values were further increased based on [6]. In [6] the authors found that the Swedish household WTPs had more than doubled between 2004 and 2017 (increases between 125 and 187% depending on outage type and duration). This rise indicates that the importance of reliable electricity supply for households has grown significantly possibly due to more electricity-centric lifestyles. Assuming similar linear growth, we utilize a 100% increase in hourly WTPs from 2012 to 2022, the inflation-adjusted average Finnish WTP is still smaller (2.68 €/h) than the inflation-adjusted WTP for one-hour unplanned outage in Sweden (3.25 €/h) described in [6]. As Sweden and Finland are neighboring countries with many similarities, the obtained 100% increase in WTP can be regarded a realistic assumption.

After calculating the one-hour WTPs for winter and summer outages in Finland, we further utilized the Swedish study [6] to scale hourly WTPs for shorter and longer outages. In [6], the study described Swedish consumer WTPs for unplanned outages of durations 3 min, 1 h, 4 h & 12 h. These values were used to scale the Finnish winter and summer one-hour outage WTP to identical durations. The resulting yearly averages of the scaled WTPs are around 17% smaller than the inflation adjusted values in Sweden presented in [6].

To valuate outages that are shorter or longer than the durations of the estimated WTPs, we utilized power function models as presented in Eq. (21). Initially we applied log-transformation to both outage duration and hourly WTP to linearize the relationship, allowing us to fit a linear regression model to the log-transformed data. Afterwards, we exponentiated the linear model's coefficients to revert to the original data scale, where the intercept a represents the power function's coefficient, and the slope b denotes its exponent. Models were separately fitted for summer and winter season outages of less than one hour, between one and four hours, and over four hours.

$$WTP\left(t_{outage}\right) = a t_{outage}^{b} \tag{21}$$

By utilizing this method, we can estimate the average hourly WTPs for power outages of differing durations and ascertain that there exist no irrationalities in the results (e.g., long outages with total WTP lower than for shorter outages) as would arise with, for instance, linear or piecewise linear functions. It should be noted that the resulting average hourly WTP values do not differ between households as it does with the utilized VOLL methodology.

In Fig. 3, we have plotted the average hourly and total WTPs for both summer and winter season power outages of durations less than six hours. As can be seen there exists two break points in the lines (at hours 1 & 4) due to the three different power functions. Based on the figure, the total WTP to avoid a single outage is considerably higher (64–67%) in winter than in summer depending on the duration of the outage. As the SESAME study did not specify the winter and summer seasons, we assume that winter season consists of the six months from October to March, and summer is from April to September. This winter-season assumption coincides well with the heating season in Finland. These winter and summer WTP models were used to calculate the total WTP for each power outage handled by the bidirectional EV utilization.

2.6. Data and resources

The household automatic meter reading (AMR) dataset includes every detached household in the subarctic Finnish municipality, Orivesi. The data obtained from this mostly rural municipality in central Finland is well-suited for researching power outages, as up to half of Finnish detached homes are located in similar semi-urban or rural municipalities [52] that are more prone to power outages than urban areas [40]. This

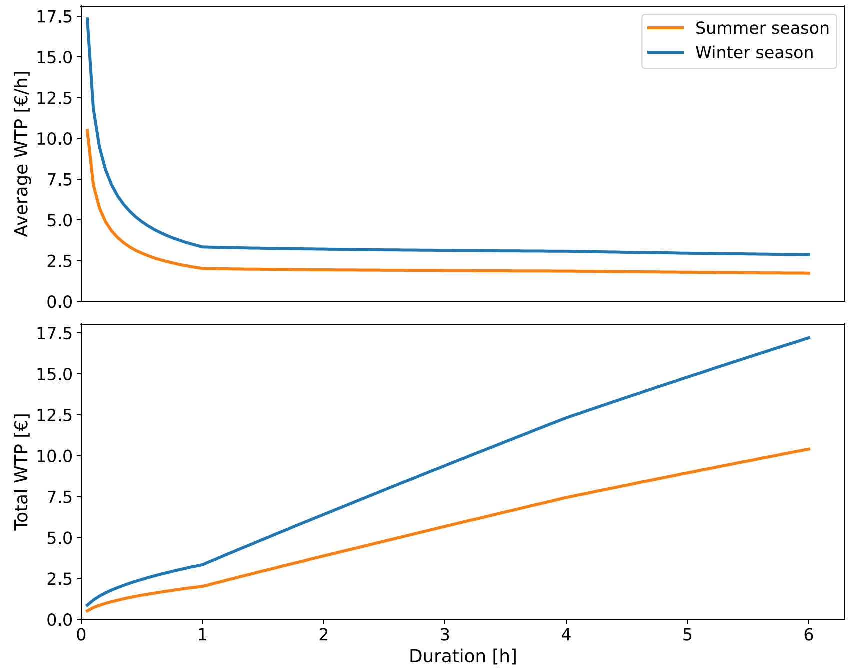

Fig. 3. Average hourly and total WTP of summer and winter season outages.

AMR dataset was cleaned by removing outlier households, such as households with multiple long gaps and missing values, households with yearly consumption >40 MWh or <2 MWh, and households with clear signs of high-power EV charging. Additionally, the few households where electricity was transferred back to the grid were removed from the sample to concentrate on typical households with no self-generation. After data cleaning, the dataset included 5-min interval electricity usage data from approximately 400 detached households without EV charging in 2022. The average yearly electricity consumption for the resulting household sample 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. Similar statistics for the different primary heating source clusters are presented in Table 3. Fig. 4 further illustrates the differing temperature normalized electricity consumption behavior between these clusters. It should be noted that the high midnight peaks in the electricity heated cluster result from night-time domestic water heating.

A Finnish charging point operator (CPO) provided the EV charging event dataset that covers all charging events conducted in 2022 on private EV charging points installed to household customers in Helsinki. EV charging data from Orivesi was not used as none of the contacted CPOs could not provide the EV charging event dataset covering all detached households from Orivesi without compromising customer privacy. It should be noted that the majority of EV home charging is typically conducted by using standard household sockets or charging points not connected to any CPO service [53]. The EV charging event dataset was cleaned by removing clearly erroneous charging events, such as events with NULL values, zero energy transfer, and impossible charged energies. Test events and events lasting either <5 min or longer than a week were removed from the dataset. Next, charging points not in active use for the whole year, points with utilization by multiple EVs and slow charging points were discarded. The resulting charging points had

Table 3
Annual electricity consumption statistics for household heating source clusters [MWh].

	GSH	Oil	DH	Elec
Average	14.3	7.4	10.0	22.4
Median	14.3	7.8	10.4	20.7
Std	1.8	2.7	2.4	5.3

on average approximately 220 acceptable charging events in 2022. The main features of the charging event data are; plug-in time, duration, and energy transferred from the charging point during the event. Fig. 5 illustrates the distributions of the most important variables of the EV charging event dataset. In the distributions of event duration (Fig. 5b) and energy (Fig. 5c), the last bin encompasses all values with durations exceeding 24 h or transferred energies over 60 kWh. It is noteworthy that the average duration for the charging events is relatively long at 12.8 h, while the average energy transfer is relatively low at only 14.6 kWh. Given the plug-in time distribution (Fig. 5a), this suggests a prevalence of short trips and overnight charging among EV users.

Household electricity consumption data and EV charging events that occurred in different charging points were paired by generating all possible combinations, leading to around 4,000 unique combinations of detached households with EV charging. When considering the three alternative customer preference assumptions and the two different EV-utilization cases, this leads to around 24,000 different yearly cases, and to over 5 million different charging event and household load combinations, without considering baseline cases without outage response or the multiple separate runs with different power outage samples to ensure robust and generalizable results. The initial AMR and EV charging event datasets used in this study are similar to those utilized in [27].

Additionally we utilized hourly electricity spot price data downloaded from the ENTSO-E Transparency portal [54] and temperature data downloaded from the open data portal of the Finnish Meteorological Institute [55]. Table 4 shows technical EV and EV charger specifications used in this study. As shown in this table, a bidirectional EV charging point is assumed to both charge and discharge with a power rating of 11 kW, similar to [34], with assumed efficiencies of 85% and 70%, as in [56–58]. The presented battery size assumption was adjusted for charging points with events non-viable with the initial assumption, i.e., with charged energies larger than 60 kWh. The battery lifetime assumption of 1,500 cycles is based on lifetime of Tesla Model 3 battery modules [59], and is similar to the Optimistic/Tesla scenario of [60]. The battery replacement cost was assumed to be 10,000 € similarly as in [34].

All models in the study were implemented in Python 3.10. The LP model was implemented using Python-MIP, while other tasks and analyses utilized libraries such as scikit-learn, NumPy, and Pandas. The major computations were carried out using the high-performance

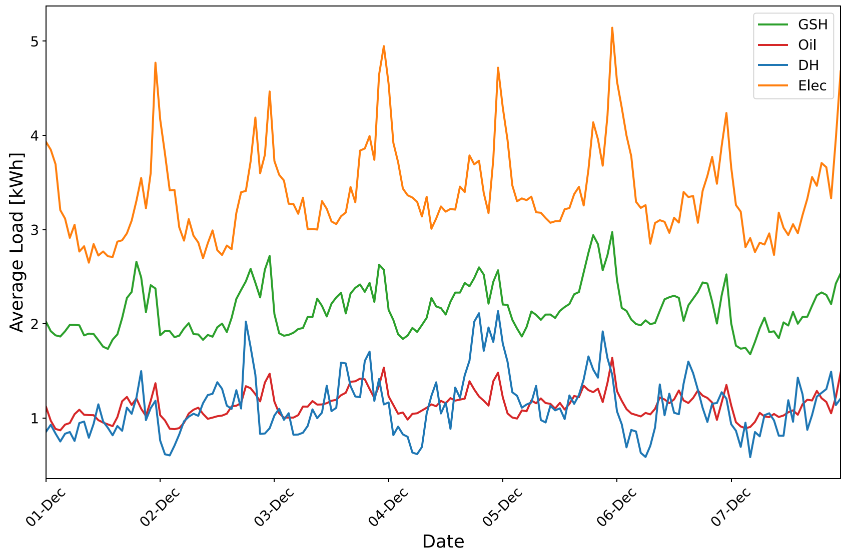

Fig. 4. Average load curves of the heating type clusters for the first week of December.

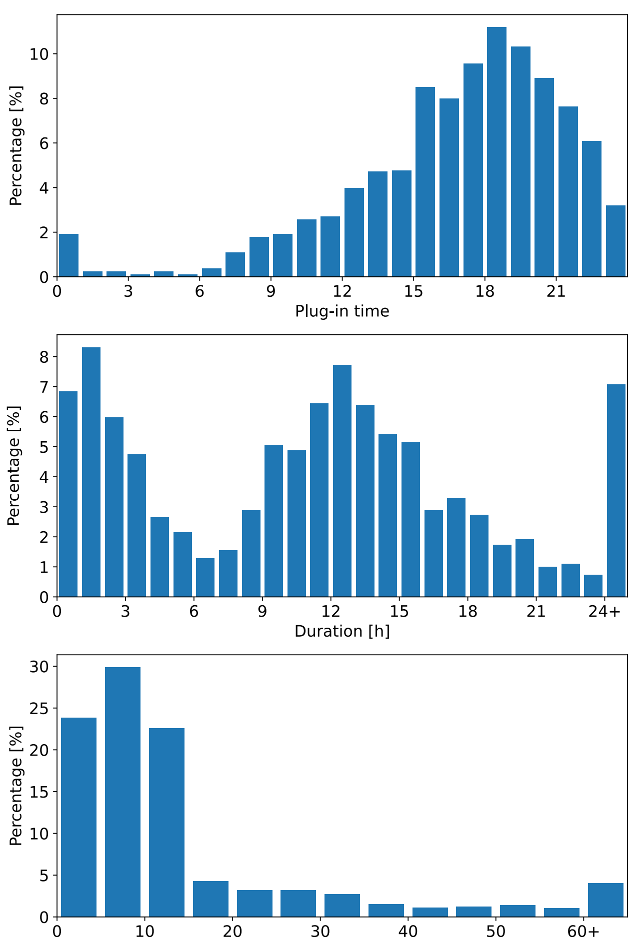

Fig. 5. Distributions of EV plug-in time, duration, and transferred energy.

computing cluster within the Aalto University School of Science “Science-IT” project. On a laptop workstation with an Intel Core i5-1145G7 CPU and 16GB of RAM, the average time for running the computations for all charging events of a single household considering all customer preference assumption and EV-utilization cases was approximately 14 min.

Table 4
Technical specifications.

Specification	Value
Battery capacity [kWh]	60
Max. Charging power [kW]	11
Max. Discharging power [kW]	11
Charging efficiency [%]	85
Discharging efficiency [%]	70
Battery lifetime cycles	1,500
Battery replacement cost [€]	10,000

3. Results

3.1. Power outage self-sustainment capabilities

Statistics for all different household heating types and customer preference assumption cases utilizing bidirectional EV charging to improve household self-sustainment capabilities during power outages are presented in Table 5. This table contains the average percentages of fully self-sustained power outages in total, and during EV plug-in period. Additionally, percentage of outage events where outage response was stopped due to reaching of the preference-specific discomfort-SOC are presented. Values are presented for long outage events and in total, except for the outages handled with no difference in end-SOC where the

Table 5
Power outage self-sustainment statistics for households with different primary heating and different customer preference assumption cases.

	Fully self-sustained outages [%]		Fully self-sustained outages during plug-in period [%]		Response stopped; Discomfort-SOC reached [%]	
Case	All	Long	All	Long	All	Long
DH_OAverse	96.3	84.8	98.6	97.1	0.0	0.0
Elec_OAverse	89.6	72.2	91.6	84.6	0.1	0.3
GSH_OAverse	96.1	83.8	98.1	96.1	0.0	0.1
Oil_OAverse	97.3	85.3	99.7	99.2	0.0	0.0
DH_HSavings	94.1	82.8	97.0	95.2	1.7	2.1
Elec_HSavings	87.0	69.5	89.2	81.8	2.9	3.9
GSH_HSavings	93.6	80.9	96.0	93.3	2.3	3.1
Oil_HSavings	95.4	83.1	97.9	97.2	1.7	1.9
DH_HSOC	85.7	71.4	90.2	85.1	8.7	12.9
Elec_HSOC	77.3	56.2	81.5	69.6	12.7	20.6
GSH_HSOC	84.0	67.4	88.0	80.9	10.6	16.6
Oil_HSOC	87.2	72.7	91.3	88.0	8.4	11.4

averages are presented for long and short outages separately. We note that an outage can be fully self-sustained if V2H can be used to fulfill the total load of the household during each minute of the outage, with no need to decrease electricity use from the actual AMR data. That is, a fully self-sustained outage implies that all electricity use regardless of reason (heating, TV, cooking) during the outage can be met with no need to decrease consumption. In all cases, EV plug-out happens in the middle of an outage in 2.2% 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 performs better than other preference assumptions with regards to fully sustained outages regardless of the heating type. The outage response of OAverse-cases almost never terminates due to reaching of the discomfort-SOC 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 preference assumption leads to worst outage self-sustainment performance, with for instance, only around 70% of long outages fully sustained during EV plug-in in electric heated households.

The primary factors behind non-perfect outage self-sustainment differ between customer preference assumptions. As can be seen from Table 5, under HSOC preference assumptions, outage response is terminated in 8.4–12.7% of outages due to reaching of the discomfort-SOC constraint. That is, the discomfort-SOC constraint accounts for approximately 88.5% of the outages that are not perfectly managed under HSOC. In contrast, under the outage averse preferences the V2H discharge power constraint covers nearly all non-perfectly handled outages. Overall, it can be stated that the main constraint leading to the non-perfect outage response during EV plug-in is discomfort-SOC, i.e., the available battery capacity.

The percentual average suffered power outage durations and not-fulfilled household demand during EV plug-in are presented in Table 6. This table also contains the average total self-sustained 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 average annual suffered outage time being close to zero regardless of the household heating type. Overall worst performers are the high end-SOC preference assumption in electric heated households, which on average suffer over 18% (around 30 min) of total outage duration in a year and cannot cover around 22% of the household outage electricity demand during EV plug-in.

Overall, based on Tables 5 and 6 it can be stated that electric heated households suffer most disruptions regardless of customer preference assumptions. However, the impact of customer preference assumptions is higher than the impact of primary heating source on overall outage handling.

Table 6
Average suffered outage time, total self-sustained outage time and not-fulfilled household demand during EV plug-in.

Case	Suffered power outage time during plug-in [%]	Not fulfilled energy demand during plug-in [%]	Total self-sustained outage time during the year [h]
DH_OAverse	0.0	0.8	3.2
Elec_OAverse	0.1	3.1	3.2
GSH_OAverse	0.0	0.6	3.2
Oil_OAverse	0.0	0.2	3.2
DH_HSavings	1.8	2.8	3.1
Elec_HSavings	3.7	6.9	3.1
GSH_HSavings	3.1	3.8	3.1
Oil_HSavings	2.3	2.5	3.1
DH_HSOC	12.4	14.1	2.9
Elec_HSOC	18.5	21.9	2.6
GSH_HSOC	15.9	17.2	2.7
Oil_HSOC	12.3	12.9	2.8

3.2. Value of avoided power outages

Average total yearly VOLL and WTP for households with different primary heating sources are presented in Fig. 6, for all three customer preference assumptions. The total yearly VOLL for an average household is 19.5–23.2€ with WTP being 10.1–11.5€ depending on customer preference assumptions.

From Fig. 6, it can be noted that the average total WTPs are quite consistent within each customer preference assumption, that is, there are no major differences between heating types. This is consistent with the method used to calculate outage specific WTPs introduced in section 2.5.2, as the willingness to pay to avoid a single outage depends only on season and duration of an outage (not on heating type or annual electricity consumption). However, the average total VOLLs differ both between customer preference assumptions and between heating types. This is logical as household specific VOLLs (€/kWh) are very dependent on annual electricity consumption, as discussed further in section 3.3 covering sensitivity analysis of the study. Overall highest average total yearly VOLLs are reached in GSH households, over 23€ under OAverse assumptions.

Maximum total yearly VOLL and WTP for all three customer preference assumptions and households with different primary heating sources are presented in Fig. 7. It should be noted, as described in sections 2.5.1 & 2.5.2, that the WTP metric Eq. (21) is uniform for all households (different in winter and summer), and that the VOLL metric Eq. (20) differs between households only based on annual electricity consumption, leading to somewhat limited consideration of differences between individual households. Notably, the clearly highest maximum total annual VOLLs are observed in Oil heated households where the total VOLLs are around 330€ regardless of customer preference assumptions. These maximums result from low yearly electricity consumption (around 3,600 kWh) and multiple power outages (21) randomly sampled to this household that were all handled perfectly, with the total supplied electricity during outages being over 21kWh. Additionally, it can be noted that the maximum yearly total WTPs are clearly smaller than maximum total VOLLs. On average yearly maximum WTP is only a third of maximum VOLL, with highest differences in Oil heated households, this results mainly from the limited consideration of differences between households in the WTP metric, as discussed previously.

The average total yearly benefit from *bidirectional charging* is presented in Fig. 8 for all primary heating source groups and different customer preference assumption cases. Here the yearly benefit is the extra savings compared with the *implicit demand response* scenario, and it encompasses the estimated monetary value of power outage prevention (VOLL or WTP), direct savings/earnings gained with bidirectional utilization (V2H and V2G), and extra costs resulting from battery degradation due to increased cycling. We are comparing the annual benefits with *implicit demand response* scenario as a major part of the total financial benefits arise from optimization of EV charging time (*implicit DR*). If the *bidirectional charging* scenario would be compared with *dumb charging*, the yearly benefits would be significantly higher, but on average around 75% of these benefits would result from *implicit DR*, that is, from conventional smart charging, making the results arbitrarily high. Further, it should be noted that the differences between VOLL and WTP values in Fig. 8 are the same as in Fig. 6.

Overall, it can be noticed that the lowest average yearly benefits are under the outage averse customer preferences where the outage handling is superior to other preference assumptions as discussed in the previous section. Highest yearly benefits are gained in electric heated households and under the high savings customer preference assumption. High benefits in electric heated households result from high monetary savings gained through bidirectional EV utilization, as in electric heated households there is more possibilities to gain savings through electricity usage optimization due to higher electricity consumption, especially in winter.

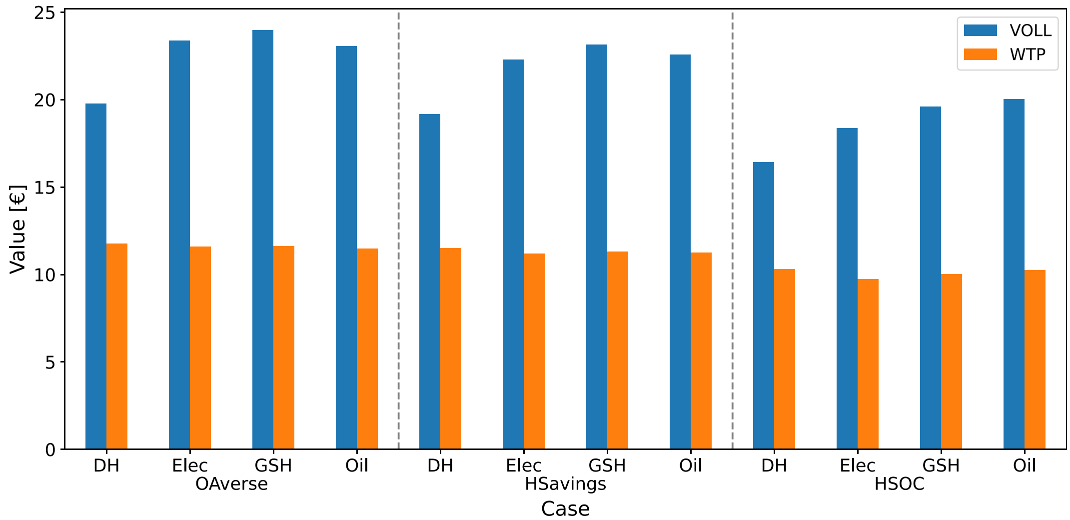

Fig. 6. Yearly average total VOLL and WTP.

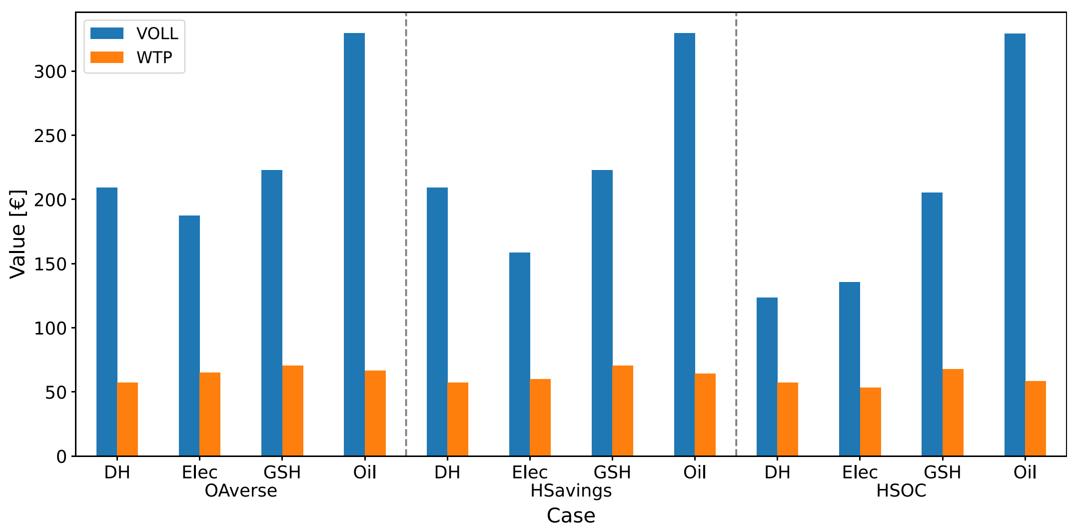

Fig. 7. Yearly maximum total VOLL and WTP.

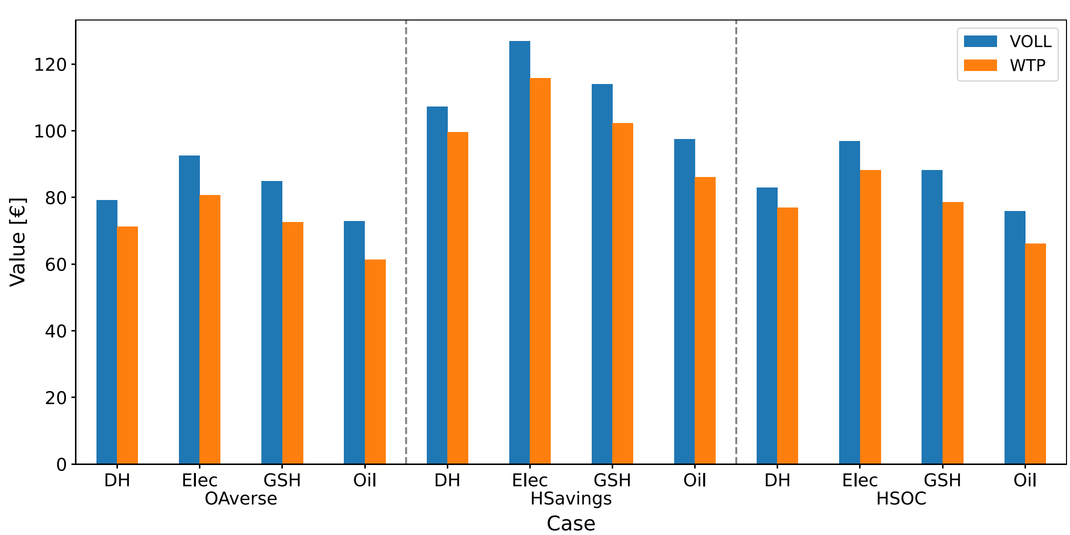

Fig. 8. Average total yearly benefit from bidirectional charging.

The maximum total yearly benefit from *bidirectional charging* is presented in Fig. 9. These maximums are the values of the households that gain most benefit from bidirectional EV utilization compared with *implicit DR* scenario in the same household.

Here, in Oil heated households the maximum total yearly benefit with VOLL clearly dominates with annual benefits up to 420€ under high savings customer preferences when compared with *implicit DR* scenario (980€ compared with *dumb charging*). All these Oil heated household maximums occur in the same household and result mainly from large total yearly VOLL (330€) presented in Fig. 7. If WTP is used to estimate the value of outages, then maximum total yearly benefits are reached in electric heated households regardless of customer preference assumption. On average, highest maximum and average yearly benefits are reached under the high savings assumptions, which further points out that the benefit from outage self-sustainment is consistently lower than monetary benefits gained through electricity use optimization.

An important aspect to consider in bidirectional EV charging applications is the increased battery degradation, which can lead to additional inconveniences and costs, such as a reduced battery lifespan. Based on our results, bidirectional operation leads to an average of 52.1 annual EV battery cycles, representing almost a 50% increase compared to the *implicit DR* case. However, with an assumed battery lifetime of 1,500 cycles, this means the cycling lifetime would not be reached until over 28 years of similar utilization. Given that the calendar lifetime targets for EV batteries are considerably <28 years, bidirectional operation does not diminish battery lifetime based on our results. Additionally, with an overall maximum of 1.3 extra annual cycles, the increased cycling due to outage self-sustainment is insignificant in the bidirectional operation case.

3.3. Sensitivity analysis

Sensitivity analysis of yearly total VOLL of an average household is presented in Fig. 10. Here we see the impact of ±20% change in input factors on the yearly average total VOLL. As can be seen, changes in f_{sub}, $T_{leisure}$, w_{avg} and $E^{Fulfilled}$ result in identical change in the output. Changes in N_{emp} and $N_{non-emp}$ have a lesser, but still symmetrical, impact on the output. However, decrease in the annual household electricity consumption EC_h increases the yearly average total VOLL by over 25%, while an increase of 20% in EC_h leads to a decrease of around 17% in total VOLL. This highlights the previous assessment that electricity consumption has a significant impact on VOLL, which easily leads to lower total yearly VOLLs for households with large annual electricity use e.g., for electric heated households.

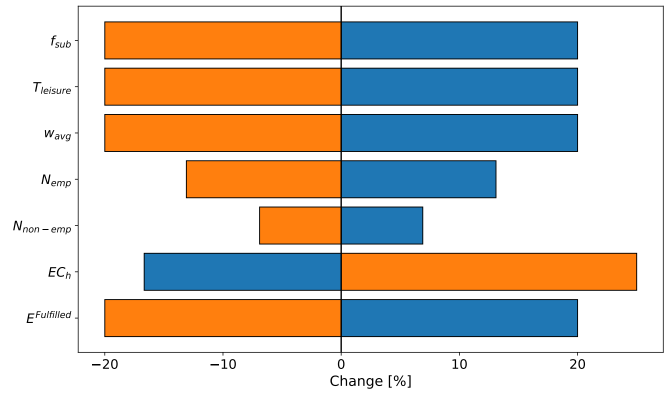

Fig. 10. Sensitivity analysis of yearly total VOLL (blue +20%, orange −20% change in factor).

In Fig. 11, we present the impact of ±20% changes in the most important factors affecting yearly total WTP. As can be seen, total WTP is less affected by changes in a single input parameter than the total VOLL. Changes in most factors lead to symmetrical change in the output, for instance lower one-hour winter season outage WTP decreases yearly total WTP and vice versa. The most sensitive factors are the WTP for one-hour winter season outages WTP_{1h}^{winter} (±16%) and the average number of winter-related outages O_{count}^{winter} (±11%). The average number of short fast

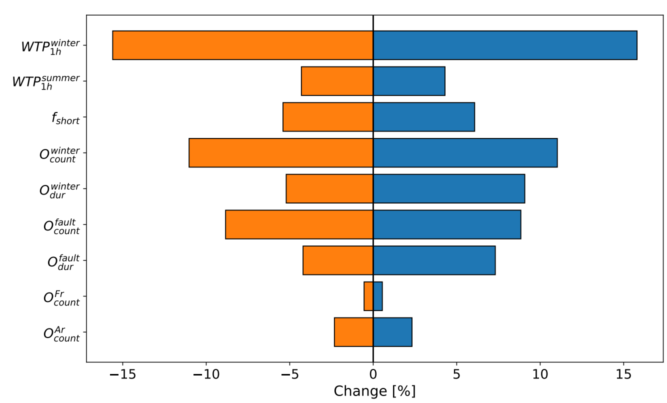

Fig. 11. Sensitivity analysis of yearly total WTP (blue +20%, orange −20% change in factor).

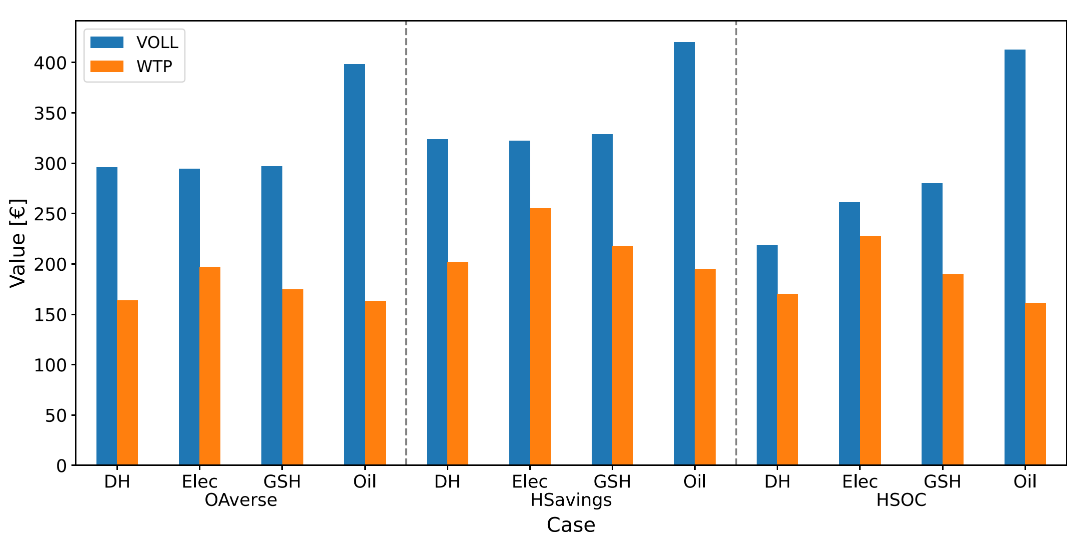

Fig. 9. Maximum total yearly benefit from bidirectional charging.

or automatic reconnection outages O^{Fr}_{count} & WTP^{Ar}_{count} has the least impact on total yearly WTP, ±0.6% and ± 2.3% respectively. The only factors that are not perfectly symmetrical are the average durations of fault and winter-related outages, increases in these averages result in 7–9% higher total yearly WTPs, whereas reductions in the factors have a pronounced effect on the total yearly WTP (4–5%).

4. Discussion

Based on the results of this study, *bidirectional charging* can fully prevent around 82–99% of outages during the EV plug-in period, depending on household heating source and customer preference assumptions. However, regardless of these factors, the average annual value of power outage prevention with *bidirectional charging* remains relatively low, being less than €12 when calculated with WTP and less than €24 with the VOLL approach. While the average annual values calculated with VOLL are significantly higher than those with WTP, they are still low, implying that purchase of a bidirectional EV charger cannot be regarded profitable based on outage prevention alone. However, in the rare maximum case the total yearly self-sustainment value calculated with VOLL can reach up to 330€. This peak value is observed in a single oil-heated household with low yearly electricity consumption experiencing multiple power outages. It is important to note, though, that this should not be considered an absolute maximum across all Finnish households. The value is influenced by multiple factors, with low annual electricity consumption and multiple outages being most significant in this context.

When the total yearly benefit from *bidirectional charging* is compared with conventional *implicit demand response* (smart charging), the yearly benefits are considerably higher. This yearly benefit encompasses the estimated monetary value of power outage prevention (VOLL or WTP), direct savings/earnings gained with bidirectional utilization (V2H and V2G), and extra costs resulting from battery degradation due to increased cycling. These benefits differ between households with different heating sources, but larger variance is noted between different customer preference assumption scenarios. Highest average yearly benefits are gained under *high savings* preference assumptions and in electric heated households, with the highest average reaching 126€ when calculated with VOLL. Additionally, if annual benefits from *bidirectional charging* would we compared to *dumb charging*, the benefits would be significantly higher, but on average 75% of these benefits would be attributable to charging time scheduling with *implicit DR*, supporting our choice of using *implicit DR* as the main reference point. Maximum yearly benefits from *bidirectional charging* are reached under *high savings* preferences in the same oil heated household that has the largest total yearly VOLL, here the annual benefits reach 420€ (980€ if compared with *dumb charging*). On average, it can be stated that most of the yearly benefit results from direct savings/earnings gained with bidirectional utilization, not from outage prevention, and that *implicit DR* should be used as the main reference point to correctly assess the benefits gained from bidirectional operation.

The inconvenience caused by power outages is a highly subjective matter and some customers might valuate mitigation of outages much higher than assessed in this study with WTP and VOLL. However, based on the results of this study, the annual total benefits of bidirectional operation are relatively low when compared with easily adoptable smart charging. This implies that, with the current high pricing, bidirectional chargers are not yet a cost-effective option for most consumers. Currently there exists only few consumer-oriented bidirectional chargers on the market, for instance the Ford Charge Station Pro priced very affordably at around 1,200€ [61], it should however be noted that this charger requires a separate Home Integration System which with installation costs can increase the total acquisition costs to over 16,700€ [62]. As of now, there exist no dependable estimates regarding how the acquisition costs of bidirectional EV chargers might change in the future, but it is probable that the costs will decrease through wider market adoption and increased competition. It should be noted that bidirectional EV utilization enables storage of self-generated electricity and participation on different explicit demand response marketplaces, such as in symmetrical FCRs, that can increase the annual non-outage centric monetary benefits, these combined with the presumed decreasing bidirectional charger prices in the future can make bidirectional chargers financially viable for household consumers. Moreover, rural households, which often face frequent and prolonged power outages, may be reluctant to invest in alternative solutions for outage self-sustainment (stationary PV and BESS) due to declining property values. However, they might be inclined to consider bidirectional EV chargers, particularly if they already own an EV. Reluctance towards investing in PV systems can be estimated to be especially pronounced in Nordic regions, where the utility of PV is significantly limited by minimal or non-existing sunlight during winter months. Additionally, as battery degradation and capacity fading are sometimes seen as significant concerns for bidirectional EV operation, future research and long-term optimization models should incorporate these factors to alleviate consumer concerns. Based on our results, bidirectional operation does not diminish the overall battery lifetime, and capacity fading in our one-year optimization timeframe can be regarded as insignificant.

The most significant shortcomings in this research arise from the estimation of monetary value of avoided power outages. In this study we utilized the two most popular metrics to encapsulate the value of outages in monetary terms; willingness to pay (WTP) and value of lost load (VOLL). Earlier studies in both WTP and VOLL generally present point estimates and population averages, however the specific costs and values connected to power outages vary, for instance, between end-users, use-cases, locations and time and duration of outages and the estimates with these metrics have been criticized of hypothetical bias and oversimplification [7,10,11,42]. As there exists no recent estimates of WTP or VOLL in Finland, nor a generally accepted methodology for estimation of WTP and VOLL for specific detached household customers, we calculated these metrics for Finnish detached household customers based on earlier studies [6,9,42,51] and up-to-date statistics. This method required significant assumptions and can at best be used only to estimate the average value of outages and outage prevention for the assessed households. As noted in the sensitivity analysis of both yearly total VOLL and WTP, both of these metrics are quite sensitive to changes in input parameters. Yearly total value of outage prevention with VOLL is most sensitive to changes in yearly electricity consumption, while total WTP is very sensitive to the estimated hourly WTP of winter season outages. It should be noted that the discomfort from power outages is highly subjective and both VOLL and WTP can at best be used only to estimate the average consumer's perspective. Additionally, as household VOLL is derived only from leisure time, these estimates do not correctly quantify the value of lost loads during remote work. An alternative approach to evaluating the willingness to pay for outage avoidance could involve drawing comparisons with uninterruptible power supplies (UPS), thus viewing the outage self-sustainment functionality as a form of insurance against power interruptions. Such an analogy could be particularly useful in assessing the value of outage avoidance, especially among consumers who are highly sensitive to power disruptions.

As there exists no previous studies that have assessed the monetary value of power outage self-sustainment enabled by bidirectional EV charging, benchmarking of our results is difficult. However, the VOLL and WTP estimates used in the analysis are consistent with previous studies [6,9], and as we utilized national power outage statistics, and real data of EV charging and household electricity use, the methodology and results can be regarded robust and representative of the general impact of power outages on Finnish non-urban households. A possible way to further and benchmark this research would be to conduct similar analyses with larger datasets from different geographical locations. If real large datasets are not easily available, for instance, the multivariate copula procedure introduced in [63] could be leveraged in creation of large realistic EV charging event datasets based on limited input data. Due to significant geographical variations in power outage frequencies, durations, and household electricity usage patterns — with Finnish winters exhibiting particularly high electricity usage compared to southern countries — our results are not universally applicable. Nevertheless, these findings hold substantial relevance within the Nordic context, as Nordic countries not only share a common electricity market but also have similar climate and building stock. Further, the results regarding household self-sustainment during power outages with bidirectional charging is consistent with findings of previous studies such as [24,26,27], that is, V2H can in most cases be used to maintain household loads during outages. It should be noted that the results of our study are based on the assumption of no reductions in household loads during outages, that the outages are not known in advance, and that the EV plug-out can occur even during an outage. If household consumption was to be lowered during outages, if mobility was not prioritized, and if outages were known in advance, the self-sustainment potential would be even higher. However, the current results and methodology apply well to the "business as usual" case where no reaction is needed from the households due to outage occurrence. Overall, the presented methodology offers broad applicability, enabling utilization in various countries and use cases, contingent upon availability of analogous data.

Future research regarding valuation of power outages should focus on developing more robust, refined and context-specific methodologies, particularly for residential demographics in different geographical locations. It would be important to also incorporate the growing trend of remote working to VOLL and WTP estimates, as outages during remote work can indue larger inconveniences and lost productivity during highly ICT-dependent remote working periods. Emphasis should be placed on longitudinal studies to understand how technological advancements, climate change, and ever-more electricity-centric consumer lifestyles affect outage valuations. Based on [15,16], one of the key barriers for large scale adoption of bidirectional charging was customer resistance and lack of awareness of the technology and its benefits. Power outage self-sustainment might be one of the keys to lowering this resistance and thus pave the way for higher adoption of bidirectional chargers. Consequently, it would be interesting to study how EV owners valuate the impact of power outages, and further how much emphasis households give to possible outage aversion with bidirectional EV charging. Overall, it can be concluded that more robust estimates of the value of outage aversion is needed in order to assess the value of outage self-sustainment with bidirectional EV charging more accurately. Effective real-time deployment of the model would additionally require future work encompassing household demand forecasting, more comprehensive EV usage data, weather forecasts, and information of power grid conditions.

5. Conclusions

This study presented the first available assessment of the value of power outage self-sustainment with bidirectional electric vehicle charging for household consumers. The study concentrates on detached households with different primary heating sources located in subarctic Finland. The findings regarding outage self-sustainment capabilities indicate that regardless of the primary heating type, bidirectional charging is effective in averting the vast majority of power outages that occur while the EV is plugged in. Overall, *bidirectional charging* can be used to fully prevent between 81.5 and 99.7% of all outages occurring during EV plug-in period, depending on household heating source and customer preference assumptions. During these outages, the electricity consumption of the household can be fully sustained by V2H in each timestep, that is, the household does not need to decrease electricity consumption and does not suffer from any noticeable disruption to electricity supply.

When compared with other financial benefits enabled by *bidirectional charging*, the annual value of outage self-sustainment is on average relatively modest. Moreover, the valuation of outage prevention is significantly influenced by the choice of valuation metric used in the analysis. The value of annual outage self-sustainment is relatively low regardless of the valuation metric, primary heating source of the household, and customer preference assumptions regarding EV utilization, but can reach up to 330€ in the maximum case. For an average household, the value of this annual outage self-sustainment is less than 12€ if calculated with willingness to pay (WTP) and less than 24€ if calculated with value of lost load (VOLL) approach. Overall, the total yearly benefits of *bidirectional charging* can reach up to 420€ when compared with *implicit demand response* (smart charging), and up to 980€ when compared with *dumb charging*. This total yearly benefit encompasses the estimated monetary value of outage self-sustainment, direct savings/earnings gained through bidirectional utilization, and extra costs attributable to battery degradation from increased cycling.

As modern societies continue to grow ever more electricity-dependent, the impacts of power outages become increasingly significant. In this context, bidirectional EV charging offers a particularly promising solution, especially for detached households to self-sustain during disruptions in power supply. Outage self-sustainment capabilities might also prove to be one of the key factors to increase consumer interest in bidirectional charger adoption.

CRediT authorship contribution statement

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

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.

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