Journal of Energy Storage 48 (2022) 103806

Contents lists available at ScienceDirect

Journal of Energy Storage

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

Grid congestion mitigation in the era of shared electric vehicles☆

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ARTICLE INFO

Keywords:
Car sharing
Electric vehicle
Smart charging
Grid congestion
Low voltage grid

ABSTRACT

Rapid integration of photovoltaic systems and electric vehicles in low-voltage grids increasingly causes grid congestion. To avoid costly grid reinforcements, distribution system operators are looking into applying electric vehicle smart charging algorithms to shift part of the load to off-peak hours. However, multiple barriers hamper the large-scale implementation of smart charging. These barriers can be alleviated when using electric vehicles in car sharing schemes for smart charging. Shared electric vehicles make up an increasing share of the car fleet and using these vehicles for smart charging exhibits different advantages over using private vehicles, including better predictable departure times and higher acceptance for smart charging. This study proposes a system for grid congestion mitigation using only shared electric vehicles and assesses this system's techno-economic potential. Results affirm that grid congestion problems can be fully mitigated in most grids using shared electric vehicles at relatively low car sharing adoption rates. Also, the costs increase of using this system is negligible compared to a system with combined grid congestion mitigation of privately-owned and shared EVs.

1. Introduction

High adoption of Electric Vehicles (EVs) puts stress on Low-Voltage (LV) grids, since EV charging can easily double the grid load and can cause high peak loads, induced by high simultaneity in EV charging moments [1,2]. As the extra load of EV charging was not foreseen when designing the majority of LV grids, Distribution System Operators (DSOs) increasingly experience grid congestion and power quality problems.

The connection time of an EV to a charging station generally largely exceeds the required charging time [2,3]. Hence, EV charging demand can be shifted to off-peak hours using smart charging, or EVs can inject electricity to the grid using vehicle-to-grid (V2G) technology without compromising on the battery energy level at departure [4,5]. Mitigating grid congestion using EV smart charging is more cost-effective than reinforcing the grid [6,7].

However, large-scale deployment of EVs as a flexibility resource by DSOs is hindered by multiple barriers. First, it requires secure and verifiable communication between grid operators and many decentralized actors (i.e., EV users, aggregators) [8,9]. Implementation of such complex communication frameworks could lead to high costs. Second, a considerable share of the EV users may be hesitant to allow their EV battery to be used for smart charging or V2G [10,11]. Third, grid operators need to be conservative in their EV smart charging algorithms, since the forecasting accuracy of the EV departure time is low [12] and EV users should not be faced with an insufficient battery level for their intended trip at departure.

These barriers can be alleviated if DSOs contract EVs in car sharing schemes for the provision of flexibility for grid management. Car sharing is an alternative to car ownership and provides users short-term access to a fleet of shared cars managed by a third-party organization [13]. Car sharing is rapidly emerging worldwide, especially in urban residential areas; the number of car sharing members has grown by a factor of 40 between 2006 and 2018 [14] and further growth in the adoption of car sharing is expected [15–17]. Since the transport system is rapidly electrifying, most shared cars are likely to be electric in the future.

Using shared EVs instead of privately-owned EVs for grid management provides multiple advantages. Departure times of shared EVs are highly predictable, as they are booked through a reservation system. Consequentially, smart charging algorithms can be less conservative, increasing the potential for providing grid services. Moreover, the complexity of communication platforms is reduced as grid operators

☆ This study was supported by the European Regional Development Fund 'EFRO Kansen voor West II' through the project 'Smart Solar Charging' and by the Topsector Energy subsidy scheme of the Dutch Ministry of Economic Affairs and Climate Policy through the project 'Slim laden met flexibele nettarieven (FLEET)'. The authors want to thank Robin Berg, Henk Fidder and Bart van der Ree for their contributions to this research.

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https://doi.org/10.1016/j.est.2021.103806
Received 15 September 2021; Received in revised form 8 December 2021; Accepted 9 December 2021
Available online 14 January 2022

Nomenclature

Indices and sets

$r \in \mathcal{R}$	Set of charging transactions of privately-owned EVs.
$s \in \mathcal{S}$	Set of charging transactions of shared EVs.
$t \in \mathcal{T}$	Set of timesteps in assessment timeframe.

Variables

$c_{battdeg}$	Battery degradation costs for all shared EV charging transactions in studied LV grid.
c_{ch}	Total charging costs for all shared EV charging transactions in studied LV grid.
$e_{ch,tot}$	Net accumulated charging volume at the EV battery for a charging transaction.
p_{ch}	Charging power at the EV battery.
p_{disch}	Discharging power at the EV battery.
p_{grid}	Transformer load.
δ	Depth of discharge of a charging or discharging cycle.

Parameters

Δt	Duration of one timestep.
Φ	Battery degradation function.
C	Time-of-use tariff for electricity.
E_{req}	Required charging volume of a transaction at the EV battery.
$P_{ch,max}$	Maximum charging power of a charging transaction.
$P_{disch,max}$	Maximum discharging power of a charging transaction.
P_{PV}	PV generation in studied LV grid.
P_{res}	Residential load in studied LV grid.
$P_{trans,max}$	Transformer capacity.
η_{ch}	Charging efficiency.
η_{disch}	Discharging efficiency.
t_{arr}	Arrival time of a charging transaction.
t_{dep}	Departure time of a charging transaction.

Scenario development

$E_{priv,org}$	Charging demand of all privately-owned EVs in the LV grid in the assessment timeframe without adoption of shared EVs.
E_{priv}	Predicted charging demand of all privately-owned EVs in the LV grid in the assessment timeframe.
E_{shared}	Predicted charging demand of all shared EVs in the LV grid in the assessment timeframe.
α_{shared}	Adoption rate of shared EVs.
γ_{vkt}	Reduction in vehicle-kilometers traveled when adopting a shared EV.

only need to communicate with a few car sharing companies when utilizing EVs for grid management. Lastly, less adjustments to the charging schedules of privately-owned EVs will be required to mitigate grid congestion, causing private EV owners not to unexpectedly face a low battery energy volume at departure.

Only few studies have looked into the future grid integration of shared EVs. In previous work, the authors have looked into the charging patterns of shared EVs [18]. Other authors studied the financial potential of shared EV participation in electricity markets [19,20]. To our knowledge, no study assessed the potential of shared EVs to provide local grid services.

This study proposes a novel system approach for mitigating grid congestion in LV grids solely using shared EVs. This system can alleviate the barriers to smart charging for mitigating grid congestion and can thus avoid or delay grid reinforcements. It presents a model in which shared EVs cost-optimize their charging while respecting grid constraints, and privately-owned EVs can charge freely without considering grid constraints. The techno-economic potential of the proposed system is analyzed.

The novelty and relevance of this work can be highlighted as follows:

- To the best of our knowledge, this is the first work proposing the concept of using only shared EVs for the mitigation of grid congestion. As outlined above, this concept can alleviate several barriers of using EVs as a flexibility resource by DSOs, which can delay or avoid costly grid reinforcements;
- A system approach for the mitigation of grid congestion using only shared EVs is presented in this work, outlining the actions required by different actors and the needed communication framework between them;
- This work translates a system in which grid congestion is mitigated using only shared EVs into an optimization model for the charging of shared and privately-owned EVs;
- The viability of a system in which only shared EVs are used for the mitigation of grid congestion is extensively assessed from a techno-economic perspective;
- This study is one of the first studies using high-quality and real charging data of both shared and privately-owned EVs.

The paper is outlined as follows. Section 2 describes the architecture of the proposed system and Section 3 provides the charging model formulation. Section 4 introduces the considered scenarios, the used input data and the outline of the model simulations. Subsequently, the results are presented in Section 5. The discussion in Section 6 and the conclusion in Section 7 are the last two sections of this work.

2. System architecture

This study proposes a system in which all transformer congestion problems in LV grids are mitigated using shared EVs. This implies that privately-owned EVs can charge freely without considering grid constraints, and that no curtailment of photovoltaic (PV) systems nor load shifting of residential appliances is required. Shared EVs assure that no transformer congestion occurs (i.e., the power flows through the transformer remain below the transformer capacity). In order for such a system to function, a communication framework between different actors and different system components is required, which is visualized in Fig. 1. This communication framework covers one LV grid and needs only two main actors; the DSO and the operators of car sharing platforms with shared EVs charging in the specific LV grid.

Grid congestion is mitigated using shared EVs using the following actions:

1. The DSO contracts one or multiple car sharing operators for the provision of flexibility using shared EVs;
2. The DSO forecasts the total residential load, PV generation and EV charging demand of privately-owned EVs for each timestep;
3. The DSO calculates the total forecasted transformer load excluding the load of shared EVs for each timestep and communicates this to the contracted car sharing operators;
4. The operators of the car sharing platforms use the reservation system of their car sharing platform to forecast the number of shared EVs connected to their own charging stations for each timestep and their respective charging demand. The operator of these car sharing platforms perform an economic optimization of the charging schedules of their shared EV fleet, and assure that the total transformer load will not exceed the transformer capacity;

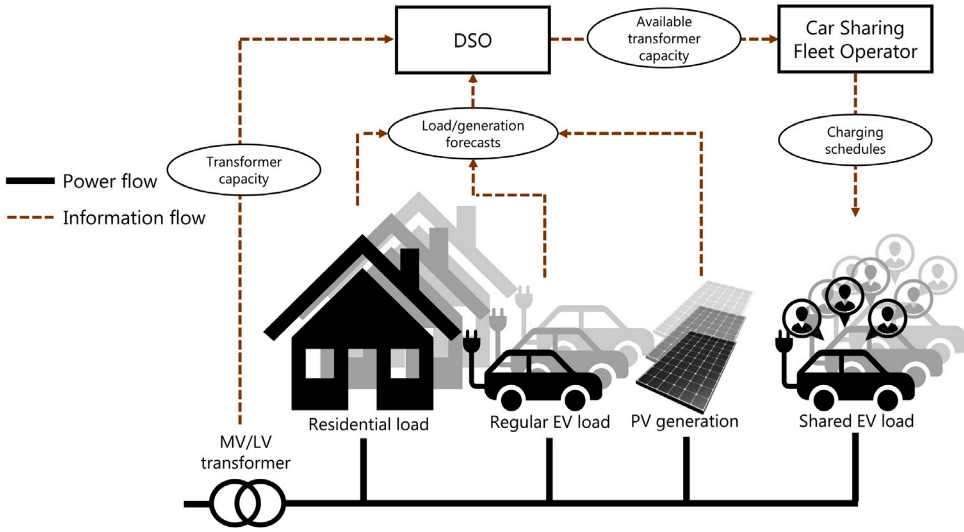

Fig. 1. Visualization of the information flows and physical power flows in the proposed car sharing system architecture.

5. The operators of the car sharing platforms send the optimized charging schedules to the individual charging stations;
6. The car sharing platforms receive financial remuneration for the provision of flexibility to the DSO.

To be able to bring the transformer load below the transformer capacity when the communicated transformer load by the DSO already exceeds the transformer capacity for different timesteps, the shared EVs in the proposed system should be able to provide V2G services.

3. Model formulation

3.1. Optimization model of the proposed system

The economic optimization in step 4 of the proposed system in Section 2 can be translated to a mixed-integer optimization problem, in which shared EV operators minimize charging costs based on Time-of-Use (ToU) tariffs while also mitigating transformer congestion.

3.1.1. Objective function

This model aims to minimize charging costs for shared EVs for all charging transactions in one LV grid over the assessment timeframe, considering electricity costs and battery degradation costs:

$$\text{minimize} \sum_{t=1}^{T} (\mathrm{c}_{\mathrm{ch},t} + \mathrm{c}_{\mathrm{battdeg},t}), \tag{1}$$

where c_{ch} represents the electricity cost function for shared EV charging for the studied LV grid, $\mathrm{c}_{\mathrm{battdeg}}$ represents the battery degradation cost function for the studied LV grid, t represents a timestep and T represents the length of the assessment timeframe.

The electricity cost function for shared EV charging is defined as:

$$\mathrm{c}_{\mathrm{ch},t} = \mathrm{C}_t \sum_{s=1}^{S} \left(\frac{1}{\eta_{\mathrm{ch}}} \mathrm{p}_{\mathrm{ch},s,t} - \eta_{\mathrm{disch}} \mathrm{p}_{\mathrm{disch},s,t}\right) \Delta \mathrm{t} \ \forall t, \tag{2}$$

where C_t represents the ToU-tariff for electricity at time t, p_{ch} and $\mathrm{p}_{\mathrm{disch}}$ represent the charging and discharging power at the EV battery, respectively, η_{ch} and η_{disch} represent the charging and discharging efficiency, respectively, $\Delta \mathrm{t}$ is the duration of one timestep and S is the set of charging transactions for shared EVs, indexed by $s = 0, 1, \dots, S$.

Every charging/discharging cycle shortens the battery lifetime due to cycling aging [21]. Battery degradation costs caused by cycling aging are incorporated in the objective function to make sure that the battery only charges and discharges if the electricity cost benefits exceed the extra battery degradation costs. Battery degradation costs are a function of the battery investment costs $\mathrm{C}_{\mathrm{batt}}$, the piece-wise linear battery degradation function Φ and the depth of discharge of a charging or discharging cycle δ:

$$\mathrm{c}_{\mathrm{battdeg},t} = \sum_{s=1}^{S} (\mathrm{C}_{\mathrm{batt},s} \Phi(\delta_{s,t})) \ \forall t. \tag{3}$$

Ref. [6] provides detailed insight in the composition of this battery degradation function.

3.1.2. EV charging constraints

The charging and discharging power of shared EVs are bounded by the maximum charging or discharging capacity of the EV or the charging station ($\mathrm{P}_{\mathrm{ch,max},s}$ & $\mathrm{P}_{\mathrm{disch,max},s}$):

$$0 \le \mathrm{p}_{\mathrm{ch},s,t} \le \mathrm{P}_{\mathrm{ch,max},s} \ \forall t \in \{t_{\mathrm{arr},s}, t_{\mathrm{arr},s} + \Delta \mathrm{t}, \dots, t_{\mathrm{dep},s}\}, s, \tag{4a}$$

$$0 \le \mathrm{p}_{\mathrm{disch},s,t} \le \mathrm{P}_{\mathrm{disch,max},s} \ \forall t \in \{t_{\mathrm{arr},s}, t_{\mathrm{arr},s} + \Delta \mathrm{t}, \dots, t_{\mathrm{dep},s}\}, s, \tag{4b}$$

where $t_{\mathrm{arr},s}$ and $t_{\mathrm{dep},s}$ are the arrival and departure time of an EV, or start and end of a charging transaction s, respectively.

In addition, the optimization model ensures that all shared EVs have met their charging demand before departure:

$$\mathrm{e}_{\mathrm{ch,tot},s,t_{\mathrm{dep},s}} = \mathrm{E}_{\mathrm{req},s} \ \forall s, \tag{5}$$

where $\mathrm{e}_{\mathrm{ch,tot},s,t_{\mathrm{dep},s}}$ is the net accumulated charging volume at the EV battery for a transaction s at $t_{\mathrm{dep},s}$, and $\mathrm{E}_{\mathrm{req},s}$ is the required charging volume of s at the EV battery. $\mathrm{e}_{\mathrm{ch,tot},s,t}$ at time t depends on the accumulated charging volume at the previous timestep and on the charging and discharging power at time t:

$$\mathrm{e}_{\mathrm{ch,tot},s,t} = (\mathrm{p}_{\mathrm{ch},s,t} - \mathrm{p}_{\mathrm{disch},s,t}) \Delta t \ \forall t \in \{t_{\mathrm{arr}}\}, s, \tag{6}$$

$$\mathrm{e}_{\mathrm{ch,tot},s,t} = \mathrm{e}_{\mathrm{ch,tot},s,t-\Delta \mathrm{t}} + (\mathrm{p}_{\mathrm{ch},s,t} - \mathrm{p}_{\mathrm{disch},s,t}) \Delta \mathrm{t} \quad \forall t \in \{t_{\mathrm{arr},s} + \Delta \mathrm{t}, t_{\mathrm{arr},s} + 2\Delta \mathrm{t}, \dots, t_{\mathrm{dep},s}\}, s. \tag{7}$$

During all timesteps, the accumulated charging volume of a charging transaction cannot exceed the required charging energy to avoid overcharging of the EV battery. In most cases, the car fleet operators do not know the battery State-of-Charge (SoC) and the battery could theoretically be empty at arrival. For this reason, the accumulated charging volume during a charging transaction must exceed the accumulated discharging volume at all timesteps. This is implemented in (8) by setting the lower boundary of the accumulated charging energy at zero:

$$0 \le \mathrm{e}_{\mathrm{ch,tot},s,t} \le \mathrm{E}_{\mathrm{req},s} \ \forall t \in \{t_{\mathrm{arr},s}, t_{\mathrm{arr},s} + \Delta \mathrm{t}, \dots, t_{\mathrm{dep},s}\}, s. \tag{8}$$

3.1.3. Grid constraints

The power balance constraint is formulated in (9):

$$p_{grid,t} = P_{res,t} - P_{PV,t} + \sum_{r=1}^{R}\left(\frac{1}{\eta_{ch}} p_{ch,r,t} - \eta_{disch} p_{disch,r,t}\right) + \sum_{s=1}^{S}\left(\frac{1}{\eta_{ch}} p_{ch,s,t} - \eta_{disch} p_{disch,s,t}\right) \forall t, \tag{9}$$

where p_{grid} represents the transformer load, P_{res} represents the residential load, P_{PV} represents the PV generation and $\mathcal{R}$ is the set of charging transactions for privately-owned EVs, indexed by $r = 0, 1, \dots, R$.

To avoid transformer congestion, the transformer load constraint assures that the transformer load does not exceed the transformer capacity ($P_{trans,max}$) at all timesteps:

$$-P_{trans,max} \leq p_{grid,t} \leq P_{trans,max} \ \forall t. \tag{10}$$

3.2. Additional optimization models

Different other optimization models have been applied in this study to find the load-minimization potential of shared EVs, to simulate the charging patterns of privately-owned EVs in case of cost-optimization of those EVs and to determine EV charging costs in case of combined cost-optimization of shared and privately-owned EVs.

3.2.1. Load minimization of shared EVs

An additional load minimization optimization model has been applied in Section 5.1 to shared EVs to provide insight in the potential of shared EVs to reduce the transformer load in different scenarios. The objective of this optimization model is to minimize the transformer peak load during the assessment timeframe:

$$\text{minimize } \max\{p_{grid,t=1}, p_{grid,t=2}, \dots, p_{grid,T}\} \tag{11}$$

This model was subject to the constraints in (4)–(9).

3.2.2. Cost optimization of privately-owned EVs

This analysis considers scenarios which study the potential of shared EVs to mitigate transformer congestion when privately-owned EVs cost-optimize their charging demand with and without considering V2G functions (see Section 4.1). The optimization model applied to privately-owned EVs is very similar to the optimization model in Section 3.1, but is different in some aspects:

- Privately-owned EVs do not consider the transformer load in their charging optimization, thus the power balance and the transformer load constraints in (9) and (10) are not applied;
- The objective function in (1) and all EV charging constraints in (4)–(8) are applied to charging transactions of privately-owned EVs;
- The optimization models for privately-owned EVs that do not consider V2G, do not consider battery degradation costs in the objective function and do not consider discharging variables in (4), (7) and (9).

3.2.3. Combined cost-optimization and congestion mitigation of shared and privately-owned EVs

In Section 5.2, the economic viability of the proposed system is assessed by comparing the charging costs of the proposed system with a reference case in which both privately-owned EVs and shared EVs adapt their charging schedule to mitigate grid congestion. In contrast to the optimization model in Section 3.1, (2), (3) and (4)–(8) are applied to charging transactions of both privately-owned and shared EVs.

4. Scenario development, data inputs & model simulations

4.1. Scenario overview

The effectiveness of the proposed system is analyzed by applying the optimization model to a case study LV grid in a residential area for a wide range of scenarios. This study considers scenarios for: (i) different adoption rates of shared EVs, (ii) different reductions in vehicle-kilometer traveled (VKT) with adoption of shared EVs, (iii) different transformer capacities, (iv) different charging strategies of privately-owned EVs and (v) different electricity markets which are considered in the cost-optimization of EV charging.

4.1.1. Adoption scenarios of shared EVs

The adoption rate of shared EVs can differ significantly between different areas. The expected adoption of shared EVs is higher in urban areas due to the higher availability of alternative modes of transport [22]. To provide insight in the potential of shared EVs to mitigate grid congestion for different adoption rates of shared EVs, this study considers adoption rates between 5% and 95%.

4.1.2. VKT reduction scenarios

Shifting from private car ownership to car sharing generally reduces the number of trips by car by a person, as users in car sharing schemes have less direct access to a car. This lower car-usage is reflected in a reduction in VKT, which affects the number of shared EVs charging in a grid and thus affects the potential of shared EVs to mitigate grid congestion. Estimations on the reduction in VKT when adopting a shared EV show a wide range of values. Ref. [23] estimates a reduction in VKT of 15%–20% for the Netherlands, However, a literature review of North American studies by [23] shows reductions in VKT between 3%–80%. Ref. [24] compares reductions in VKT between different car sharing schemes and different European cities, and arrives at reductions in VKT ranging between 5%–92%. This study considers reductions in VKT of 0%, 40% and 80%.

4.1.3. Transformer capacity scenarios

The transformer capacity affects the amount of transformer congestion and thus affects the effort required from shared EVs to mitigate transformer congestion problems. This analysis is conducted for transformer capacities of 250 kVA and 400 kVA, as these are typical transformer capacities for residential areas [25].

4.1.4. Charging scenarios for privately-owned EVs

Privately-owned EVs do not need to consider grid constraints when determining their charging patterns in the proposed system, but they can follow different charging strategies. This study considers scenarios for the following charging strategies of privately-owned EVs:

- Uncontrolled charging: EVs charge at maximum charging power after arrival until their charging demand is met;
- Cost-optimized charging without V2G: EVs minimize their charging costs by charging at moments with low ToU-tariffs. V2G functions are not considered here;
- Cost-optimized charging with V2G: EVs minimize their charging costs based on the ToU-tariffs. V2G functions are available here, allowing EVs to inject electricity to the grid at moments with high ToU-tariffs.

4.1.5. Electricity market scenarios

The most accessible method for EVs to cost-optimize their charging demand is by participating in the day-ahead electricity market. However, EVs are also increasingly considered for the provision of grid services, for instance by participating in the automatic Frequency Restoration Reserves (aFRR) market [9,26]. Since the price volatility in this market is substantially higher, the economic analysis in Section 5.2 is conducted using both day-ahead prices and aFRR prices as price inputs.

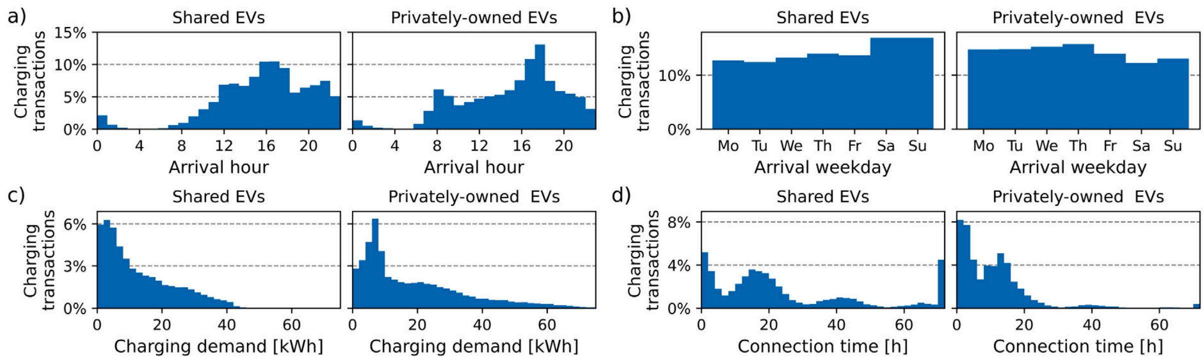

Fig. 2. Histograms comparing key charging characteristics of shared and privately-owned EVs in the input data. Subplot (a) shows the distribution of arrival hours for shared and privately-owned EVs. Subplot (b) shows the distribution in arrival weekdays for shared and privately-owned EVs. Subplot (c) shows the distribution in EV charging demand for charging transactions of shared and privately-owned EVs. Subplot (d) shows the distribution in connection time for charging transactions of shared and privately-owned EVs. The data behind this figure considered 9548 charging transactions of shared EVs and 32801 charging transactions of privately-owned EVs.

4.2. Data inputs

4.2.1. EV charging data

This study used EV charging transaction data from between 8 January 2019 and 12 March 2020 from 277 charging stations with two charging sockets in residential areas in the city of Utrecht, the Netherlands. The charging stations log the arrival time, departure time, charging volume and car-ID for each charging transaction. A subset of these charging stations also log the charging power over time on a 5 or 10 min basis, which is used to determine the average charging power, maximum charging power and actual charging duration for each charging transaction.

Some of the charging stations are used by shared EVs from the car sharing company *We Drive Solar* [27]. Customers of the *We Drive Solar* car sharing company need a subscription and also pay per driven kilometer. In March 2020, the company's car fleet comprised three Tesla Model 3's with a 50 kWh battery capacity and 72 Renault ZOE's with a battery capacity ranging from 44–52 kWh. The IDs of *We Drive Solar* EVs were used to make a distinction between privately-owned and shared EVs in the EV charging data. The used data consists of 32,801 charging transactions of privately-owned EVs and 9,548 charging transactions of shared EVs.

The charging patterns of the considered charging transactions of privately-owned and shared EVs are substantially different, which is highlighted in Fig. 2. This figure compares key charging characteristics of privately-owned and shared EVs. The figure indicates that the arrival moments of privately-owned and shared EVs are not similar. Fig. 2a illustrates that the arrival hours of privately-owned EVs peak between 17:00–19:00, while this peak is less evident for shared EVs. Besides, a relatively high share of the shared EVs arrive after 20:00, in contrast to privately-owned EVs. In addition, shared EVs arrive more-frequently in weekends compared to privately-owned EVs, as shown in Fig. 2b. Both observations could indicate that privately-owned and shared EVs are used for different purposes; privately-owned EVs are generally more used for commuting, while shared EVs are more used for leisure purposes.

From Figs. 2c and 2d can be deducted that the flexibility in charging is generally higher for shared EVs. On the one hand, Fig. 2c shows that the charging demand of privately-owned EVs is generally higher compared to the charging demand of shared EVs. On the other hand, Fig. 2d outlines that the connection time of shared EVs is on average higher compared to privately-owned EVs, indicating low utilization of shared EVs at some moments.

4.2.2. Simulation of EV charging transactions

A probabilistic model from [18] is used to simulate future EV charging transactions of privately-owned and shared EVs. This model requires historical EV charging data and the predicted total charging requirement of all charging transactions in one LV grid during the assessment timeframe as inputs for the simulation of charging transactions.

All scenarios assume a fully electrified car fleet. The predicted total charging demand of privately-owned and shared EVs in the assessment timeframe ($\mathrm{E}_{\mathrm{tot,priv}}$&$\mathrm{E}_{\mathrm{tot,shared}}$) depends on the adoption rate of shared EVs (α_{shared}), the reduction in VKT when adopting a shared EV (γ_{vkt}) and the total charging demand of privately-owned EVs without adoption of shared EVs ($\mathrm{E}_{\mathrm{priv,org}}$):

$$\mathrm{E}_{\mathrm{priv}} = \mathrm{E}_{\mathrm{priv,org}}(1-\alpha_{\mathrm{shared}}) = \sum_{r=1}^{R} \mathrm{E}_{\mathrm{req},r}, \tag{12a}$$

$$\mathrm{E}_{\mathrm{shared}} = \mathrm{E}_{\mathrm{priv,org}}\alpha_{\mathrm{shared}}(1-\gamma_{\mathrm{vkt}}) = \sum_{s=1}^{S} \mathrm{E}_{\mathrm{req},s}. \tag{12b}$$

A value of 530 MWh was used for $\mathrm{E}_{\mathrm{priv,org}}$ for the selected case study grid, based on an average annual car mileage of 13,000 km [28], a car ownership ratio of 0.6 cars/household [29] and a fuel consumption of 0.2 kWh/km [30].

4.2.3. Grid data and electricity price data

A LV-grid in the residential Lombok district in Utrecht, the Netherlands is used as a case study grid in this analysis. The grid serves 340 connection points, of which the majority are households, with an average annual electricity demand of 3420 kWh per connection point. The capacity of the transformer of this grid has recently been reinforced from 250 kVA to 400 kVA. This study assumes a future installed PV capacity of 200 kWp. Normalized PV generation profiles from three large PV systems in the studied residential area were used as PV generation profiles in this analysis. Residential load profiles were generated using the standardized NEDU-profiles [31] and the total annual electricity demand of all connection points in this grid.

Day-ahead market prices and aFRR market prices in the Netherlands for 2019 [32] are used as price inputs in this study.

4.3. Model simulations

Model simulations for all considered scenarios are conducted in Python [33] using the Gurobi Modeling and Optimization package [34] using a high performance computing cluster. The assessment timeframe of all analyses is one year using 15 min timesteps, but to reduce the computational burden, this was split in three model simulations of four months. Charging transactions of five additional days before the assessment timeframe are also considered in the optimization model to assure that a representative number of EVs is connected to the grid at the beginning of the assessment timeframe. The model is run for five

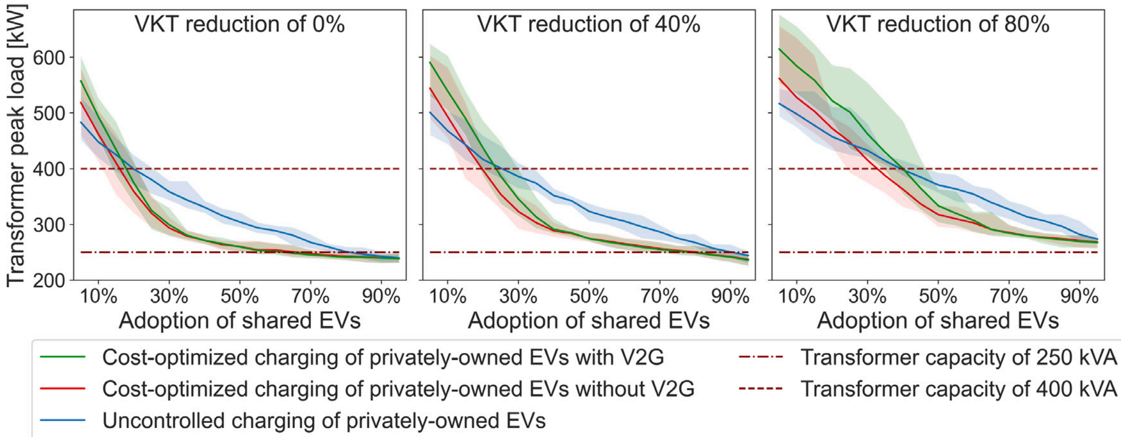

Fig. 3. Annual transformer peak loads when applying a transformer peak load minimization algorithm to shared EVs for different considered scenarios. The values in the plots represent the average annual transformer peak load for the ten model runs. The shaded area represents the range in results between the ten model runs.

extra days after the end of the assessment timeframe to allow EVs that connected to the grid just before the end of the assessment timeframe to finish their charging session. This study used battery degradation parameters from [6] to model battery degradation, assuming a battery capacity of 50 kWh in case the battery capacity of the EV was unknown. A charging and discharging efficiency of $\sqrt{0.87}$ is used in this analysis [35]. Every scenario is run ten times using a newly-simulated set of EV charging transactions to obtain insight in the variability in results.

5. Results

5.1. Load minimization potential of shared EVs

5.1.1. Impact of shared EV adoption rate

Shared EVs are able to bring down transformer peak loads below the transformer capacity at relatively low adoption rates of shared EVs. This is presented in Fig. 3, which reports transformer peak loads when a peak load minimization algorithm has been applied to shared EVs.

The capability of shared EVs to lower the transformer peak loads increases rapidly with higher adoption of shared EVs. This is induced by two mechanisms. First, higher adoption of shared EVs induces a shift away from private car ownership and thus causes a reduction in the charging demand of privately-owned EVs. As privately-owned EVs can charge without considering grid constraints in the proposed system, a reduction in their charging demand reduces the overall transformer load that shared EVs need to minimize. Second, more shared EVs are available at high adoption of shared EVs to inject electricity to the grid when the transformer load is high, resulting in an increased load-minimization potential.

From Fig. 3, it can be observed that shared EVs can mitigate all transformer congestion problems in grids with a 400 kVA transformer at relatively low adoption of rates; in all considered scenarios, they can bring the peak transformer load below 400 kVA with only a 20 to 30% adoption rate or higher. The potential of shared EVs to fully mitigate transformer congestion problems is lower in grids with a 250 kVA transformer. In such grids, shared EV adoption rates of 60 to 90% are required to bring the transformer peak load below its capacity, depending on the specific scenario.

5.1.2. Impact of the charging strategy of privately-owned EVs

The peak load-minimization potential of shared EVs is highly affected by the charging strategy of privately-owned EVs. Cost-optimization of privately-owned EVs with or without V2G causes large peaks in their charging demand at moments with favorable ToU-tariffs, and low charging demand at moments with less-favorable ToU-tariffs. At low adoption rates of shared EVs, only a limited number of shared EVs are connected to the grid at the moments with high charging demand of privately-owned EVs, limiting the potential to minimize transformer peak loads. The load-minimization potential of shared EVs in this scenario increases considerably with higher adoption of shared EVs; there are sufficient shared EVs connected to the grid at moments with high charging demand of privately-owned EVs to bring down the transformer load, while shared EVs can easily meet their own charging demand at the substantial share of time with very low charging demand of privately-owned EVs.

The charging demand of privately-owned EVs is less concentrated on specific moments when they charge in an uncontrolled manner. This increases the load-minimization potential of shared EVs with low adoption of shared EVs, due to the absence of high charging demand peaks. On the other hand, the constant load of privately-owned EVs causes that shared EVs constantly need to feed back electricity to the grid to minimize the peak transformer load while simultaneously meeting their own charging demand. This causes the peak load-minimization potential of the proposed system to be lower at high adoption of shared EVs when privately-owned EVs charge in an uncontrolled manner.

5.1.3. Impact of VKT reduction and variability in results

Higher VKT reductions reduce the potential to mitigate grid congestion problems using shared EVs only, since in this case less shared EVs are required to meet the passenger car traveling demand of shared EV users. As a consequence, less shared EVs are connected to the grid to reduce transformer peak loads.

All model runs are repeated ten times using different sets of simulated EV charging transactions. Fig. 3 indicates that the spread in results among different model runs is relatively high, in particular with low adoption of shared EVs and with higher VKT reduction rates. The transformer load minimization potential of shared EVs depends on their availability at the moments with peak transformer loads. With relatively little shared EVs charging in the grid, the risk that a limited number of shared EVs is available to reduce transformer loads at one of those peak moments is high. This underlines that a minimum adoption rate of shared EVs is necessary before it can be considered as a reliable technology for the mitigation of grid congestion problems.

5.2. Economic viability of proposed system

The charging costs of the proposed system could be higher compared to a system in which private and shared EVs put in combined efforts to avoid grid congestion, since more flexibility options are available in the latter option. The economic attractiveness of the proposed system is determined by comparing the overall charging costs of the proposed system with the reference case in which both privately-owned

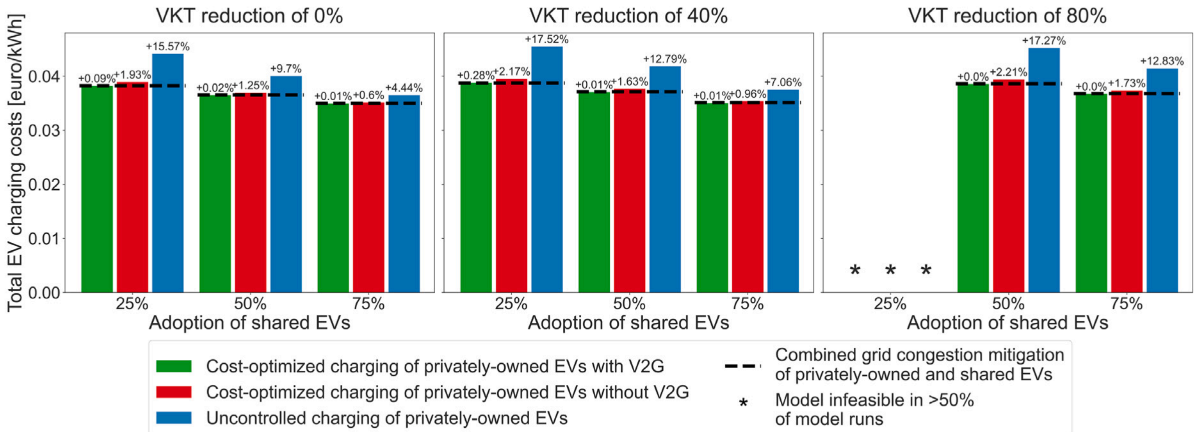

Fig. 4. Combined average EV charging costs (electricity costs in the day ahead market and battery degradation costs) of privately-owned and shared EVs when using the proposed system in different scenarios. Results are presented for a grid with a 400 kVA transformer and in all scenarios, EVs only participate in the day-ahead electricity market. The dashed lines represent the average charging costs of a reference case with combined grid congestion mitigation of privately-owned and shared EVs. The cost-increase of using the proposed system compared to the reference case is reported as a percentage value.

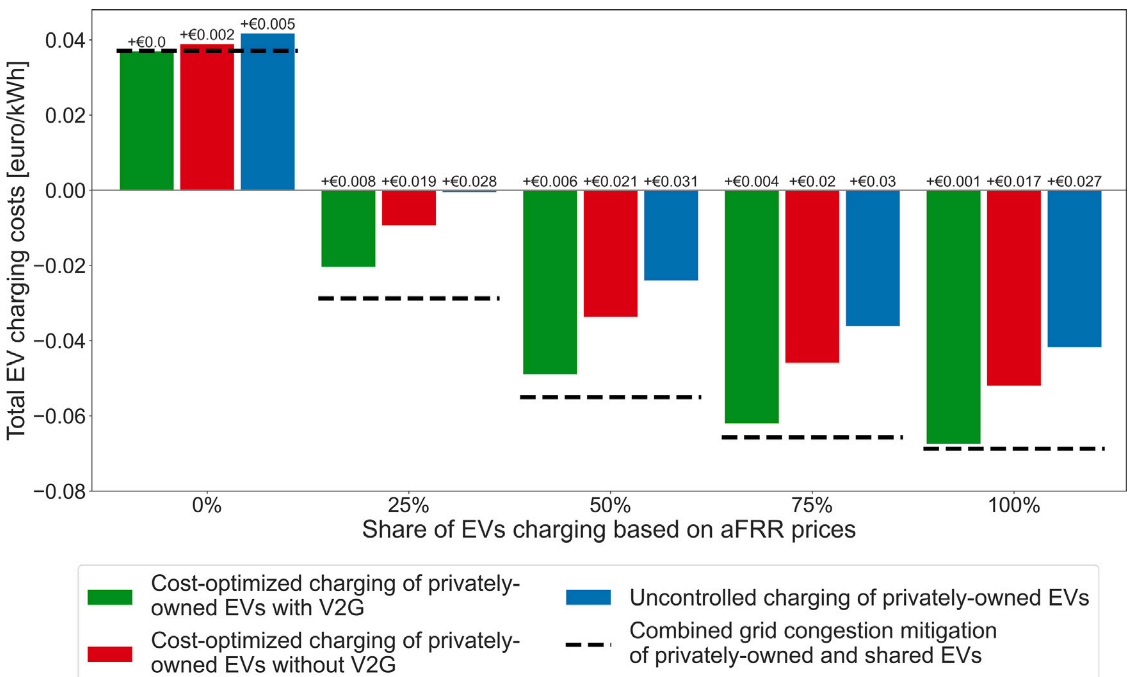

Fig. 5. Combined average EV charging costs (electricity costs in the day ahead and aFRR markets and battery degradation costs) of privately-owned and shared EVs when different shares of the EV fleet charge based on aFRR prices using the proposed system. Results are presented for a grid with a 400 kVA transformer, a 50% EV adoption share and a VKT reduction of 40%. The dashed lines represent the average charging costs of a reference case with combined grid congestion mitigation of privately-owned and shared EVs. The values above the bars present the cost-increase of using the proposed system compared to the reference case in euro/kWh.

and shared EVs consider transformer congestion in the optimization of their charging schedules. Fig. 4 presents this comparison when EVs charge in the day-ahead market in a grid with a 400 kVA transformer capacity, considering different charging strategies of privately-owned EVs, different adoption rates of shared EVs and different VKT reductions when adopting a shared EV. The cost increase of when using the proposed system (colored bars) compared to the reference case (dashed lines) is indicated as a percentage value.

5.2.1. Impact of the charging strategy of privately-owned EVs

The cost difference is marginal when grid congestion is mitigated using shared EVs only and privately-owned EVs cost-optimize their charging demand using V2G (green bars in Fig. 4). In all cases, the average cost increase compared to combined grid congestion mitigation is less than 0.3%, corresponding to less than 0.0001 euro/kWh. Using only shared EVs for the mitigation of grid congestion problems leads to slightly higher charging costs of shared EVs. However, a large part of this cost-increase is offset by the fact that privately-owned EVs can charge more economically-efficient, since the grid capacity is not considered in their charging optimization.

The increase in total charging costs with the proposed system is more considerable when looking at other charging strategies of privately-owned EVs. These higher overall charging costs are caused by an increase in charging costs of privately-owned EVs, which do not have the opportunity to use V2G in these charging strategies and thus have less options for cost-optimization. This is in contrast to combined cost-optimization of shared and private EVs, where privately-owned EVs can use V2G functions.

5.2.2. Impact of shared EV adoption rate, VKT reduction and transformer capacity

With higher adoption of shared EVs, the share of shared EVs in the total number of charging transactions occurring in a LV grid increases. Since shared EVs have a longer average connection time to the charging station compared to privately-owned EVs (see Fig. 2), there is more room to move charging to moments with low ToU-tariffs. This results in lower overall charging costs with higher shared EV adoption. The difference in charging costs between the reference case and the charging scenarios for privately-owned EVs which do not consider V2G (blue and red bars in Fig. 4) decreases with higher shared EV adoption. In these scenarios, only shared EVs use V2G and the share of the total EV fleet that cost-optimizes their charging demand without V2G thus decreases with higher shared EV adoption.

Overall charging costs and the rise in charging costs when using the proposed system increase slightly with higher reductions in VKT when adopting a shared EV. The lower number of shared EVs required to meet the traveling demand of shared EV users with higher VKT reduction causes that less shared EVs are available as a flexibility resource, resulting in less-efficient mitigation of grid congestion. This also explains why the model is infeasible at low EV adoption rates with high VKT-reduction rates; too little shared EVs are connected to the grid to bring the transformer peak load below the transformer capacity, as was also seen in Fig. 3.

Mitigating grid congestion using shared EVs in a grid with a 250 kVA transformer leads to higher overall charging costs (+8%) when charging in the day-ahead market, since more deviations from the economically-optimal charging schedule are required when mitigating grid congestion compared to a 400 kVA transformer. Besides, the cost increase compared to combined grid congestion mitigation of privately-owned and shared EVs is slightly higher with a 250 kVA transformer, in particular at low shared EV adoption rates. With a 250 kVA transformer, more efforts from shared EVs are required to mitigate charging peaks caused by privately-owned EVs, providing less room for them to charge economically at moments with beneficial ToU-tariffs.

5.2.3. Impact of selected pricing scheme

To assess the impact of considered electricity market on the economic viability of the proposed system, a sensitivity analysis has been performed in Fig. 5. In this figure, aFRR market prices are used for the optimization of charging schedules for varying shares of the EV fleet. Day-ahead electricity market prices are used for the remainder of the EV fleet. The price volatility in the aFRR market is substantially higher compared to the day-ahead market, which explains why EV charging costs decrease and even become negative with increasing shares of the EV fleet participating in the aFRR market.[1]

The difference in charging costs between the proposed system and the reference case of combined grid congestion mitigation of shared and privately-owned EVs increases with partial participation of EVs in the aFRR market, although the difference between the reference case (dashed line) and the scenario of cost-optimization of privately-owned EVs using V2G (green bar) remains below 0.01 €/kWh in all cases. The connection time of shared EVs is generally longer (see Fig. 2d) and therefore shared EVs can benefit most from the high price volatility in the aFRR market. Since transformer congestion is only considered in the charging schedules of shared EVs in the proposed system, transformer congestion cannot be mitigated using shared EVs charging in the day-ahead market only and shared EVs charging in the aFRR market are required to deviate from their cost-optimal charging schedules. This is in contrast to the reference case of combined grid congestion mitigation of shared and private EVs, where most transformer congestion problems can be mitigated by only adjusting the charging schedules of private and shared EVs participating in the day-ahead market. With higher shares of EVs participating in the aFRR market, deviations from the cost-optimal charging schedules of shared EVs participating in the aFRR market are also required in the reference case to avoid transformer congestion. As a consequence, this cost difference decreases with higher shares of the EV fleet participating in the aFRR market.

6. Discussion

6.1. Implications and limitations

This work should be regarded as an exploratory study, presenting the theoretical techno-economic potential of using shared EVs for the mitigation of transformer congestion. The practical potential of shared EVs to mitigate transformer congestion is lower, as this study assumed perfect foresight for different aspects, including the grid load, EV charging demand, electricity prices and the arrival and departure times of EVs, while there is uncertainty on these aspects in practice. One of the main benefits of using shared EVs, namely their more predictable departure times via the usage of a reservation system, was not considered, causing that shared EVs will be charged less conservatively compared to private EVs in practice. Therefore, the increase in charging costs when using the proposed system approach will be lower in practice, further pronouncing the economic viability of this system.

The results in this analysis indicated that a 20%–30% shared EV adoption rate is required in a specific LV grid to be able to mitigate all transformer congestion problems. In 2020, around 6.6% of the Dutch population with a driving license made use of a car sharing platform [36,37], while the share of the population that fully shifted to car sharing is substantially lower. A 20%–30% adoption rate of shared EVs on a national level is therefore not realistic on the short term. However, shared cars are increasingly considered in densely-populated urban areas as a solution to reduce the land use of parking spaces. This is illustrated by different newly-constructed urban districts, in which all parking spots can exclusively be used by shared cars [38,39]. Therefore, it is realistic that the minimum required adoption rate of shared EVs is met relatively soon in an increasing number of urban LV-grids.

Important to note is that a well-functioning remuneration system is crucial for successful implementation of the proposed system. The proposed system can lead to unfair allocation of costs and benefits between car sharing companies and private EV owners, since charging costs for car sharing operators increase if they adjust their charging schedules to mitigate grid congestion, while charging costs of private car owners decrease since they do not need to consider grid congestion when scheduling their EVs. For this reason, the development of a fair remuneration scheme or local electricity market which provides financial incentives to car sharing operators to participate in such system should become a priority for grid operators. The local electricity market design under coordination of a community manager (e.g., the grid operator) proposed in [40] could serve as a blueprint for a fair allocation mechanism for costs and benefits between all involved stakeholders.

High quality forecasts of the grid load are a prerequisite for high effectiveness of the proposed system architecture. Forecasting errors can lead to transformer overloading or to imbalance costs to operators of car sharing schemes if shared EVs need to deviate from their optimal charging schedules to correct for forecasting errors. For this reason, grid operators should invest in monitoring equipment for LV grid data and should invest in the development of advanced forecasting methods in order to arrive at more accurate forecasts. Also, investments in communication infrastructure are mandatory for a well-function system.

This study made use of a rich data set of charging transactions of shared EVs. Since all charging transactions in this study are from a

[1] It should be noted that it is very complex to accurately forecast aFRR prices, since these are mostly dependent on live imbalance volumes. Therefore, scheduling EVs mostly based on aFRR prices is a high-risk strategy. The goal of this analysis is to provide insight in the robustness of the economic results in this study when considering electricity markets with a higher price volatility.

station-based car sharing scheme in an urban area, the results cannot be generalized to other types of car sharing schemes. New user groups could adopt shared EVs with higher adoption of car sharing, which potentially results in higher utilization rates of shared EVs and different arrival times or lower connection times of shared EVs. In contrast, it can be expected that an overcapacity in the number of shared EVs will always remain to assure availability of shared EVs to users, causing the flexibility in charging demand not to change considerably with higher shared EV adoption.

6.2. Future research

Next to mitigating transformer congestion, EVs can also be used to mitigate cable congestion or other power quality issues, including voltage issues and voltage fluctuations [41]. Future research could adapt the proposed system to analyze its potential in mitigating other LV grid problems using shared EVs only. In addition, future research could further enhance the proposed system by suggesting methods on how to allocate the responsibility of mitigating grid congestion among car sharing operators when two or more car sharing operators charge shared EVs in the same LV grid. Lastly, the lower uncertainty about the departure time of shared EVs compared to privately-owned was not considered in this research. Future studies could quantify this lower uncertainty and consider this in optimization models, in order to fully capture the added value of mitigating grid congestion problems using shared EVs only.

7. Conclusion

This study proposed a novel system approach for mitigating transformer congestion in LV grids using shared EVs and assessed its techno-economic potential in reducing transformer peak loads. Extensive simulations were performed using high-resolution EV charging transaction data of both privately-owned and shared EVs. The results showed a promising future potential role for shared EVs in the mitigation of transformer congestion problems in LV grids if the adoption of shared EVs continues to rise. Shared EVs are able to avoid all grid congestion problems in grids with a 400 kVA transformer at relatively low adoption rates. However, high adoption rates of shared EVs are required in grids with 250 kVA transformers. The techno-economic assessment indicated that the extra charging costs when mitigating grid congestion using shared EVs only are negligible compared to the reference case with combined grid congestion mitigation of privately-owned and shared EVs. Shared EVs can alleviate barriers for using EV smart charging to grid problems and this study showed that transformer congestion can be mitigated using shared EVs only at relatively low shared EV adoption rates and at negligible extra costs. Therefore, further stimulation of car sharing by governments is not only attractive from an environmental perspective, but also from a grid management perspective.

CRediT authorship contribution statement

Nico Brinkel: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Tarek AlSkaif:** Conceptualization, Methodology, Writing – review & editing. **Wilfried van Sark:** Conceptualization, Writing – review & editing, 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.

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