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Electric vehicle based smart e-mobility system – Definition and comparison to the existing concept

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HIGHLIGHTS

- Control authority in smart e-mobility is usually on the side of charging stations.
- Electric vehicle based concept is an alternative where vehicles control charging.
- In a proposed concept charging stations are merely an enabling infrastructure.
- Electric vehicle based system yields higher revenues for the vehicle owners.

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ABSTRACT

The existing models designed to reap the benefits of electric vehicles' flexibility in the literature almost exclusively identify charging stations as active players exploiting this flexibility. Such stations are seen as static loads able to provide flexibility only when electric vehicles are connected to them. This standpoint, however, suffers from two major issues. First, the charging stations need to anticipate important parameters of the incoming vehicles, e.g. time of arrival/departure, state-of-energy at arrival/departure. Second, it interacts with vehicles only when connected to a specific charging station, thus overlooking the arbitrage opportunities when they are connected to other stations. This conventional way of addressing the electric vehicles is referred to as charging station-based e-mobility system. A new viewpoint is presented in this paper, where electric vehicles are observed as dynamic movable storage that can provide flexibility at any charging station. The paper defines both the existing system, where the flexibility is viewed from the standpoint of charging stations, and the proposed one, where the flexibility is viewed from the vehicles' standpoint. The both concepts are mathematically formulated as linear optimization programs and run over a simple case study to numerically evaluate the differences. Each of the four issues identified are individually examined and omission of corresponding constraints is analysed and quantified. The main result is that the proposed system yields better results for the vehicle owners.

1. Introduction

Much focus has been given lately to the decarbonization of the electricity production, however a greater challenge might be doing the same with the heating and transportation sector. The transition from conventional vehicles to low carbon emission ones is moving slower than anticipated, despite that its importance is highlighted in all relevant policy documents [1]. The solutions for changing transportation habits and preferences of end-users [2] require an integrated approach, especially in designing models for end-users and encouraging them to make a quicker transition to electrified transport, as designed by the relevant regulatory goals [3]. This means being aware of technical, economic and social constraints when creating models to make electrification of the transport an alternative new flexibility source. If electric vehicles (EVs) are charged uncontrollably [4], i.e. charging at maximum power until fully charged, power system's hunger for flexibility increases, calling for additional investments in peaking units and grid infrastructure upgrades. On the other hand, if EVs are charged in a controllable manner [5], they resemble features of both demand response and energy storage. Shifting their charging times represents the aspect of demand response. This is often referred to as Grid-to-Vehicle (G2V) mode, which requires unidirectional controllable chargers [6]. A possibility to discharge a part of the surplus energy when not needed for motion, often referred to as Vehicle-to-Grid (V2G) mode, corresponds to the energy storage aspect of EVs and requires bidirectional controllable chargers [7,8]. Detailed overviews of EV charging modes are available

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Fig. 1. Illustrative example composed of three EVs and three CSs - general overview.

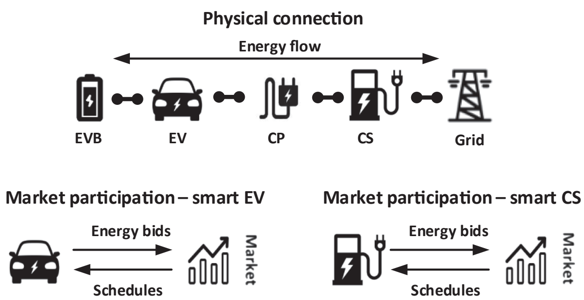

Fig. 2. Physical connection and market participation of EV-based and CS-based smart e-mobility models.

in [9,10].

This paper proposes a new concept of using the EV flexibility more efficiently in a world with a multitude of new data streams relying on information-communication technologies in vehicles and without any loss of comfort for EV drivers. We argue that the state-of-the-art literature, research projects and e-mobility sector currently conceive the smart e-mobility in a way which leads to an underutilization of the EV flexibility and to insufficient financial returns. The usual understanding of smart e-mobility is that Charging Stations (CSs) use EVs to provide flexibility to the power system (we define this as the CS-based concept), whereas this paper challenges this approach and reverses the roles by identifying EVs themselves as smart players that provide flexibility and the CSs as merely an enabling infrastructure (we refer to this as the EV-based concept).

The *smart e-mobility* term used in this paper refers to an advanced multisector system where the main actors are: EVs, CSs, Electric Vehicle Aggregators (EVAs), power grid and electricity market operators. Merchant actors within this ecosystem have at their disposal smart EV charging and discharging options to provide flexibility to the power system and in return receive monetary reward. This paper analyzes a basic illustrative example with three EVs and three CSs. The purpose of the example is to highlight certain issues in the state-of-the-art, after which we define a new mathematical model and demonstrate how the issues of the current state-of-the-art are eliminated using our model through a detailed case study.

This paper contributes to the body of knowledge in the field of EV aggregation by providing the following:

1. a design and a formulation of a novel EVA model tracking the EVs during their trips, thus capturing all relevant trip and battery information,
2. a systematic and rigorous comparative assessment of the CS-based and EV-based models,
3. a demonstration that aggregate EV models without relevant features, such as power levels and grid tariffs, result in incorrect conclusions regarding the cost of EV charging.

2. Illustrative example

2.1. Assumptions and description

An illustrative example presented in Figs. 1–3 compares the current smart e-mobility CS-based model with the proposed EV-based concept. Several simplifications and assumptions are made to keep this example concise. We observe three EVs and three CSs (Fig. 1) and their behavior through a 24-h period with 1-h time resolution. Each EV can be charged at different CSs and each driving period, i.e. period when EV is not connected to any CS, lasts one hour. Each EV has one Battery (EVB) and one On-Board Charger (OBC), while each CS encompasses three Charging Points (CPs), meaning it can serve all three EVs at a time. All three CPs within a CS are AC and have chargers of same power capacity.

Let us assume that both EVs and CSs can individually participate in the wholesale electricity market,[1] namely the day-ahead market, and that their objective is to minimize the purchasing costs of electricity for mobility purposes and/or to maximize revenue through energy arbitrage.

A smart e-mobility system can therefore be conceived as an EV-based or a CS-based, as illustrated in Fig. 2. In the former model, the EVs are the smart entities negotiating market strategy while the CSs are merely an infrastructure with their technical constraints (CP power capacity) and economic parameters (CS utilization fee). The latter model observes the same entities, but from an opposite standpoint. The CSs are the smart entities negotiating market strategy, while the EVs only impose technical constraints (OBC power capacity) and economic charges (battery utilization fee). The CSs must pay a fee to use the EVs' physical equipment (battery) and the energy stored within the EVBs when performing arbitrage (V2G mode). On the other hand, they receive payments by the EVs for the energy they charge for driving purposes. Currently, the roads are populated with both hybrid and full EVs. Hybrid EVs can be seen as a part of the bridging process toward the full transportation electrification. Our focus is on future scenarios where electrification is already in its final steps and where full EVs are a dominant technology. Therefore, we do not explicitly model the hybrid EVs in this paper.

2.2. EV-based vs. CS-based smart e-mobility model

We use the graphs in Fig. 3 to describe the differences between the EV-based and the CS-based smart e-mobility models. The graphs to the left show charging profiles of the three EVs, while the ones to the right show charging profiles of the three CSs. All graphs are created from the same data, but observed from different viewpoints: graphs to the left are relevant for the EV-based, while the ones to the right are relevant for the CS-based smart e-mobility model.

EVs in Fig. 3 are shown in different colors: EV1 – turquoise, EV2 – orange, and EV3 – purple. Their respective OBC maximum powers (OBC_LIM) are marked with straight lines: EV1 – low-power OBC (4 kW), EV2 – medium-power OBC (8 kW), and EV3 – high-power OBC (12 kW). The EVs can charge at three CS types: CS1 is a home charger (4 kW) – green, CS2 is charger at work (8 kW) – blue, and CS3 is charger at a shopping mall (12 kW) – red. EVs have different driving profiles. EV1 has a *home-work-home* profile: it is connected to CS1 from midnight to 07:00, drives to CS2 where it stays from 08:00 to 16:00, and drives back to CS1, where it is connected from 17:00 to midnight. Charging profile of EV2 is *home-mall-home*, while EV3's profile is *home-work-mall-home*. Each charging period is colored according to the corresponding CS.

The CS charging curves are composed of the charging curves of the EVs connected to it. For example, the graph for CS1 (upper-right in

[1] Currently this is done through aggregators due to energy bid thresholds in most markets.

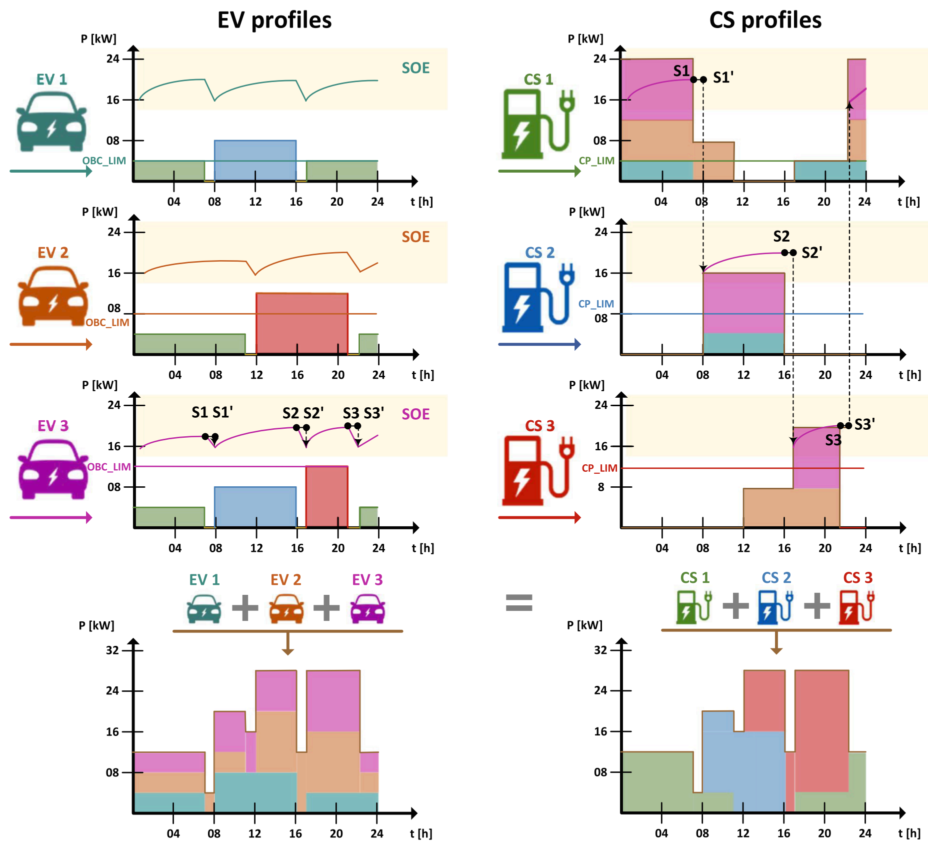

Fig. 3. Illustrative example - daily curves for three EVs and three CSs; left figures - EV view on charging profiles, right figures - CS view on charging profiles.

Fig. 3) shows that all three EVs are connected to it from 00:00 to 07:00. The power required at CS1 during that time is the sum of the OBC powers of the EVs using it. EV2 (orange) is staying longer at CS1 (until 11:00), while EV1 (turquoise) comes back home earlier than others (at 17:00). Since EV1 and EV3 are at work during the morning and midday hours, CS2 has two connected EVs from 08:00 to 16:00 (turquoise EV1 and purple EV3), and no connected EVs in other hours. EV2 goes to a shopping mall, where it charges at CS3 from 12:00 to 21:00, while EV3 goes to the mall after work form 17:00 to 21:00 (third graph on the right-hand side). The areas in the graphs to the right correspond to stacked OBC powers, while the maximum CP power limits are indicated with fixed straight lines. In instances where *CP_LIM* is lower than *OBC_LIM*, the CP is the limiting factor for charging power.

The lower graphs in Fig. 3 are aggregate curves based on the EVs' behavior (on the left) and the CSs' behavior (on the right). The colors display which EV (on the left) or CS (on the right) contributes to the aggregated behavior at a specific period of time. The outline curve is the same in the left and the right graphs, meaning that if there is only one central aggregation entity that oversees all EVs and CSs, it does not matter whether it is defined as an EV- or a CS-based. However, it does matter when multiple aggregators enter the market. Interesting research concerning EV and CS measurements data sets can be found in [11] where they observe similar issue of EV and CS viewpoints.

The areas with the yellow background in the graphs in Fig. 3 show the EV state of energy (SOE) throughout the day. In graphs to the left, each SOE curve corresponds to the corresponding EV, while in graphs to the right only the SOE curve of EV3 is displayed for simplicity.

Both concepts base their predictions for available power and energy on the accurate SOE estimations. Those estimations itself could be highly uncertain due to differences in chemical structure of the cells and due to different algorithms used for the estimations [12,13].

From the ecological perspective, EV batteries effect greenhouse emission at both the production and the utilization stages. The production stage contributes to around 150–200 kg CO_2-eq/kWh according to [14], where most of production-stage emissions are the result of battery manufacturing and material processing. Manufacturing and processing are mostly nonflexible, meaning that the energy mix of the power system defines the exact level of emissions. A solution to lower the emission at the production stage is therefore decarbonization of the power system. The concepts of smart EV charging does not directly lower the production emissions, but they do foster the power system decarbonization. In other words, the EV-based e-mobility system could significantly increase the share of renewable power in power systems.

Research carried out in [15] concludes that the emissions related to EVs during the utilization phase are by far the lowest in high-renewable energy case studies. European Energy Agency confirmed that decrease of emissions from transport electrification is significantly higher than the increase in emissions due to higher electricity production to support transportation electrification [16]. In this paper we assume that electricity price follows the renewable generation, i.e. low price indicates abundance of renewable generation and vice versa. Therefore, the EV scheduling by price minimization also tends to maximize renewable generation utilization. However this is not always the case. Thus, if an EV user wants to schedule its EV directly to maximize renewable generation, the objective function should be reformulated to consider the amount of renewable generation in the system. In general, the proposed EVBA concept allows decarbonization due to its better adaptability to changes in the power system, resulting in reduced system operator's flexibility needs.

2.3. Data transfer

Different data forms must be exchanged between the EVs and the CSs, which is essential for proper smart e-mobility operation in both the EV- and CS-based system. In the EV-based system the CS data must be sent to EVs, while in the CS-based system the EV data must be sent to CSs.

Required EV data are:

1. technical data – parameters such as OBC power levels, battery capacity, etc.,
2. infrastructure cost – expenses arising from EV usage apart from mobility reasons, such as V2G battery degradation,
3. preferences – EV users' desires related to charging, such as minimum SOE under which an EV does not offer flexibility, targeted SOE at some point in time, etc.,
4. behaviour – historic driving/parking data which serve as a base for future EV behaviour forecasts.

Required CS data are:

1. technical data – parameters such as CP connector type and CP power levels,
2. infrastructure cost – expenses arising from the CS usage for any kind of charging and discharging, e.g. CS operation and maintenance cost, CS investment return, and grid fees.

3. Issues and proposed solution

In the CS-based smart e-mobility system the CSs submit their individual bids in the market. Each of them runs their own optimization algorithm based on their own predictions. However, this results in the issues individually elaborated below, each followed by a proposed solution using the EV-based concept.

3.1. Issue 1 – insufficient information on EVs' behavior at other CSs

3.1.1. CS-based issue

The first issue is that a CS only tracks the EVs' SOE in the periods when they are connected to it. From the mathematical standpoint, power to be charged/discharged and the SOE while the EVs are either parked at other premises or driving are unknown and included in the model as stochastic parameters. Only when EVs are connected to this CS those values become controllable variables. If observing the SOE curve of EV3 in Fig. 3, it is broken down into several segments (at points S1-S3), where each CS can see only one part of it but not the entire daily curve. This is a major drawback since the values of the (dis) charging variables should come directly from forecasting the four main attributes of each EV:

1. arrival time of vehicle v (t_v^{ARR}),
2. SOE at arrival (SOE_v^{ARR}),
3. departure time (t_v^{DEP}),
4. required SOE at departure (SOE_v^{DEP}).

For the CSs in the presented example, the following stands for EV3:

- CS1 forecasts t^{DEP} and $SOE_{v,cp1}^{\mathrm{DEP}}$ at S1 and t^{ARR} and at S3',
- CS2 forecasts t^{ARR} and $SOE_{v,cp2}^{\mathrm{ARR}}$ at S1' and t^{DEP} and $SOE_{v,cp2}^{\mathrm{DEP}}$ at S2,
- CS3 forecasts t^{ARR} and $SOE_{v,cp3}^{\mathrm{ARR}}$ at S2' and t^{DEP} and $SOE_{v,cp3}^{\mathrm{DEP}}$ at S3.

The CSs must do the same for all EVs coming to charge. Mathematically, this is represented as follows:

$$\text{if} \quad t \in \Omega_{v,cp}^{T\text{parked\_at\_observed\_CS}}$$
$$soe_{v,t}^{\mathrm{EV}} = soe_{v,t-1}^{\mathrm{EV}} + e_{v,t}^{\mathrm{SCH}} \cdot \eta^{\mathrm{SCH}} - e_{v,t}^{\mathrm{DCH}} / \eta^{\mathrm{DCH}}; \tag{1}$$

$$\text{else-if} \quad t = t_{v,cp}^{\mathrm{ARR}}$$
$$soe_{v,t}^{\mathrm{EV}} = SOE_{v,cp}^{\mathrm{ARR}}; \tag{2}$$

$$\text{else-if} \quad t = t_{v,cp}^{\mathrm{DEP}}$$
$$soe_{v,t}^{\mathrm{EV}} \geqslant SOE_{v,cp}^{\mathrm{DEP}}; \tag{3}$$

$$\text{else} \quad t \in \Omega_{v,cp}^{T\text{driving\_or\_parked\_at\_other\_CS}}$$
$$soe_{v,t}^{\mathrm{EV}} \quad \text{unconstrained} \quad \forall\, v,\, t. \tag{4}$$

The first equation tracks an EVB while the EV is parked at the observed CS ($\Omega_{v,cp}$ is a set of EVs v at charging point cp at time t), with variables $soe_{v,t}^{\mathrm{EV}}$, $e_{v,t}^{\mathrm{SCH}}$ and $e_{v,t}^{\mathrm{DCH}}$ denoting the EV's SOE, energy charged and discharged, respectively, and η^{SCH} and η^{DCH} the corresponding efficiencies. Eqs. (2) and (3) set the $soe_{v,t}^{\mathrm{EV}}$ at arrival/departure based on the SOE forecasts or requirements. The periods when an EV is driving or parked at other CSs are not explicitly modeled and its behavior during these periods can only be considered through the forecasted values of unknown parameters, eq. (4).

The questions that inspired this research were: How would each of the CSs forecast the four uncertain values (arrival time, SOE at arrival, departure time and required SOE at departure) for all the EVs with sufficient accuracy? How would they anticipate the EVs' behavior while driving and especially while at other CSs? One option is that each EV sends its data to all the CSs where it could potentially park and charge. Another option is that each CS sends its own forecasts for each EV to all CSs in surroundings, i.e. all the CSs should optimize their portfolio in a joint optimization or using separate optimizations with coupling SOE constraints. On top of the issue of global optimality of such approach, the amount of data to be transmitted becomes critical and data security issues could easily render such model inapplicable.

3.1.2. EV-based solution

In the EV-based smart e-mobility system, the three EVs in Fig. 3 submit their individual bids to the market operator. Each of them runs its own independent optimization algorithm based on own predictions. Contrary to the CS-based system, each EV knows its behavior (SOE curve) throughout the day wherever it is. From the mathematical standpoint, power to be (dis) charged and the SOE is always known to the EV. If the SOE curve of EV3 in Fig. 3 is observed, EV3 sees it as a continuous line without interruptions at points S1-S3, while the CSs see only their portion of this curve. The EV-based model can thus be mathematically represented as follows:

$$soe_{v,t}^{\mathrm{EV}} = soe_{v,t-1}^{\mathrm{EV}} + e_{v,t}^{\mathrm{SCH}} \cdot \eta^{\mathrm{SCH}} - e_{v,t}^{\mathrm{DCH}} / \eta^{\mathrm{DCH}} - E_{v,t}^{\mathrm{RUN}} / \eta^{\mathrm{RUN}} + e_{v,t}^{\mathrm{FCH}} \cdot \eta^{\mathrm{FCH}} \quad \forall\, v,\, t; \tag{5}$$

It sets the EVs' SOE considering the SOE from the previous time step, charging at a slow CS (SCH), energy discharged in V2G mode (DCH), discharged for driving purposes (RUN), and energy charged at fast charging stations (FCH). Compared to Eqs. (1)–(4) in the CS-based system, this model observes and controls all variables at all time periods. The forecasting effort is drastically reduced and simplified since the EV predicts its own behavior, while in the CS-based system each CS must predict behavior of a multitude of EVs. There is no need for the EV-to-CS communication nor for additional CS-to-CS communication. Each EV keeps its driving/parking information and its technical data to itself and does not send any data to other entities. The complexity of data flow is reduced, while its security is increased as compared to the CS-based model.

3.2. Issue 2 – inability to transfer flexibility between CSs

3.2.1. CS-based issue

The second issue in the CS-based system relates to daily human activities and the way the CSs are usually organized. In our example, CS1 is a home charger and has access to the EVs mostly during the night. On the other hand, CS2 has EVs connected to it only during daytime, while the EVs are at CS3 mostly during the evening periods. When performing energy arbitrage, the energy should be shifted from peak to low-price periods. Usually, the prices are lower during the night (when the consumption is low) and midday (when PV generation is high and load is at its local minimum), while the peak prices occur in the morning and evening (when PV generation is low and consumption high). The CSs aiming to perform energy arbitrage with EVs should thus roughly follow the sequence: night→charging, morning→discharging, midday→charging, evening→discharging. CS1 has only one EV connected to it in the morning and the evening so it cannot discharge all the EVs at peak periods. At midday it does not have any EVs connected to it and thus cannot recharge them. CS2 cannot transfer energy from night to evening periods because it does not have any EVs connected to it in the evening, but can discharge the EVs in the morning and recharge them at midday. However, to have enough energy to discharge EVs in the morning it must communicate with CS1 and request additional charging (more than necessary for mobility). CS3 can discharge EVs in the evening, but it needs to communicate the additional energy with CS2.

3.2.2. EV-based solution

The EV-based concept follows the EVs throughout the day. EV3 in Fig. 3 can provide optimal charge–discharge sequence following the typical daily price curve elaborated above. It can charge during the night at CS1 and discharge in the morning at CS2, where it can also recharge around midday. Then, it can discharge in the evening at CS3 and start charging at CS1 late in the evening. In the EV-based system, the EV flexibility can thus be fully exploited without the need for CS-to-CS communication. To summarize, the proposed EV-based concept results in higher savings, no privacy issues and lower communication burden.

3.3. Issue 3 – insufficient power constraints

3.3.1. CS-based issue

Throughout the day, EVs with their own OBC power capacities park at CSs with various power capacities. This issue is illustrated in the graphs to the right in Fig. 3, where each CP installed power capacity is shown with a fixed value, CP_LIM, while the EVs' OBC power constraints are shown as stacked colored areas. If the OBC power constraints are omitted, the CSs could end up scheduling higher power than technically possible to deliver, e.g. EV1 at CS2. On the other hand, if the OBC power constraint is higher than the CP power constraint, the CP constraint is binding and does not affect the EV scheduling, e.g. EV2 at CS1.

Such events can cause differences between the scheduled and delivered energy and lead to additional balancing costs. The OBC installed power is an additional parameter that all EVs must communicate to the CSs or CSs must anticipate, which can lead to errors. Furthermore, this EV-to-CS communication is highly inconvenient due to large amount of dynamic data as well as security issues.

3.3.2. EV-based solution

EVs change their location during the day. In our example EV1 and EV2 park at two, while EV3 parks at three different locations. Since CSs have different installed charging powers, the EVs must anticipate the installed power of the CSs where they park. This is illustrated in Fig. 3 on graphs to the left, where each EV's OBC installed power (OBC_LIM) is shown as a fixed value, while the CSs' capacities vary through the day (visualized as stacked colored areas). If the CS power constraint is omitted, the EVs whose OBC is of higher power than the CS's maximum power could schedule more charging power than possible in reality, e.g. EV2 during night/morning parked at CS1.

As in the CS-based concept, both the OBC and CS maximum charging power constraints need to be included in the optimization model. However, most CSs publicly publish their chargers' technical parameters, such as connector type and installed power, and EVs can easily download the required data. The EV-to-CS communication is again avoided making the EV-based system easier to implement than the CS-based system.

3.4. Issue 4 – incomplete costs

3.4.1. CS-based issue

Each EV must pay energy cost for its basic mobility charging in the electricity market (through its CS supplier). Apart from energy expenditures, each load must pay a grid fee (upper part of Fig. 2). CSs are connected to the low voltage distribution grid and the grid fees account for a significant share in their total costs transferred to the EVs. To properly address the cost of EV charging, grid fees must be taken into account.[2]

Apart from energy cost and grid fees, there is a cost associated with remuneration between the EVs and the CSs. When it comes to basic mobility charging, EVs pay fees to the CSs to recover the operation and maintenance costs, as well as the investment. However, when CSs use EVBs for energy arbitrage or other actions beside basic mobility charging, they should pay a fee to the EVs for using their battery since increased battery cycling causes faster degradation. In the CS-based system, a CS must obtain data from EVs on their infrastructure (battery) costs. Again, the EVs must send their private data to all relevant CSs.

3.4.2. EV-based solution

In the EV-based system, EVs obtain data on CS infrastructure costs and grid fees. Unlike the EVs, the CSs are public and already publish their prices online to attract EVs. In the proposed EV-based system, EVs must pay a fee to CSs whenever they use them for energy arbitrage and/or basic mobility charging. The EV-to-CS communication is not necessary as the relevant CS data are available online.

4. Current state-of-the-art, industry practices and proposed concept

4.1. Literature review

State-of-the-art literature on smart e-mobility scheduling can be divided into several research approaches. Table 1 summarizes the literature considering three topics (smart home/microgrids, EV aggregators, smart parking lots/charging stations) and the way they tackle the four issues detected in Section 3. Under *Issue 1* we add an intermediate step between the CS-based and EV-based concepts for papers using equations similar to (5), but not specifying chargers or considering only residential chargers.

4.1.1. Smart homes/microgrids

Smart home algorithms often include EVs as one of the demand response appliances that help minimize the total home electricity bill [17–21,24,27,28]. Papers [17,27] seek to optimize a smart home comprising of demand response devices, PVs, energy storage and EVs to cut down the peak power and electricity cost. Paper [18] consists of two parts: EV charging scheduling algorithm for smart homes/buildings and implementation of a prototype application for home/building EMS. In [19] a detailed structure of a household user capable of energy transactions between consumers and load-serving entities is presented. Authors in [20] propose a heuristic method that suggests most suitable charging/discharging instances for an EV battery in a time-of-day regime. Paper [21] investigates the optimal sizing of PV, wind turbine, and storage in a smart home with EV. In [24] the authors presented a model for participation of sub-aggregators in the aggregation of EVs in

[2] Generation facilities mostly do not pay the grid fees. In case of V2G discharging, such fees could have a major effect on its financial profitability.

Table 1
Categorization of research papers related to *Issues 1–4* (comm. – commercial; ch. – charging; inf. – infrastructure; deg. – degradation).

	Issue 1 – insufficient information on EVs' behavior at other CSs			*Issue 2* – inability to transfer flexibility between CSs		
Literature type	CS-based	EV-based with only 1 CS	EV-based	Households	Work/comm. ch. station	Multiple
hline Smart homes/ microgrids	[17–26]	[27–29]	–	[17–23,27,28,24–26]	–	[29]
EV aggregators	[30–41]	[42,43]	–	[30–34,36,38,42,43],	[39]	[35,37,40,41]
Parking lots/ ch. stations	[44–58]	–	–	[50]	[44–49,51–58]	–
Proposed concept	–	–	✓	–	–	✓
	Issue 3 – insufficient power constraints			*Issue 4* – incomplete costs		
Literature type	Fixed	CP or OBC only	Both CP and OBC	No grid/inf./deg. cost	With grid fee/ inf. cost	With deg. cost
Smart homes/ microgrids	[17–22,27–29,24–26]	[23]	–	[17,18,20–23,28,29,24–26]	[19]	[27]
EV aggregators	[30,32–34,36–43]	[31,35]	–	[30–35,37,38,43]	[39]	[36,40,42,41]
Parking lots/ ch. stations	[44–46,48–52,54–56],	–	[47]	[44–46,48–56],	[47]	[53,57,51]
Proposed concept	–	–	✓	-	✓/✓	✓

a residential complex. In [28] authors propose an EV charge/discharge management framework for the effective utilization of PV output through coordination of home and grid energy management systems. All these algorithms observe only a single EV at a single location, which directly makes them susceptible to *Issues 1* & *2*.

EVs and smart homes can also be grouped under a microgrid where EVs act as flexibility providers [22,23]. In future interconnected smart grid, EVs will be able to interact both with the smart communities (local microgrids) and the central grid to offer their services [29]. The smart building could also be considered a microgrid (including vehicle-to-building control strategy to dispatch the EVs as a flexible resource) where the objective function is minimization of microgrids/buildings electricity costs [25]. Optimization of a microgrid could also be made in a multi-objective manner where microgrid (containing EVs) is optimized regarding cost-economy, operation-efficiency and system-security [26]. Table 1 shows that papers related to home/microgrids are mostly CS-based and focused on home-chargers with fixed power levels (*Issue 3*) and consider only energy prices (*Issue 4*). Exception to the standard CS-based models are papers [27,28], which model the EV behavior throughout the day in a parking-driving sequence, but neglect the possibility of charging at other CSs. In addition to home charging, only paper [29] considers parking lots and charging stations, but as independent entities capable of utilizing the EVs' flexibility.

4.1.2. EV aggregators

Apart from observing a single CP or locational aggregation through microgrids, EVs can be seen as a decentralized source scheduled by an aggregator and without considering their location. Such models can have various goals, such as minimizing the EVs' total charging costs [30,31,33,35,38,39,43], minimizing frequency deviations [32,36] maximizing conditional value-at-risk [34], optimizing reserve provision [37] or maximizing revenue [42,40,41]. Paper [30] investigates a joint optimization of EVs and home energy scheduling, while [31] proposes a two-stage charging scheme for an EV aggregator to minimize the charging costs while taking uncertain renewable generation and aggregator's capacity into account. In [33,35] the authors describe a new optimization algorithm for optimizing manual reserve bids of EV aggregator. Paper [38] determines the optimal bidding strategy of an EV aggregator participating in the day-ahead energy and regulation markets using stochastic optimization. Authors of [39] develop a smart charging framework to identify the benefits of non-residential EV charging to the demand aggregators and the distribution grid. Paper [43] proposes necessary market adaptations to include EV aggregation in electricity markets. Paper [40] proposes a multi-stage stochastic model of a PEV aggregation agent to participate in day-ahead and intraday electricity markets. On the hand paper [41] aims to determine the potential value that EVs could generate by providing reserve and identify EV user impacts on the provision of reserves.

Table 1 shows that papers related to EV aggregators mostly focus on home chargers within the CS-based concept (in [39] only non-residential chargers are observed) (*Issues 1 and 2*) and consider fixed power levels and only energy prices (*Issues 3 and 4*). For example, paper [36] presents a CS-based framework where aggregators group CSs while EVs migrate among them. On the other hand, authors of [42,43] do indeed model EVs' behaviour throughout the day, but only as availability periods at unspecified types of chargers, i.e. they do not address the fact that EVs charge and discharge at other CSs as well.

Although papers [30–36,38,42,43,41] model EVs connected to the distribution grid, they take into account only energy and/or balancing prices without network fees or infrastructure costs (*Issue 4*). Paper [39] apart energy tariffs take into account the peak demand chargers as well.

4.1.3. Parking lots/charging stations

In addition to residential parking, EVs can also be charged at workplace/commercial/leisure parking lots or fast charging stations. EVs generally park at parking lots for longer times and power capacity of AC CPs is usually low to medium. On the other hand, EVs do not park at fast (DC) charging stations but only stop to charge, resembling the existing gas stations. Both the smart parking lot and charging station algorithms aim either at maximizing the benefits [44,45,47–51,57], or minimizing electricity costs [46,51–54] while preserving customers expectations. Parking lots could be seen equal to conventional technologies in power system operation process where they provide both energy and reserve [55]. Since many parking lots have integrated photovoltaics, it could be beneficial to optimize the charging at charging station and PV generation [56]. Table 1 shows that papers related to parking lots/charging stations are CS-based and specific locations are observed without proper multiple power levels (*Issue 3*) or costs (*Issue 4*). In [54] authors proposed optimal bi-directional charging control strategies to integrate electric vehicle in commercial and public parking facilities into the power grid as distributed energy resources for demand response programs by two-stage distributed optimization and water-filling algorithm. Paper [44] studies the optimal EV charging scheduling in a workplace parking lot, powered by both the PVs and the power grid. Research done in [45] solves the parking-lot EV charging scheduling problem through a noncooperative game approach. In [47] an optimization model for determining optimal mix of solar-based DG and storage units, as well as the optimal charging prices for EVs has been presented. Authors of [48] propose a centralized EV recharging scheduling system for parking lots using a realistic vehicular mobility/

parking pattern. In [49] an online intelligent demand coordination of EVs in distribution systems has been proposed. Paper [50] formulates an optimization model with central scheduler aiming to maximize the profit of smart household users. Authors in [51] propose an online charging strategy for EV charging stations in distribution systems while obeying power flow and bus voltage constraints. Paper [52] model a game that aims to minimize the total electricity cost at the utility company meanwhile maximizing the payoff of each charging station. In [53] the authors propose a novel cooperative charging strategy for a smart charging station in the dynamic electricity pricing environment, which helps EVs to economically accomplish the charging task by the given deadlines.

Papers [44–49] model workplace/commercial parking lots, while [50,57] observes residential private and public parking lots. Similarly, all the papers modeling CS operation tackle a specific CS connected to a single point in the grid and managed by a centralized controller [51–53], inflicting *Issues 1* & *2*.

With respect to *Issue 3*, i.e. insufficient power constraints, papers [44–46,49,50,57,51,55] use fixed CP power constraints at a parking lot or a CS without considering the OBC maximum power. In [48] the authors use one fixed value for OBC (the one of Nissan Leaf). Only paper [47] defines both the EV and the CP power limits, but it only considers CPs at their own parking lot. All the papers investigating CSs use only chargers' power limits without mentioning the OBC power levels [51–53].

Unlike the majority of papers which do not consider any grid fees (*Issue 4*), the cost of charging in [47] includes both the electricity price and the grid fees, while [53,57] takes into account battery degradation costs.

4.2. Industry practices and research projects

Current e-mobility related companies can be seen through three business schemes: Charging Point Operators (CPOs), E-Mobility Providers (EMPs), and energy-related companies (electricity suppliers, grid operators). CPOs are the companies operating and maintaining a pool of CPs, while EMPs provide charging services to EV users by enabling them access to CPs (authentication) and offering payment options. EVs have contracts only with EMPs who forward their customers' payments to the CPOs. EMPs have contracts with many CPOs, while the CPOs have contracts with energy suppliers as well as grid operators. If energy arbitrage or flexibility provision through an aggregator is the target, EVs and EMPs cannot directly provide it, only the CPOs can. This is in line with the CS-based smart e-mobility, as illustrated in Fig. 4. On the other hand, in the EV-based e-mobility approach the aggregator

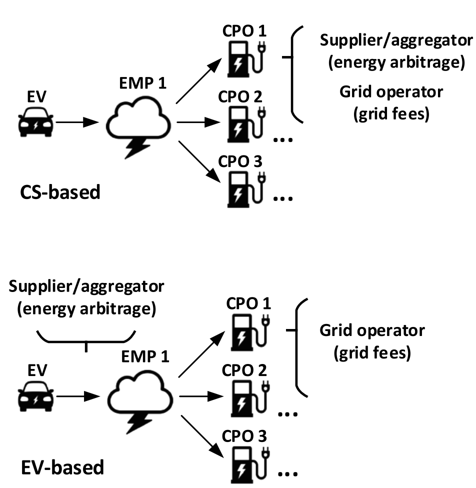

Fig. 4. Position of an aggregator and grid operator in the CS-based and EV-based concepts.

must be connected to EVs or EMPs. Grid fees are still assigned to CPOs because the physical connection does not change (see Fig. 2).

The Internet-of-Things (IoT), energy and e-mobility companies already took the CS-based path of the smart e-mobility [59–62]. The smart charging in the current industry practices usually means scheduling charging for household users at low electricity tariffs or cutting the peak load of larger CSs. Research projects such as [63–65] tackle mostly the issue of V2G testing on bidirectional chargers without integrating an aggregator into a real-world e-mobility system.

It is clear that the e-mobility industry does not yet operate within the EV-based smart e-mobility concept, which would change the role of the main beneficiaries in the smart environment from CPOs to EMPs.

4.3. Proposed concept

The CS-based concept arises from a conventional way of addressing the EVs – they are an electric load stationary connected at a specific location to a specific CS. This CS does not have information about the EV's battery SOE prior and after the connection and must forecast those values. In this sense, an EVA aggregates specific CSs physically located at households, parking lots or dedicated charging stations and their proper name should be EV Charger Aggregator or EVCA.

We argue that EVs should not be observed as conventional loads but as mobile batteries. EVA should not aggregate specific CSs but the EVs with their batteries. The new concept of EVA is therefore named EV Battery Aggregator or EVBA. EVBA continuously monitors and records EV information (SOE, planed trips) as a part of the future IoT concept. CPOs should allow all EVs to connect without restrictions but for a charging fee. CPOs should be understood as infrastructure operators similar to transmission/distribution system operators and charging a fee in a way that transmission and distribution fees (tariffs) are charged.

Additional benefits of the EVBA concept are the payment possibilities. Slow chargers are usually part of other consumer facilities and they are controlled within their smart environment (smart households, buildings, parking lots, etc.). It is not quite clear how an EVCA can aggregate CPs at someone else's property. That is why each EV should have its own independent metering device so energy to/from an EV can be exactly measured as in the EVBA case.

Although EVBA is contrary to scientific research and current industry practises, as discussed in Sections 4.1 and 4.2, it is in line with the ISO 15118 standard, which foresees two controllers essential for deployment of a smart e-mobility system: an EV communication controller and a CP communication controller. In such advanced communication architecture, the EVBA can easily communicate the schedules to its EVs and the EVs can send all required data back to the EVBA. The data transfer between EVs and CSs can be easily achieved through EV and CP controllers.

5. Models

To demonstrate the arguments, models of both the EV-based (EVBA) and the CS-based aggregator (EVCA) are formulated in the following subsections and evaluated in the case study presented in Section 6.

5.1. Nomenclature

5.1.1. Abbreviations

BMS Battery management system.
CC-CV Constant-current-constant-voltage.
CP Charging point.
CS Charging station.
DOD Depth-of-discharge.
EV Electric vehicle.
EVBA Electric vehicle battery aggregator.
EVCA Electric vehicle charge aggregator.

LIB Lithium-ion battery.
OBC On-board charger.
OF Objective function.
SOE State-of-energy.
V2G Vehicle-to-grid.

5.1.2. Sets and indices

$\mathcal{CP}$ Set of charging points, indexed by *cp*.
$\mathcal{T}$ Set of time steps, indexed by *t*.
$\mathcal{V}$ Set of vehicles, indexed by *v*.

5.1.3. Input parameters

C_v^{BAT} Capital battery cost of vehicle v (€).
$C_{v,t,cp}^{\text{CP-FCH}}$ Charging point fee for fast chargers at charging point cp (€/kWh).
$C_{v,t,cp}^{\text{CP-SCH}}$ Charging point fee for slow chargers at charging point cp (€/kWh).
C_t^{EP} Electricity price during period t (€/kWh).
$C_{v,t,cp}^{\text{G-FCH}}$ Grid tariff for fast chargers at charging point cp (€/kWh).
$C_{v,t,cp}^{\text{G-SCH}}$ Grid tariff for slow chargers at charging point cp (€/kWh).
CAP_v^{BAT} Battery capacity of vehicle v (kWh).
D_1^{BAT} Fixed battery degradation coefficient for higher values of depth-of-discharge.
D_2^{BAT} Variable battery degradation coefficient (based on discharged energy) for higher values of depth-of-discharge.
D_3^{BAT} Variable battery degradation coefficient (based on depth-of-discharge) for higher values of depth-of-discharge.
D_4^{BAT} Variable battery degradation coefficient (based on discharged energy) for lower values of depth-of-discharge.
$E_{cp}^{\text{CP-MAX}}$ Maximum energy limit of charging point cp during one time step (kWh).
$E^{\text{FCH-MAX}}$ Maximum energy limit of fast charging point during one time step (kWh).
$E_v^{\text{OBC-MAX}}$ Maximum energy limit of OBC of vehicle v during one time step (kWh).
$E_{v,t}^{\text{RUN}}$ Energy consumed for mobility purposes of vehicle v during time step t.
$SOE_{v,cp}^{\text{ARR}}$ Anticipated SOE at time of arrival at cp of vehicle v in a CS-based system.
SOE_v^{CV} SOE curve breaking point between CC and CV charging phases of vehicle v (%).
$SOE_{v,cp}^{\text{DEP}}$ Anticipated SOE at time of departure from cp of vehicle v in a CS-based system.
SOE_v^{MIN} Minimum allowed SOE of vehicle v (%).
SOE_v^{MAX} Maximum allowed SOE of vehicle v (%).
SOE_v^{0} Initial SOE of vehicle v (%).
$T_{v,cp}^{\text{ARR}}$ Time step when vehicle v arrives at charging point cp in a CS-based system.
$T_{v,cp}^{\text{DEP}}$ Time step when vehicle v departs from charging point cp in a CS-based system.
$T_{v,cp}^{\text{OFF}}$ Set of time steps when vehicle v when vehicle v is disconnected from charging point cp in a CS-based system.
$T_{v,cp}^{\text{ON}}$ Set of time steps when vehicle v is connected to charging point cp in a CS-based system.
η^{DCH} EV V2G discharging efficiency.
η^{FCH} EV fast charging efficiency.
η^{RUN} EV mobility discharging efficiency.
η^{SCH} EV slow charging efficiency.
$\mathbb{1}_{v,t,cp}$ Matrix indicating whether vehicle v is connected to charging point cp at time step t.

5.1.4. Variables

$c_{v,t}^{\text{DEG}}$ Degradation cost of vehicle v at time t (€).
c^{EV} Overall cost of charging all EVs (€).
$e_{v,t}^{\text{DCH}}$ Energy discharged from vehicle v at time t (kWh).
$e_{v,t}^{\text{FCH}}$ Energy fast charged to vehicle v at time t (kWh).
$e_{v,t}^{\text{SCH}}$ Energy slow charged to vehicle v at time t (kWh).
$soe_{v,t}^{\text{EV}}$ State-of-energy of vehicle v at time t (kWh).

5.2. Mathematical formulation of an EV-based aggregator

Objective function minimizes the total EV charging costs:

$$\min_{\Xi^{\text{OF}}} c^{\text{EV}} = \sum_{v\in\mathcal{V}}\left[\sum_{t\in\mathcal{T}}(e_{v,t}^{\text{SCH}}\cdot(C_t^{\text{EP}}+C_{v,t,cp}^{\text{G-SCH}}+C_{v,t,cp}^{\text{CP-SCH}})-e_{v,t}^{\text{DCH}}\cdot C_t^{\text{EP}}+c_{v,t}^{\text{DEG}} + e_{v,t}^{\text{FCH}}\cdot(C_t^{\text{EP}}+C^{\text{G-FCH}}+C^{\text{CP-FCH}}))\right]. \tag{6}$$

The first row in Eq. (6) corresponds to payments due to EV charging at slow chargers, where $e_{v,t}^{\text{SCH}}$ is charged energy, C_t^{EP} is energy price, $C_{v,t,cp}^{\text{G-SCH}}$ is the grid fee for slow chargers[3] and $C_{v,t,cp}^{\text{CP-SCH}}$ is the CS fee. The second row represents EV discharging income and cost of degradation, where $e_{v,t}^{\text{DCH}}$ is the amount of discharged energy, C_t^{EP} is V2G revenue and $c_{v,t}^{\text{DEG}}$ battery degradation cost. The third row captures payments due to EV charging at fast chargers,[4] where $e_{v,t}^{\text{FCH}}$ is the amount of charged energy, $C^{\text{G-FCH}}$ is the grid fee for fast chargers, and $C^{\text{CP-FCH}}$ is the fast CS fee. EV slow charger charging fees depend on the type of charger, e.g. this fee is zero for home chargers. On the other hand, EV fast charging is modeled using only one fast charging type and cost.In order to add additional services to grid operators, the objective function should be reformulated with new revenue streams/costs. For example, provision of reserves would require addition of the reservation and activation fees. Grid congestion management could be added by reformulating the grid fees and making them more expensive during the peak periods etc.

Charging/discharging energy constraints are:

$$e_{v,t}^{\text{SCH}},\ e_{v,t}^{\text{DCH}},\ e_{v,t}^{\text{FCH}} \geqslant 0 \quad \forall\, v\in\mathcal{V},\ t\in\mathcal{T}; \tag{7}$$

$$e_{v,t}^{\text{SCH}} \leqslant \sum_{cp\in\mathcal{CP}} \mathbb{1}_{v,t,cp}\cdot E_{cp}^{\text{CP-MAX}} \quad \forall\, v\in\mathcal{V},\ t\in\mathcal{T}; \tag{8}$$

$$e_{v,t}^{\text{DCH}} \leqslant \sum_{cp\in\mathcal{CP}} \mathbb{1}_{v,t,cp}\cdot E_{cp}^{\text{CP-MAX}} \quad \forall\, v\in\mathcal{V},\ t\in\mathcal{T}; \tag{9}$$

$$e_{v,t}^{\text{SCH}} \leqslant E_v^{\text{OBC-MAX}} \quad \forall\, v\in\mathcal{V},\ t\in\mathcal{T}; \tag{10}$$

$$e_{v,t}^{\text{DCH}} \leqslant E_v^{\text{OBC-MAX}} \quad \forall\, v\in\mathcal{V},\ t\in\mathcal{T}; \tag{11}$$

$$e_{v,t}^{\text{SCH}} \leqslant E_v^{\text{OBC-MAX}}\cdot\frac{1-soe_{v,t}^{\text{EV}}}{1-SOE_v^{\text{CV}}\cdot CAP_v^{\text{BAT}}} \quad \forall\, v\in\mathcal{V},\ t\in\mathcal{T}; \tag{12}$$

$$e_{v,t}^{\text{FCH}} \leqslant \sum_{cp\in\mathcal{CP}} \mathbb{1}_{v,t,cp}\cdot E^{\text{FCH-MAX}} \quad v\in\mathcal{V},\ t\in\mathcal{T}. \tag{13}$$

Constraint (7) imposes nonnegativity on all energy variables. Constraints (8) and (9) limit the energy charged/discharged at slow CSs based on the mapping parameter $\mathbb{1}_{v,t,cp}$ that determines which EV is connected to which CP at each time step. As the EVs move between

[3] Slow chargers refer to AC chargers, i.e. the ones that require OBC to convert alternating to direct current.

[4] Fast chargers refer to DC chargers, i.e. the ones that convert alternating to direct current and circumvent the OBC. Therefore, the OBC capacity is not relevant when using fast chargers.

different CPs, maximum charging power depends on index cp. OBC limits on EV slow charging and discharging are imposed by constraints (10) and (11), respectively. The OBC power capacity $E_v^{\mathrm{OBC\_MAX}}$ depends only on the EV type. Constraint (12) additionally constrains the OBC charging power at high state-of-energy (SOE) due to inherent nature of the li-ion battery (LIB) charging process consisting of the constant-current (CC) and the constant-voltage (CV) part. Parameter SOE^{CV} is empirically obtained and indicates SOE value (in percentage) at which the constant voltage phase starts. More information on this formulation can be found in [32,66]. Finally, the fast charging power limit $E^{\mathrm{FCH\_MAX}}$ is imposed by constraint (13).

LIB degradation is calculated as follows:

$$c_{v,t}^{\mathrm{DEG}} \geqslant C_v^{\mathrm{BAT}} \cdot (D_1^{\mathrm{BAT}} + D_2^{\mathrm{BAT}} \cdot \frac{e_{v,t}^{\mathrm{DCH}}}{CAP_v^{\mathrm{BAT}}} \cdot 100 + D_3^{\mathrm{BAT}} \cdot \frac{1 - soe_{v,t}^{\mathrm{EV}}}{CAP_v^{\mathrm{BAT}}} \cdot 100) \quad \forall\, v \in \mathcal{V},\, t \in \mathcal{T}; \tag{14}$$

$$c_{v,t}^{\mathrm{DEG}} \geqslant C_v^{\mathrm{BAT}} \cdot (D_4^{\mathrm{BAT}} \cdot \frac{e_{v,t}^{\mathrm{DCH}}}{CAP_v^{\mathrm{BAT}}} \cdot 100) \quad \forall\, v \in \mathcal{V},\, t \in \mathcal{T}. \tag{15}$$

LIB degradation depends on four main variables: charging/discharging current, voltage, temperature and cell balance. In most LIB applications the last two variables are kept at optimal operating point by a dedicated battery management system (BMS) and they can be left out of the degradation model. During slow AC charging the currents are rather low (up to 0.2C[5]) and their impact on degradation is negligible. Thus, the only variable that must be taken into account is voltage, which is closely related to SOE, thus constraints (17) and (18) keep the voltage within the allowed range. In order to consider degradation, a penalization cost is introduced as in [67], but in a linearized form in order to avoid binary variables [68]. Geometric surface of the linearized degradation cost is modeled by constraint (14), which includes two variables: discharged energy and depth-of-discharge (DOD $= 1 -$ SOE). Constraint (15) is an additional geometric surface binding at higher values of SOE when surface from eq. (14) goes to zero or becomes negative. Constraint (15) depends only on discharged energy. Parameters D_{1-4} are obtained using the best-fit option applied to LIB degradation data (life-cycle loss vs. DOD) from [69].

Energy balance constraints are:

$$soe_{v,t}^{\mathrm{EV}} = soe_{v,t-1}^{\mathrm{EV}} + e_{v,t}^{\mathrm{SCH}} \cdot \eta^{\mathrm{SCH}} - e_{v,t}^{\mathrm{DCH}} / \eta^{\mathrm{DCH}} - E_{v,t}^{\mathrm{RUN}} / \eta^{\mathrm{RUN}} + e_{v,t}^{\mathrm{FCH}} \cdot \eta^{\mathrm{FCH}} \quad \forall\, v \in \mathcal{V},\, t \in \mathcal{T}; \tag{16}$$

$$soe_{v,t}^{\mathrm{EV}} \geqslant SOE_v^{\mathrm{MIN}} \cdot CAP_v^{\mathrm{BAT}} \quad \forall\, v \in \mathcal{V},\, t \in \mathcal{T}; \tag{17}$$

$$soe_{v,t}^{\mathrm{EV}} \leqslant SOE_v^{\mathrm{MAX}} \cdot CAP_v^{\mathrm{BAT}} \quad \forall\, v \in \mathcal{V},\, t \in \mathcal{T}; \tag{18}$$

$$soe_{v,t}^{\mathrm{EV}} \geqslant SOE_v^{0} \cdot CAP_v^{\mathrm{BAT}} \quad \forall\, v \in \mathcal{V},\, t = 24; \tag{19}$$

Eq. (16) is the main energy balance equation calculated for each vehicle v and time step t. Energy accumulated during the current time step must be equal to the energy accumulated in the previous time step plus the energy withdrawn from the grid via slow or fast charging points and minus the energy discharged for motion or back into the grid. In the first time step the term $soe_{v,t-1}^{\mathrm{EV}}$ is substituted with SOE_v^0, which corresponds to energy stored in vehicle v before the first time step. Constraints (17) and (18) limit the battery capacity of each EV, while constraint (19) sets the minimum SOE in the last time step (i.e. the SOE in the last timestep must be greater or equal the initial SOE).

5.3. Mathematical formulation of a CS-based aggregator

Mathematical model of the CS-based aggregator is:

[5] C-rate is the ratio of the charging (or discharging) power and battery energy capacity.

min (1)

subject to

$$(2) - (10),\ (12) - (14)$$

$$soe_{v,t}^{\mathrm{EV}} = soe_{v,t-1}^{\mathrm{EV}} + e_{v,t}^{\mathrm{SCH}} \cdot \eta^{\mathrm{SCH}} - e_{v,t}^{\mathrm{DCH}} / \eta^{\mathrm{DCH}} + e_{v,t}^{\mathrm{FCH}} \cdot \eta^{\mathrm{FCH}} \quad \forall\, v \in \mathcal{V},\, t \in T_{v,cp}^{\mathrm{ON}}; \tag{20}$$

$$soe_{v,t}^{\mathrm{EV}} = SOE_{v,cp}^{\mathrm{ARR}}, \quad \forall\, v \in \mathcal{V},\, t = T_{v,cp}^{\mathrm{ARR}},\, cp \in \mathcal{CP}; \tag{21}$$

$$soe_{v,t}^{\mathrm{EV}} \geqslant SOE_{v,cp}^{\mathrm{DEP}}, \quad \forall\, v \in \mathcal{V},\, t = T_{v,cp}^{\mathrm{DEP}},\, cp \in \mathcal{CP}. \tag{22}$$

It contains all constraints as the EV-based aggregator model except for (16), which is replaced with constraints (20)–(22). Energy balance constraint (20) does not include energy discharge for driving as it only tracks the EVs when they are connected to a CP. Hence the time domain in eq. (20) is $T_{v,cp}^{\mathrm{ON}}$. Eqs. (21) and (22) are used to set the anticipated SOE at arrival and required SOE at departure from each CP.

6. Results and discussion

The models elaborated in Section 5 are validated on the small test-case which is elaborated in details in Section 2. The small test case considers the most frequent trip combinations and therefore provides adequate representation of the EV fleet while preserving simplicity and readability of the paper. *Issues 1* & *2* (insufficient information on EV behavior at other CSs and inability to transfer flexibility between CSs) are observed together as they both depend on the EVs' daily SOE curve. *Issues 3* & *4* (insufficient power constraints and incomplete costs) are addressed individually and only for the EVBA case, as their repercussions are the same for both models.

6.1. Input data

The proposed model resembles a price taker scheme where an aggregator forecasts prices in order to efficiently submit its energy bids in the market. Although both the prices, driving activity and times of arrival and departure from CPs are stochastic parameters, we consider all parameters deterministic for better demonstration of optimality of both formulations, as well as quantification of the resulting schedules.

We use historic energy prices data for year 2018 from EPEX power exchange in France. Three sets are used resembling high, medium and low volatility of electricity prices, as shown in Fig. 5. The high-volatility prices date from Nov. 21, medium from March 11, and low from June 30. Each charger type has different grid and charger tariff fee, as listed in Table 2. All grid fees are modeled using a two-tariff system: night and day, and the fees are aligned with the ones in [70]. Grid fees represent both transmission and distribution fees, while charger fees are used to retrieve investment and cover for operation and maintenance costs of the charging infrastructure. Generally, higher charger power results in lower grid fees, but higher charger fees. Charger fees are obtained from real fast charging fees in [71,72] reduced by average energy price and grid tariff fees and scaled based on investment cost to match the corresponding charger type. The investment costs of chargers are from [73].

Efficiencies used in this paper are as follows: slow charging $\eta^{\mathrm{SCH}} = 0.95$, discharging for driving $\eta^{\mathrm{RUN}} = 0.90$, discharging to drive $\eta^{\mathrm{DCH}} = 0.85$, and fast charging $\eta^{\mathrm{FCH}} = 0.80$. SOE parameters used for all EVs are following: $SOE^{\mathrm{MAX}} = 1.00$, $SOE^{\mathrm{MIN}} = 0.20$, $SOE^{\mathrm{CV}} = 0.80$, and $SOE^0 = 0.60$. Battery capacities are 20 kWh for EV1, 40 kWh for EV2 and 60 kWh for EV3. Battery degradation parameters are: $D_1^{\mathrm{BAT}} = -0.342900$, $D_2^{\mathrm{BAT}} = 0.034030$, $D_3^{\mathrm{BAT}} = 0.004287$, and $D_4^{\mathrm{BAT}} = 0.008317$.

To highlight *Issues 1* & *2* in the EVCA model, two different values of $SOE_{v,cp}^{\mathrm{DEP}}$ are used. The first one corresponds to a conservative driver who sets the SOE before every trip to at least 95% (nearly full), and we name this model *high-SOE*. The second one corresponds to a risk-prone driver

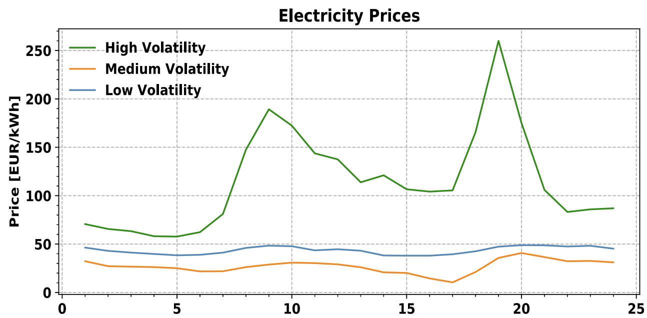

Fig. 5. Three electricity price scenarios from EPEX taken for days with the highest/average/lowest price volatility in 2018.

Table 2
Charger point (CP) data used for the simulations (kW and €/kW).

CP Type	Description	Power (kW)	Grid Low (€/kW)	Grid High (€/kW)	CP Tariff (€/kW)
1	Home	4	0.022840	0.047040	0.004000
2	Work	8	0.016120	0.033600	0.018300
3	Leisure	12	0.016120	0.033600	0.030000
4	DC Fast	100	0.010750	0.022840	0.200000

willing to earn more for providing flexibility at an expense of its EV range. This person sets the SOE before every trip to at least 60%. We name this model *low-SOE*. Note that most models in literature assume a conservative driver who always desires (nearly) full battery at departure.

6.2. Issues 1 & 2

The results related to *Issues 1* & *2* are displayed in Figs. 6–10. Results in Fig. 6a indicate that in total, i.e. combined for all three EVs, the EVBA model results in the lowest charging costs for all price volatility scenarios, followed by the EVCA low-SOE, while the worst results are achieved for the EVCA high-SOE model. Detailed individual EV costs are shown in Fig. 7, where the EVBA model provides the cheapest solution for all three EVs over all price volatility scenarios, while the two EVCA cases alternate in terms of the quality of the solution. For EV1, the high-SOE case is always a better option, while for EV2 the low-SOE case is a better option for all price scenarios. For EV3 however, in low-volatility price scenario the high-SOE case yields better results, while in medium- and high-volatility scenarios the low-SOE case performs better. The reason for EVBA superiority over the EVCA models are twofold: (i) in the EVCA models the EVs are often charged at high prices and (ii) their energy arbitrage opportunities are reduced due to strict SOE requirements. Generally, all three models discharge most energy in the high-volatility price scenario as such scenario favors arbitrage, as can be seen in Fig. 6b. In the low-volatility scenario the EVBA model is the least aggressive in V2G mode, but in the high-volatility scenario it discharges the most energy. In all price-volatility scenarios the EVBA model observes price differences during the whole day and adjusts its discharging schedule accordingly. On the other hand, in EVCA models the CSs are blind to prices outside of the timeframe when an EV is connected to them and they need to adjust their discharging quantities to keep the departing SOE at the minimum allowed level. This happens even if this discharge incurs higher recharging costs at subsequent CSs.

In general, higher price volatility yields lower costs in all three cases. However, the EVBA model is able to better monetize flexibility over the day and the charging costs reduce drastically as the price volatility increases (EV2 generates profit already in medium-volatility price scenario). This is highly related to *Issue 2* (transfer of flexibility between CSs). Since the EVBA model observes EVs throughout the day, it can schedule optimal amount of discharging when prices are high allowing the EVs to drive to another CSs with sufficient SOE.

Issue 1 (problems with SOE prediction at EV arrival) are analyzed in details in Figs. 8–10 for the highly volatile price scenario. In all three figures the periods when EVs are parked at CSs, are shaded in the respective CS color. In case of EV1 and highly volatile prices, the first driving period precedes the periods of high prices. In the EVBA model, EV1 charges before the first trip and discharges after, as shown in Fig. 8b. It recharges before the second trip (during the low-price hours 13–16) and again discharges at the next CS. It charges for the last time at the end of the day at low prices. A similar schedule is obtained with the EVCA high-SOE model. However, CS1 is oblivious to the low prices in the afternoon and slightly discharges EV1 in hour 7, as opposed to the EVBA model that charges EV1 in hour 7 (compare Figs. 8b and 8c). To make up for this lack of energy, the high-SOE EVCA model needs to charge more energy in hour 14 than the EVBA model. This is suboptimal since the price in hour 14 is much higher than in hour 7. The charging quantities in all the other hours are the same. Graph in Fig. 8d indicates that the EVCA low-SOE model behaves quite differently than the other two. Since the CS before the first trip only satisfies the EV's desired SOE of 60% at the departure and at the same time minimizes costs of EV charging only at this CS, it significantly discharges EV1 before the first trip. When prices are highest, after the first trip, EV1 discharges much less energy than in the other two cases due to lower SOE after the trip. Before the second trip, EV1 is again charged only to satisfy the desired SOE at the next departure time, and therefore has less energy to be discharged after the second trip (compare hours 19 and 20). Considering the SOE graphs and charging schedules from Fig. 8, the conclusion is that the EVCA high-SOE model performs much closer to the optimal EVBA model than the ECVA-low model.

In the case of EV2 and highly volatile prices (Fig. 9) the first driving period takes place after the periods of high prices. In the EVBA model, whose charging schedule is shown in Fig. 9b, EV2 charges early in the

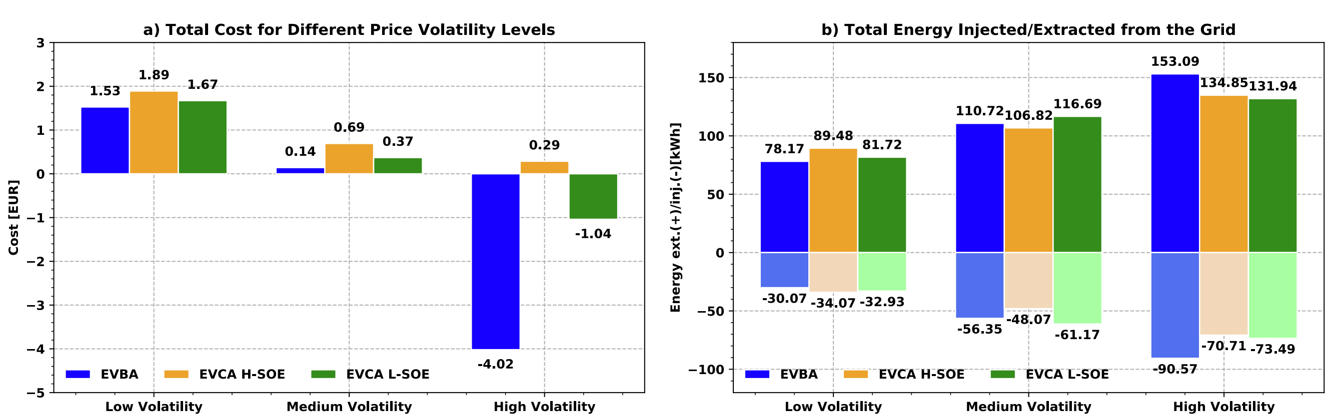

Fig. 6. Results related to *Issues 1* & *2*, showing total charging costs and energy injection/extraction for all three EVs.

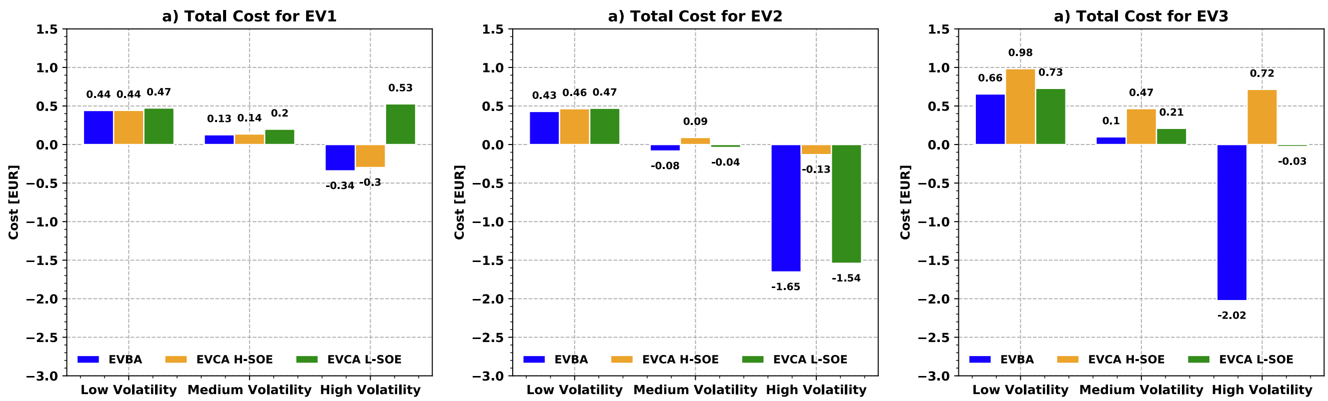

Fig. 7. Results related to *Issues 1* & *2*, showing total charging costs for each EV individually.

morning and discharges before the first trip taking advantage of peaking prices in hours 8–11. It fully recharges after the first trip (hours 15–17) to be able to fully discharge during hours 18–20. Energy for the second trip is charged just before the trip, in hour 21, at very low cost. The required SOE is achieved by charging EV2 after the final trip at low cost (hours 23 and 24). Comparison of the EVBA charging schedule and the low-SOE EVCA schedule in Fig. 9d, as well as the corresponding daily SOE curves in Fig. 9a, indicates that the low-SOE EVCA model behaves quite similar to the optimal EVBA model. The only differences are as follows:

- The EVCA low-SOE model discharges less energy in hour 11 as it requires at least 60% of SOE at departure.
- Due to higher SOE, the EVCA low-SOE model requires less charging in hour 17. Since the electricity price in hour 11 is much higher than in hour 17, this model overlooked an arbitrage opportunity between those hours.
- Again, due to 60% required SOE, the EVCA low-SOE model discharges less energy in hour 18.
- Due to higher SOE, the EVCA low-SOE model requires less charging in hour 24. Again, it did not exercise arbitrage between hours 18 and 24 due to a required SOE level at departure.

The results of the high-SOE EVCA are shown in Fig. 9c. This model does not take advantage of discharging at higher prices due to a more constrained SOE requirement at departure and thus results in much worse solution. For instance, instead of discharging in hours 8–11 as the EVBA and EVCA low-SOE models, the EVCA high-SOE model is, due to the departing SOE restriction, only able to perform partial discharge in hour 9. This repeats again in the evening hours when the EVCA high-SOE model is only able to perform discharge in hour 19, instead of hours 18–20. As a consequence, the EVCA high-SOE model is left with a lot of energy stored in the late evening hours. This energy is partially discharged in the last two hours of the day, but at a relatively low profit.

The EV3 case for the highly volatile prices is shown in Fig. 10. In the EVBA model (Fig. 10b), EV3 charges before the first trip and discharges after it to take advantage of peak hours 9 and 10. It recharges before the

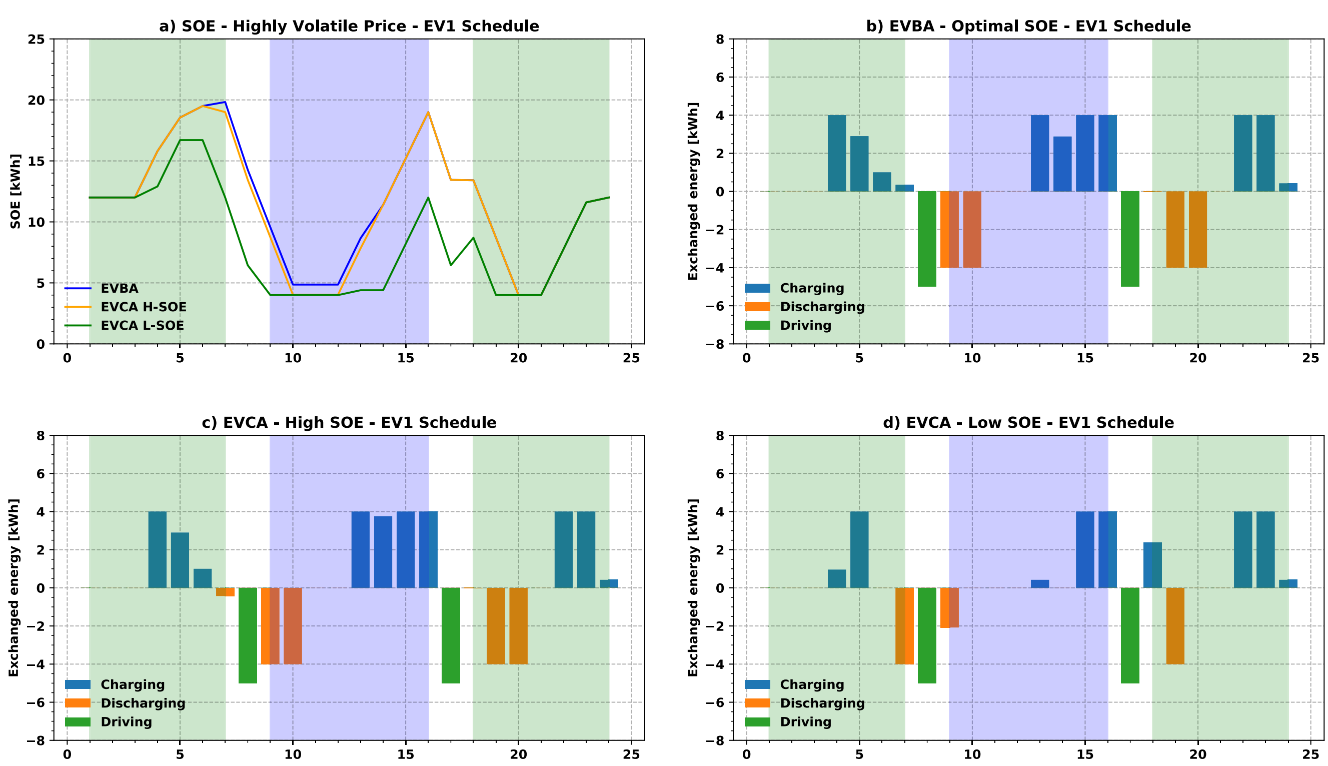

Fig. 8. Results related to *Issues 1* & *2*, EV1 schedules for the highly volatile price scenario.

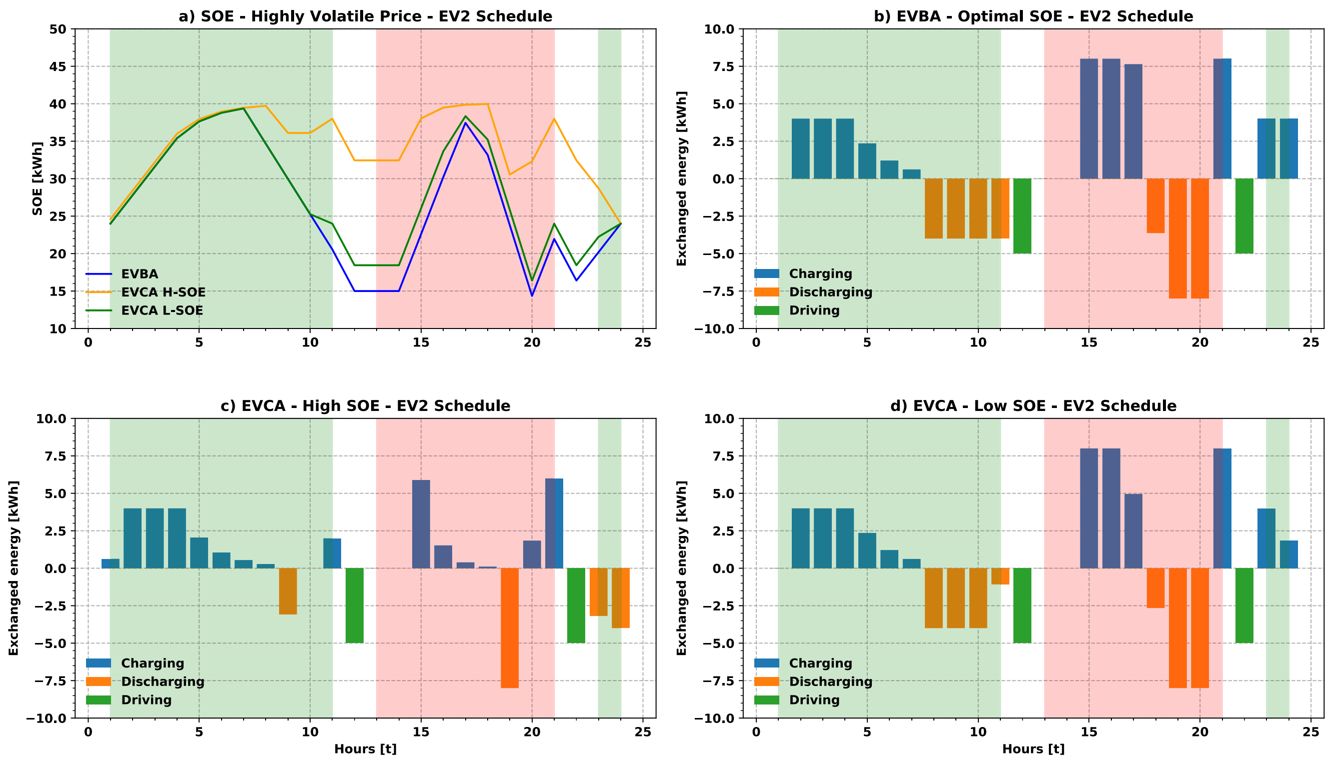

Fig. 9. Results related to *Issues 1* & *2*, EV2 schedules for the highly volatile price scenario.

second trip to be able to discharge again after the trip, thus performing arbitrage. It again recharges before and after the third trip to meet the required end-of-day SOE. Graphs in Fig. 10a indicate that optimal EVBA case is similar to the high-SOE EVCA case during the morning and the daytime, but during the evening it resembles the low-SOE case. The morning charging period at CS1 (green area) ends at hour 7, when the high-SOE EVCA model charges EV3 to 95%. This is quite similar to the optimal EVBA model, which charges EV3 only to a slightly higher SOE. At CS2 (blue area), the high-SOE model charges the EV again to 95%, while the EVBA model charges it slightly below that value. The major difference occurs in the evening hours at CS3 (red area), where the high-SOE EVCA model again charges EV3 to 95% of its SOE, while the

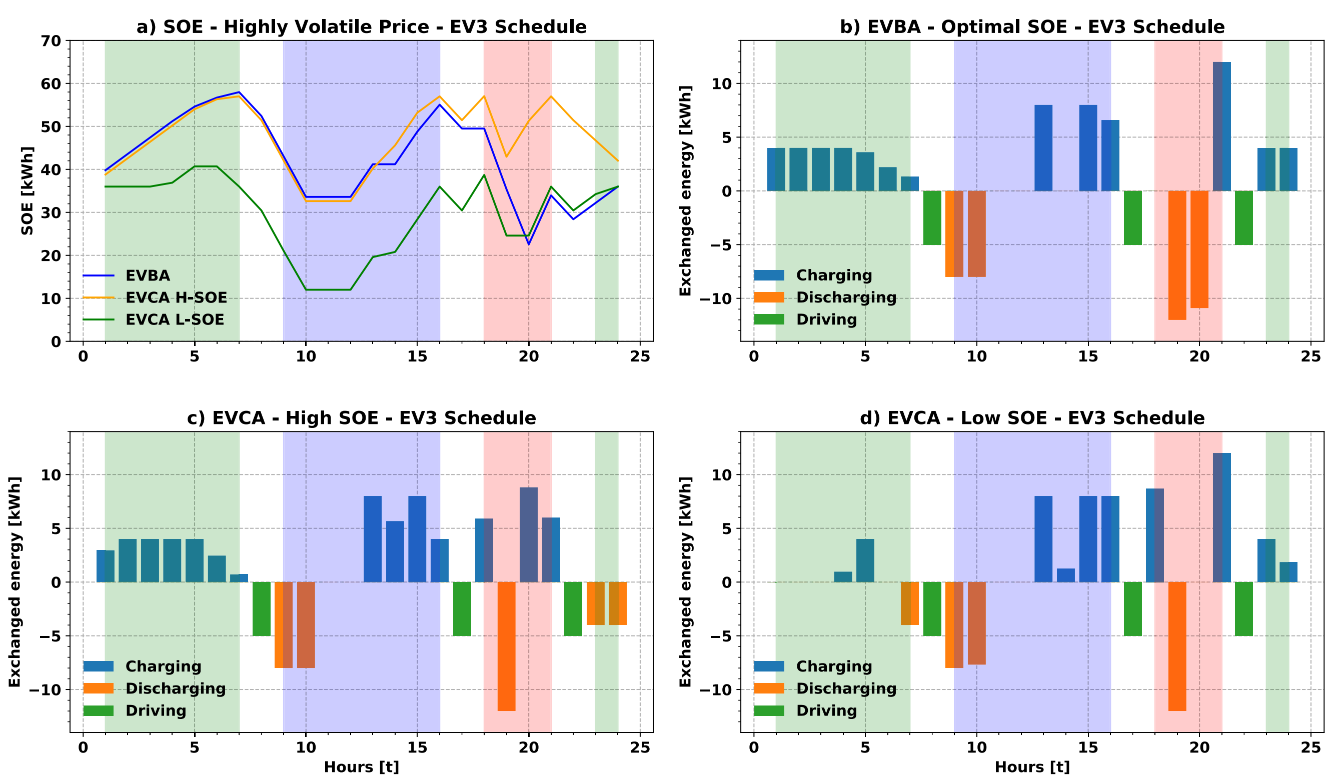

Fig. 10. Results related to *Issues 1* & *2*, EV3 schedules for the highly volatile price scenario.

EVBA model charges it to only 33 kWh in hour 21. This demonstrates the negative effect of constraint on the departure SOE in the high-SOE EVCA model. EV3 is thus required to charge instead of discharge at very high prices. Consequently, after the final trip it has more energy then required by the end-of-day SOE constraint and CS1 (green area) discharges it, but at a low gain, in hours 23 and 24.

The EVCA low-SOE case schedules EV3 quite differently before the first and second trips. It does not charge as much energy since the required SOE before the trips is only 60%. This enables it to perform arbitrage at CS1 and discharge a part of the energy in hour 7 just before the trip (Fig. 10c). Since hours 9 and 10 are peak-price hours, it discharges more energy and charges again in hours 13–16 at lower prices. It again performs arbitrage in hours 19 and 21, but with much lower energy volume than the EVBA model. Based on the conducted analysis, we derive the following conclusions:

1. for EV1, the high-SOE EVCA model is close to the optimal EVBA model;
2. for EV2, the low-SOE EVCA model is close to the optimal EVBA model,
3. in the case of EV3, the high-SOE EVCA model is close to the optimal EVBA solution until evening, but during the evening and night the low-SOE EVCA case becomes more similar to the optimal EVBA solution.

Therefore, without the EVBA optimization model there is no way to decide what is the best required SOE at the time of departure to maximally transfer flexibility and utilize daily energy arbitrage.

6.3. Issue 3

To analyze *Issue 3* (insufficient power constraints), we examine the results of the EVBA model with highly volatile prices using four different sets of power constraints. First, we use fixed power constraint of 4 kW throughout the day. Second and third sets of constraints use only OBC and CP power constraints, respectively. The fourth set of constraints uses both the OBC and CP power constraints.

As shown in Fig. 11a, the minimum expected costs are obtained when using only OBC power constraint, followed by the CP-only power constraint, then both power constraints, while the highest cost is obtained for a fixed 4 kW power constraint. This is a direct result of energy arbitrage volumes shown in the same chart. In order to verify feasibility of the obtained charging schedules, Fig. 11b shows the exceeded OBC and CP limits. The green shaded areas indicate that the injected/extracted power exceeds the CP limit, while the orange shaded areas indicate the surpassed CP limit. The CP power limit is exceeded in hours 3, 8–10, 23 and 24 by the OBC-only case as the OBC rated power is higher than the CS1 rated power. On the other hand, the OBC power capacity is exceeded in hours 15, 16, 19–21 by the CP-only case as the OBC capacity is lower than the CP capacity during those hours. Cases with fixed 4 kW power constraint and inclusion of both the OBC and CP power constraints never exceed the power limits. Therefore, the cases with only OBC and only CP power constraints provide higher revenues only at first sight. However, their real-time operation cannot be physically carried out and they would suffer from additional balancing costs not included in Fig. 11a. On the contrary, if EVs are too constrained, as in the case with fixed 4 kW power limit, the EV charging schedule is overconstrained, which diminishes the arbitrage opportunities. This brings us to conclusion that considering both the OBC and CP power constraints results in optimal solution.

6.4. Issue 4

From mathematical perspective, *Issue 4* (incomplete costs) deals with different terms in the objective function. Fig. 12 shows that adding the cost terms usually omitted in the existing literature significantly reduces the attractiveness of energy arbitrage. Five objective functions (OF) with different elements are observed:

1. OF1: base case with only the cost of electricity,
2. OF2: cost of electricity and battery degradation costs,
3. OF3: cost of electricity and grid tariff,
4. OF4: cost of electricity and CS tariff,
5. OF5: all the costs, including cost of electricity, battery degradation costs, grid tariff and CS tariff.

The graph in Fig. 12a shows that the total cost rises from −4.0 €in the electricity-only case to 3.6 €in the case with all relevant costs included, which makes a huge difference in the EV charging economics. The main factor are degradation costs (OF2 value is 2.2 €), while the lowest impact has the CS tariff (OF4 value is −1.9 €).

The overall costs are in direct relation with the volume of arbitrage as the spread in the price between the purchased and is the sold electricity needs to cover for additional costs of battery degradation and tariffs. Therefore, OF5 results in the least charged energy, followed by OF2, as shown in Fig. 12b. With respect to this, total discharged energy reduced from 90,57 kWh in the OF1 case to a mere 4,07 kWh in the all-costs case, as shown in Fig. 12c.

7. Conclusion

This paper has demonstrated on a small example the shortcomings of the Charging station based concept, which is predominantly used in the research community. The main drawback of this concept is that it observes the electric vehicle batteries only when connected to a specific charging station. This results in suboptimal charging schedules and aggregator revenues. Furthermore, charging stations have to forecast the battery parameters (arrival and departure times and SOE at arrival

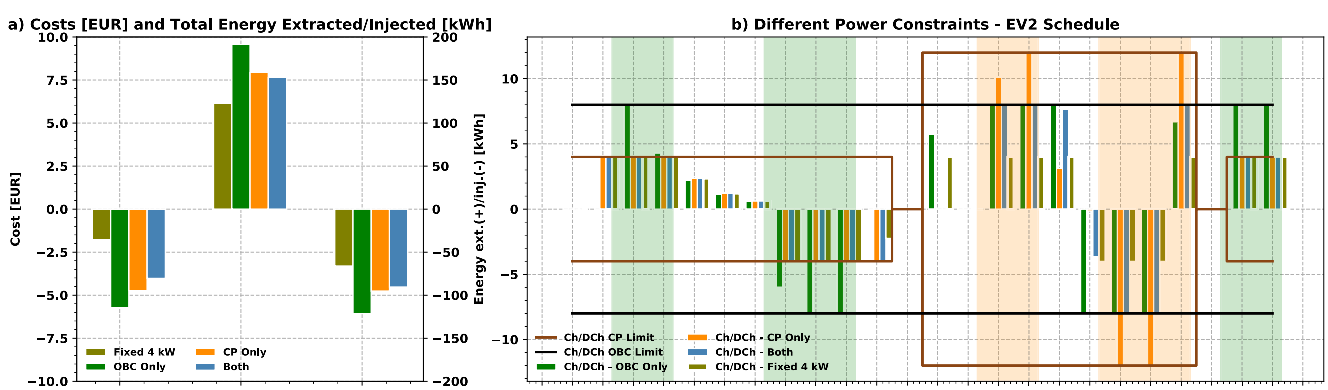

Fig. 11. Results related to *Issue 3*; left figure - total costs for different sets of power constraints, right figure - EV2 chargins schedule for different power constraints.

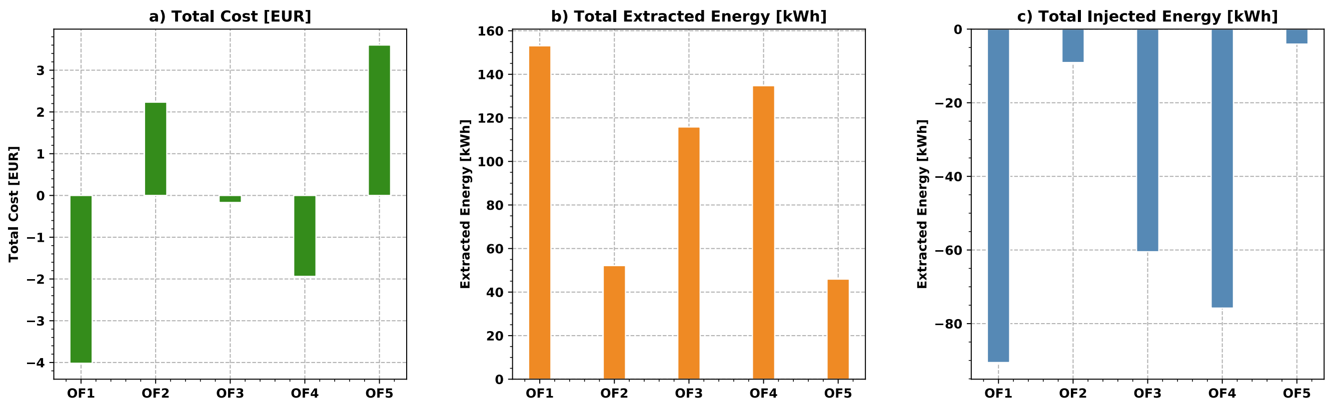

Fig. 12. Results related to *Issue 4*, total charging costs for different objective functions (OF1 – only cost of electricity; OF2: cost of electricity + degradation cost; OF3: cost of electricity + grid tariff; OF4: cost of electricity + CS tariff, OF5: electricity cost + degradation cost + grid tariff + CS tariff).

and departure), which further reduces the optimality of the charging schedule.

As opposed to the charging station based concept, which aggregates the charging stations, the proposed electric vehicle based concept aggregates vehicles themselves. This enables optimal charging schedule for each electric vehicle, regardless where it is charged. On top of this, it resolves the communication issues as there is no need for electric vehicles to send their private data to charging stations. Another issue with the current literature is the lack of power constraints. This is related to charging capacities of vehicles on-board charger and charging points, as the lower of these two values is binding and, thus, both should be considered in the models. The electric vehicle charger aggregator concept requires vehicles to send the on-board charger capacity data to charging stations in order to determine their future flexibility volume, which is avoided with the electric vehicle battery concept. The final issue we identified are incomplete costs of charging as majority of the published papers do not consider grid fees or infrastructure costs. In the charger aggregator model, this infrastructure are vehicles themselves, which means they should send their costs to charging stations so an charger aggregator can decide on its charging schedule. Again, the proposed battery aggregator model requires charging stations, which are infrastructure in this case, to send their costs to vehicles and these costs are already public.

Charging station based system yields sub-optimal results for the vehicle owners. The proposed electric vehicle based system where vehicles take the leading role in electricity markets proved to be much more economically attractive for the owners. This is especially the case when volatility of electricity prices is high. In such case the electric vehicle based model results in 3.87 times lower overall costs for the three observed vehicles than the charging station based models. Opposed to the electric vehicle based model, the analyzed charging station based models cannot accurately anticipate the optimal arriving and departing state-of-energy and cannot exchange flexibility among stations. Also, the paper showed that insufficiently modeled constraints and costs can steer the scheduling results in a wrong direction leading to infeasible charging/discharging bids and higher actual operating costs. Analysis of accurate power constraints points out the value of higher installed power capacities both for on-board charger and external charging station equipment.

The proposed model and the presented results can be of significant value for EV aggregators when developing business models and can be applied to designing charging prices when approaching potential end-users. The initial results suggest that integrating the proposed EVBA approach could create substantial market advantage and result in higher profits as compared to the traditional EVCA approach.

The validation on a small test case is a first step into the EV-based smart e-mobility system research. It provides a proof that the EV-based system yields better results than the traditional approach, however further investigation is needed to fully capture and demonstrate the significance of this improvement. Future research will focus on uncertainty in electric vehicle based models and participation of an electric vehicle battery aggregator in ancillary services markets and test the electric vehicle based concept on a large fleet.

CRediT authorship contribution statement

Ivan Pavić: Conceptualization, Methodology, Software, Investigation, Writing - original draft. **Hrvoje Pandžić:** Resources, Writing - review & editing, Supervision, Funding acquisition. **Tomislav Capuder:** Conceptualization, Resources, Supervision, 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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