Impact of Different Charging Strategies for Electric Vehicles in an Austrian Office Site

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Abstract: Electric vehicles represent a necessary alternative for wheeled transportation to meet the global and national targets specified in the Paris Agreement of 2016. However, the high concentration of electric vehicles exposes their harmful effects on the power grid. This reflects negatively on electricity market prices, making the charging of electric vehicles less cost-effective. This study investigates the economic potential of different charging strategies for an existing office site in Austria with multiple charging infrastructures. For this purpose, a proper mathematical representation of the investigated case study is needed in order to define multiple optimization problems that are able to determine the financial potential of different charging strategies. This paper presents a method to implement electric vehicles and stationary battery storage in optimization problems with the exclusive use of linear relationships and applies it to a real-life use case with measured data to prove its effectiveness. Multiple aspects of four charging strategies are investigated, and sensitivity analyses are performed. The results show that the management of the electric vehicles charging processes leads to overall costs reduction of more than 30% and an increase in specific power-related grid prices makes the charging processes management more convenient.

Keywords: electric mobility; charging strategies; economics; promotion policies; mixed-integer optimization; flexible systems

1. Introduction

The global warming and the increasing GHG emission challenges in recent years are expected to be an accelerator for the deployment of electric vehicles (EVs) as a more sustainable alternative for wheeled transportation around the world [1–4]. The European Environment Agency recognizes transport as a critical source of environmental pressures in the European Union, and it has a decisive influence on climate change and air pollution. The transport sector consumes one-third of the final energy in the European Union and is responsible for a large share of the European's greenhouse gas emissions. This makes transport one of the major contributors to climate change [5]. The Intergovernmental Panel on Climate Change (IPCC) affirms that wheeled transportation produces more than 70% of the overall greenhouse gas emissions from transport [6]. Because of their significant environmental advantages, numerous countries are working on different strategies to make EVs monetarily more convenient than traditional wheeled vehicles [7].

However, as the number of EVs increases, the negative effects of their charging on the power grid become more evident, especially at the low-voltage level. In fact, high concentrations of EVs have various harmful effects due to the overlap between EV charging, residential peak loads and renewable generation [8–10]. For these reasons, the growing number of EVs, in parallel with the growing penetration of renewable energy sources, leads the power grid facing a challenging future [11,12].

Charging management systems and different charging strategies of EVs have been extensively studied in order to reduce the greenhouse gas emissions, to improve the power grid operation and to reduce the electricity costs for end-users [13–16]. In the last decade, several unidirectional and bidirectional charging strategies of EVs have been investigated in different contributions [17–20]. Furthermore, the possibility of combining stationary battery storages (SBSs) with the charging infrastructures has also been studied in-depth, in order to further reduce the peak load power and the electricity costs and allow the fast charging of EVs even with low grid connection power [21,22].

The core objective of this study is to investigate the economic potential of different charging strategies of EVs for an existing office site in Austria with multiple charging infrastructures. The economic potential is given by trading electricity in the Day-Ahead (DA) spot market considering the overall power and energy procurement costs of the office site's charging infrastructures. Profit opportunities could incentivize the end-users to apply flexible electricity consumption patterns to their EVs charging schedules, and they could also incentivize the office site to install further SBSs.

In this paper, multiple optimization problems are defined in order to determine the monetary potential of different operating strategies for managing the EVs' charging processes. The optimization approach aims to define the power flows between the EVs, the SBSs and the power grid, in order to minimize the electricity costs and to best allocate the flexibility of the Austrian office site. However, a detailed description of the technical operation of the above-mentioned components is needed in order to implement them in a mathematical model. In this work, the components of the Austrian office site are described with the exclusive use of linear relationships, which can be implemented in mixed-integer optimization problems. The optimization problems are modeled using the *Python* toolbox *Pyomo* [23] and solved with the *Gurobi* solver [24].

The paper is organized as follows. Section 2 provides an overview of the state of the art in the scientific literature. Next, Section 3 describes the mathematical representation of the Austrian office site, including the EVs and the SBSs in the optimization problem and its objective function, which aims to minimize the overall costs. Section 4 illustrates the description of the investigated real-life use case in Austria with measured data used to simulate the different charging strategies. Section 5 presents the comprehensive results and sensitivity analyses of the case study. Finally, Section 6 concludes the paper and discusses possible directions for future research.

2. State of the Art

The growing share of renewable energy sources, such as wind and solar photovoltaic, increases the volatility of electricity generation in the power grid [25–27]. At the same time, the increasing integration of high-power consumption loads, such as EVs, are setting new challenges for the distribution system operators [28,29]. Hence, the active participation of the demand-side can play a crucial role in the European transition to a carbon-free energy sector [30–32]. For this reason, nowadays, one of the key challenges is to enhance the use of the potential flexible demand in the power grid. An EV represents a flexible load type, and the growing number of grid-connected EVs accords to them a growing flexibility potential for the power grid [33]. Flexibility is the electrical components capability to alter their scheduled consumption in reaction to external signals, for example, spot market prices or grid costs [34]. However, an exhaustive mathematical description of the flexible components, such as EVs and SBSs, is needed in order to efficiently coordinate and aggregate multiple flexible load types.

In several studies, for example [33,35,36], the flexibility of EVs is utilized in order to support the variable renewable energy injection and minimize the overall system costs. Weis et al. [37] quantify the benefits of managed charging of EVs achieving 1.5–2.3% cost savings in the simulations. Sheikhi et al. [38] introduce a charging management strategy for EVs aimed to reduce peak loads. The benefits and the drawbacks of bidirectional charging of EVs are thoroughly investigated in [39–41]. In several simulations, the electricity cost reductions achieved through the vehicle-to-grid charging are overcompensated by higher battery degradation costs. If the higher battery degradation costs are not considered, the overall costs reduction could reach 13.6% [39]. However, managed charging and

vehicle-to-grid charging of EVs are able to alleviate congestion in the power grid [42]. In the last decade, different methods were developed in order to mathematically represent flexible loads in optimization frameworks. In Hao et al. [43], a method to describe the flexibilities of different technologies as virtual batteries is presented. In this work, flexibilities are represented in a mixed-integer optimization problem with the exclusive use of linear relationships, which makes the model scalable and able to handle a growing amount of components.

This paper presents the mathematical implementation of EVs and SBSs in optimization problems, which aim to minimize the overall costs of their operation, applying peak shaving and load shifting to aggregated charging infrastructures. Furthermore, in this work different charging strategies are defined and compared in order to determine the optimal charging strategy for an office site of an electric utility company in Austria with multiple charging infrastructures. The simulated period covers the entire year 2019. The main contributions of this paper beyond the-state-of-the-art are as follows.

- Development of a method to implement EVs and SBSs in optimization problems with the exclusive use of linear relationships,
- Costs comparison of four different charging strategies of EVs,
- Investigation of the potential of coupling charging infrastructures with SBSs,
- Application of the methods to a real-life use case in Austria with measured data.

3. Methods

The real operation of EVs and SBSs is characterized by non-linear relationships, which lead to non scalability of the calculations. In Section 3.1, a simplified method to implement EVs and SBSs in optimization problems as linear systems is developed. Moreover, the optimization problem and its cost function are presented in Section 3.2. Lastly, in Section 3.3, the investigated EV charging strategies are defined.

3.1. Components

A mathematical description of SBSs and EVs is needed in order to efficiently implement them in a mixed-integer optimization problem and define the optimal allocation of their power flows using a linear optimization model. In the following Sections 3.1.1 and 3.1.2, the mathematical representations of SBSs and EVs are presented. In this work, the time is considered as discrete, and the optimized time range $\mathcal{T}$ is divided into a number of constant time intervals Δt.

3.1.1. Stationary Battery Storage (SBS)

The operation of a SBS is bounded to its physical limits such as power and capacity limits. The input and output power ($p_t^{SBS,in}$ and $p_t^{SBS,out}$) are confined between 0 and the maximum input and output power ($p_{max}^{SBS,in}$ and $p_{max}^{SBS,out}$) are specified as follows.

$$0 \le p_t^{\text{SBS,in}} \le p_{max}^{\text{SBS,in}} \qquad\qquad \forall\, t \in \mathcal{T} \qquad\qquad (1)$$

$$0 \le p_t^{\text{SBS,out}} \le p_{max}^{\text{SBS,out}} \qquad\qquad \forall\, t \in \mathcal{T} \qquad\qquad (2)$$

The capacity limits bound the state of charge of the SBS (soc_t^{SBS}) between 0 and its nominal capacity (E^{SBS}) as mathematically described below.

$$0 \le soc_t^{\text{SBS}} \le E^{\text{SBS}} \qquad\qquad \forall t \in \mathcal{T} \qquad\qquad (3)$$

If the charging and discharging efficiency ($\eta^{SBS,in}$ and $\eta^{SBS,out}$) and the standby losses percentage ($E_{Loss\%}^{SBS}$) are taken into account, the energy balance of an SBS can be defined in each time period in $\mathcal{T}$ as follows.

$$soc_t^{\text{SBS}} = soc_{t-1}^{\text{SBS}} \cdot \left(1 - E_{Loss\%}^{SBS}\right) + \left(p_t^{\text{SBS,in}} \cdot \eta^{\text{SBS,in}} - \frac{p_t^{\text{SBS,out}}}{\eta^{\text{SBS,out}}} \right) \cdot \Delta t \qquad \forall\, t \in \mathcal{T} \qquad (4)$$

Furthermore, the costs of the operation of the SBS can be implemented in the optimization problem using the levelized cost of storage (LCOS) method [44]. LCOS can be described as the cost per unit of charged electricity for a specific storage technology. It can be formally defined as follows.

$$LCOS = \frac{C_{Inv}^{\text{SBS}}}{n \cdot E^{\text{SBS}}} \qquad (5)$$

where C_{Inv}^{SBS} indicates the investment costs of the SBS and n the number of charging cycles that the SBS is able to support before its capacity falls under 80% of its original capacity [45]. Hence, the total costs of storage C_{LCOS}^{SBS} within the optimized time range $\mathcal{T}$ can be described as the LCOS multiplied by the SBS's cumulative delivered electricity and can be expressed as below.

$$C_{LCOS}^{\text{SBS}} = LCOS \cdot \sum_{t=1}^{T} \left(p_t^{\text{SBS,in}} \right) \qquad (6)$$

According to the physical limits and the total costs of storage, the optimization algorithm determines the optimal input and output power ($p_t^{SBS,in}$ and $p_t^{SBS,out}$) and the state of charge (soc_t^{SBS}) of the SBS, hence defining its optimal operation.

3.1.2. Electric Vehicle (EV)

In this paper, we consider different possibilities of charging EVs: managed charging (MC) and vehicle-to-grid (V2G). The flexibility available from a charging cycle can vary in terms of duration and amount of energy. In fact, EV batteries are only available for a limited period of time, or rather only when they are connected to the charging infrastructure. Hence, the operation of a charging cycle is bounded to its physical limits such as power, capacity and time limits. The time limits are given by the connection time (S^{EV}) and the disconnection time (D^{EV}) of the EV at the charging infrastructure. We formally consider the initial state of charge ($soc_{S^{\text{EV}}}^{\text{EV}}$) equal to 0, since most of today's charging infrastructures do not allow to know the state of charge of an EV when it is connected to one of them. Formally, the state of charge of an EV is confined as follows.

$$soc_{S^{\text{EV}}}^{\text{EV}} = 0 \qquad (7)$$

$$soc_{D^{\text{EV}}}^{\text{EV}} = E^{\text{EV}} \qquad (8)$$

$$0 \leq soc_t^{\text{EV}} \leq E^{\text{EV}} \qquad \forall t \in (S^{\text{EV}}, D^{\text{EV}}) \qquad (9)$$

The input and output power ($p_t^{EV,in}$ and $p_t^{EV,out}$) are confined between 0 and the maximum input and output power ($p_{max}^{EV,in}$ and $p_{max}^{EV,out}$) as formally described below.

$$0 \leq p_t^{\text{EV,in}} \leq p_{max}^{\text{EV,in}} \qquad \forall t \in (S^{\text{EV}}, D^{\text{EV}}) \qquad (10)$$

$$0 \leq p_t^{\text{EV,out}} \leq p_{max}^{\text{EV,out}} \qquad \forall t \in (S^{\text{EV}}, D^{\text{EV}}) \qquad (11)$$

If V2G is not considered, the maximum output power ($p_{max}^{EV,out}$) is formally set to 0. Moreover, when the EV is not connected to the charging station, the input and output power is set to 0 as specified below.

$$p_t^{EV,in} = 0 \qquad\qquad \forall t \notin (S^{EV}, D^{EV}) \tag{12}$$

$$p_t^{EV,out} = 0 \qquad\qquad \forall t \notin (S^{EV}, D^{EV}) \tag{13}$$

If the charging and discharging efficiency ($\eta^{EV,in}$ and $\eta^{EV,out}$) and the standby losses percentage ($E_{Loss\%}^{EV}$) are considered, the energy balance of an EV could be formally defined in the optimization problem in each time period in $\mathcal{T}$ as follows.

$$soc_t^{EV} = soc_{t-1}^{EV} \cdot \left(1 - E_{Loss\%}^{EV}\right) + \left(p_t^{EV,in} \cdot \eta^{EV,in} - \frac{p_t^{EV,out}}{\eta^{EV,out}}\right) \cdot \Delta t \qquad \forall t \in (S^{EV}, D^{EV}) \tag{14}$$

where the AC-DC and the DC-AC conversion losses are included in the charging and discharging efficiency factors ($\eta^{EV,in}$ and $\eta^{EV,out}$). A graphical representation and the associated power flows of the flexibility of a charging process of an EV are shown in Figure 1.
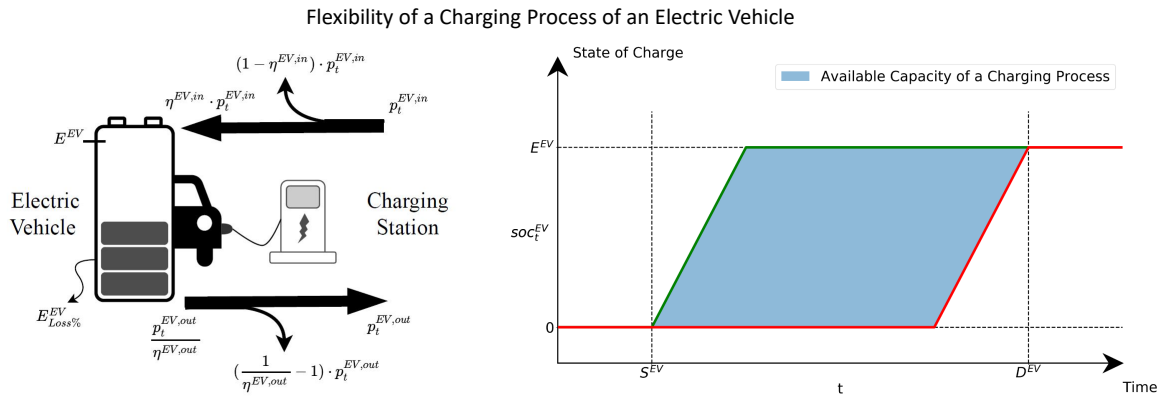

Figure 1. Power flows and available capacity of an electric vehicle during a charging process.

The graphic in Figure 1 shows the upper (green) and lower (red) capacity bounds of a charging process of an EV. The blue painted area represents the available capacity of a charging process, where the flexibility can eventually be activated.

Conforming to these formal bounds given by the physical limits of a charging process, the optimization algorithm determines the optimal operation of a charging process defining the optimal input and output power ($p_t^{EV,in}$ and $p_t^{EV,out}$) and the state of charge (soc_t^{EV}) of the EV.

3.2. Optimization Framework

The optimization framework simulates the DA electricity spot market auctions and coordinates the power flows of the flexible components in order to minimize the overall costs of the Austrian office site. The flexible components are connected to a common grid connection point (GCP). The power passing through the grid connection point ($p_t^{GCP,Load}$ and $p_t^{GCP,Feed-in}$) is directly traded in the DA spot market. A graphical representation of the flexible components and the associated power flows is shown in Figure 2.
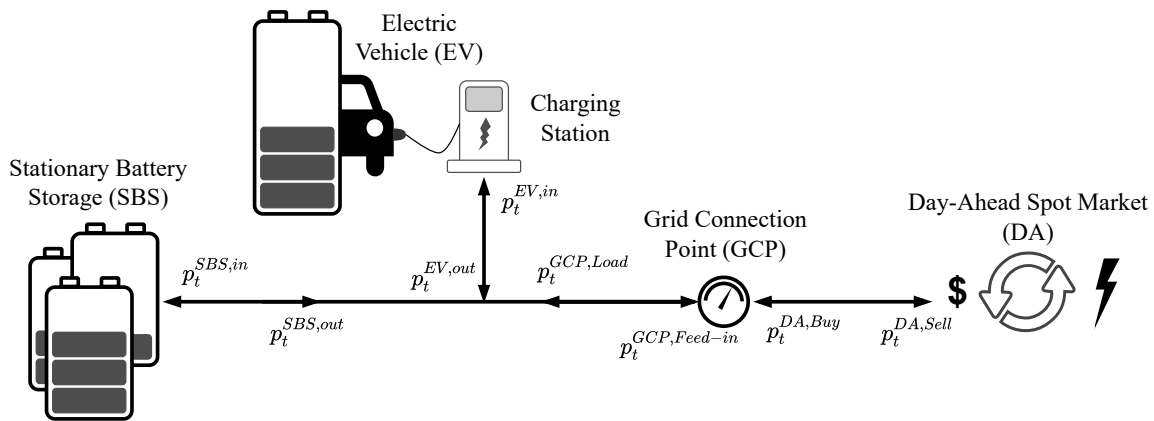
Figure 2. Flexible components and associated power flows.

The power balance equations of the interconnected flexible components can be formally defined as below.

$$p_t^{\text{EV,in}} - p_t^{\text{EV,out}} + p_t^{\text{SBS,in}} - p_t^{\text{SBS,out}} = p_t^{\text{GCP,Load}} - p_t^{\text{GCP,Feed-in}} \qquad \forall\, t \in \mathcal{T} \qquad (15)$$

$$p_t^{\text{GCP,Load}} - p_t^{\text{GCP,Feed-in}} = p_t^{\text{DA,Buy}} - p_t^{\text{DA,Sell}} \qquad \forall\, t \in \mathcal{T} \qquad (16)$$

Furthermore, the electricity procurement costs are given by the DA spot market costs (C^{DA}) and the grid costs (C^{Grid}). The DA spot market prices are implemented in the optimization problem as an exogenous time-series for each time period in $\mathcal{T}$ as follows.

$$P_t^{\text{DA}} = (P_1^{\text{DA}}, P_2^{\text{DA}} \ldots, P_T^{\text{DA}}) \qquad (17)$$

Hence, the overall DA spot market costs in $\mathcal{T}$ are given by

$$C^{\text{DA}} = \sum_{t=1}^{T} \left(P_t^{\text{DA}} \cdot \left(p_t^{\text{GCP,Load}} - p_t^{\text{GCP,Feed-in}} \right) \right) \qquad \forall\, t \in \mathcal{T} \qquad (18)$$

The grid costs (C^{Grid}) are given by three main components that vary according to the grid level, where the flexible components are connected. The three components are

- A fixed flat rate ($C^{\text{Grid,FR}}$),
- An energy-related component ($C^{\text{Grid,E}}$),
- And a power-related component ($C^{\text{Grid,P}}$).

The fixed flat rate ($C^{\text{Grid,FR}}$) depends on the time of use of the grid connection, while the energy-related component ($C^{\text{Grid,E}}$) depends on the total amount of electricity passing through the grid connection point. Moreover, the power-related component ($C^{\text{Grid,P}}$) depends on the power peak flowing through the grid connection point during the investigated year. The components that form the grid costs are formally defined below.

$$C^{\text{Grid,E}} = \sum_{t=1}^{T} \left(P^{\text{Grid,E}} \cdot p_t^{\text{GCP,Load}} \cdot \Delta t \right) \qquad \forall\, t \in \mathcal{T} \qquad (19)$$

$$C^{\text{Grid,P}} = P^{\text{Power}} \cdot p_{max}^{\text{GCP,Load}} \qquad (20)$$

$$C^{\text{Grid}} = C^{\text{Grid,E}} + C^{\text{Grid,P}} + C^{\text{Grid,FR}} \qquad (21)$$

P^{Power} and $P^{\text{Grid,E}}$ represent the specific power-related-and energy-related grid costs, which depend on the grid level, where the flexible components are connected.

Hence, the overall costs are given by the electricity trades in the DA spot market, the grid costs and the total costs of storage within the time periods in $\mathcal{T}$ and are mathematically defined as follows.

$$C^{\text{Overall}} = C^{\text{DA}} + C^{\text{Grid}} + C^{\text{SBS}}_{LCOS} \tag{22}$$

Lastly, the objective function of the mixed-integer optimization problem is the minimization of the overall costs and is defined as follows.

$$\min_{\mathcal{T}} \quad C^{\text{Overall}} \tag{23}$$

3.3. Use Cases

In this study, different EV charging strategies are analyzed and compared with traditional EV charging. In fact, nowadays, EVs are charged as soon as they are connected to the charging infrastructure. If the maximum capacity of the EV is reached before the disconnection time, then it remains connected to the charging infrastructure until the disconnection time occurs. At an office site, EV drivers usually plug in their vehicles at the same time when they start working. Consequently, unmanaged charging leads to significant peak loads, which have a large potential negative impact on the grid from a technical, financial and environmental point of view. In the case of MC, the EV is charged when it is economically more convenient taking into account the grid costs, the electricity spot market costs and the losses of the EV. Furthermore, the V2G charging strategy allows the EV to reinject electricity into the power grid at times of high electricity prices in order to achieve lower overall costs. Moreover, these two different charging strategies are investigated with the further coordination of the charging infrastructures with stationary battery storage. The investigated use cases in this work are listed below.

- Baseline (BL): This use case coincides with the unmanaged charging. The EVs are charged as soon as they are connected to the charging infrastructure and remain connected to the charging infrastructure until the disconnection time occurs.
- Managed Charging (MC): In the MC use case, the timing of EVs charging is optimized in order to minimize the overall costs.
- Vehicle-to-Grid (V2G): In this use case, the electricity of the EVs battery can be reinjected to the power grid. The EVs are charged and discharged in order to minimize the overall costs.
- Coordinated Managed Charging (CMC): In the CMC use case, the charging of EVs is managed and coordinated with the operation of a SBS.
- Coordinated Vehicle-to-Grid (CV2G): In the CV2G use case, the charging and discharging of EVs is enabled and coordinated with the operation of a SBS.

In the interests of clarity, charging processes of an EV with MC and V2G are shown and compared with the BL in Figure 3.

In Figure 3, three different EV charging strategies are observable for the same charging process. The upper graphic shows the available capacity (blue painted area), the upper (green) and lower (red) capacity bounds as already shown in Figure 1. The lower graphic in Figure 3 shows a synthetic time-series of DA spot market prices. Furthermore, the state of charge of an EV applying three different charging strategies are shown: BL in orange, MC in blue and V2G in black. As illustrated in Figure 3, when the BL strategy is applied, the EV is charged as soon as it is connected to the charging infrastructure without taking into account the DA spot market prices (purple). When the MC strategy is applied, the EV is charged when the electricity prices at the DA spot market are low in order to minimize the overall costs, despite the standby losses. The V2G strategy enables the reinjection of electricity into the power grid. As shown in Figure 3, in fact, the electricity is bought at times when prices at the DA spot market are low and then resold when the prices are high in order to minimize

the overall costs. Furthermore, charging processes of an EV with coordinated MC and coordinated V2G are shown and compared with the BL in Figure 4.
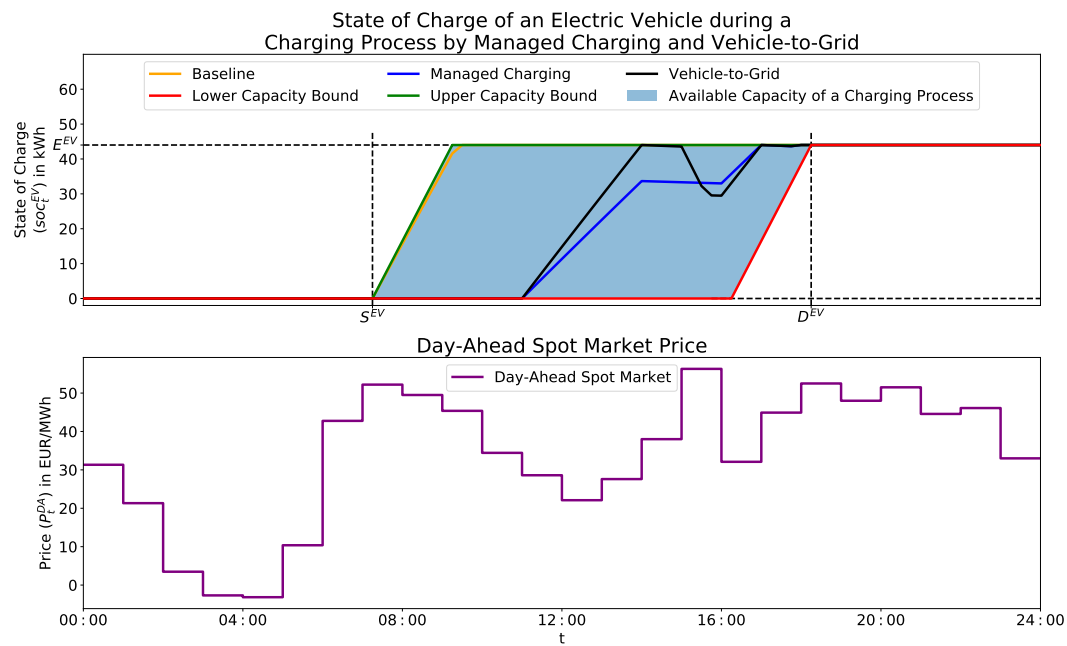

Figure 3. Charging processes of an electric vehicle by managed charging and vehicle-to-grid compared with the baseline.
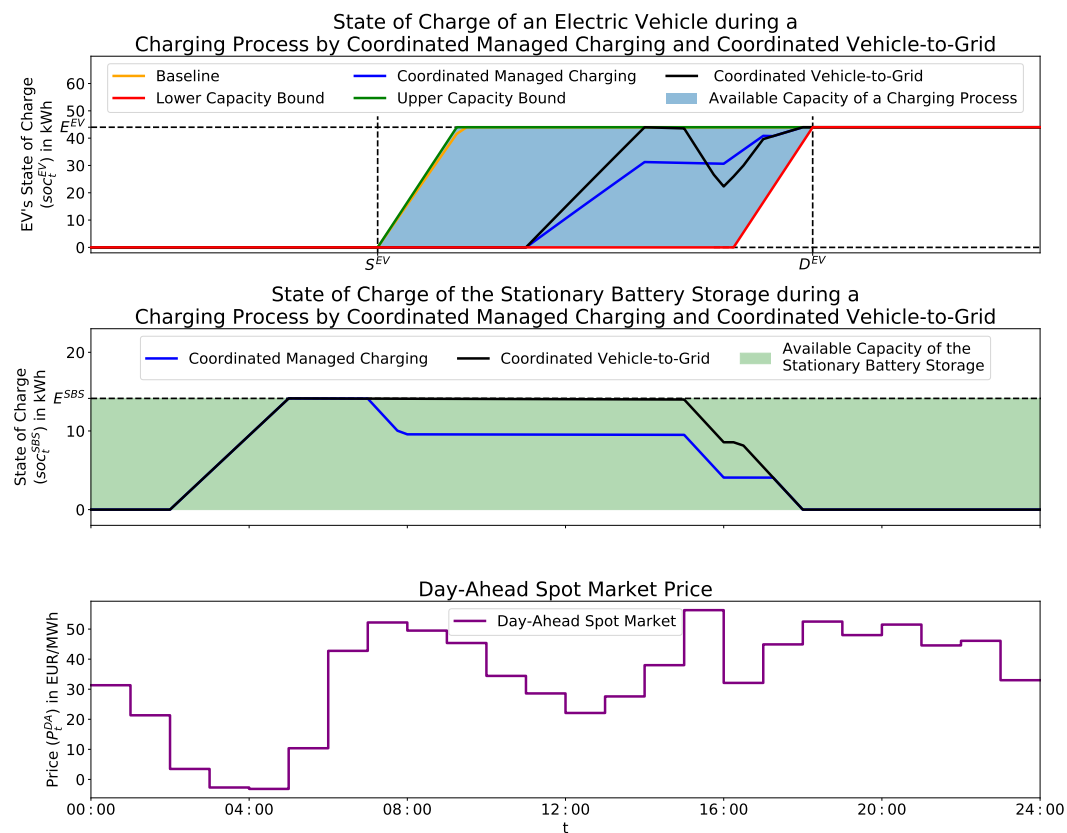

Figure 4. Charging processes of an electric vehicle with coordinated managed charging and coordinated vehicle-to-grid compared with the baseline.

Figure 4 shows the state of charge of the EVs and the SBSs during a charging process by coordinated MC and coordinated V2G. As in Figure 3, the upper graphic shows the available capacity (blue painted area), the upper (green) and lower (red) capacity bounds. Moreover, the state of charge of the EV and the SBS by CMC (blue) and CV2G (black) are illustrated. In these cases, electricity is bought before the charging process begins at a low price. The electricity bought at a low price at the DA spot market can be stored in the SBS and further sold at a high price or used to recharge the EV. The coordination between EVs and SBSs allows the system to use more price signals in order to further reduce the overall costs.

4. Description of the Case Study

In this work, the parking lot of an office site of an electric utility company in Austria is investigated (More specifically WEB, Windenergie AG, Pfaffenschlag, Austria with the coordinates N 48.843594, E 15.200681). The simulated period covers the year 2019. Furthermore, the considered grid tariffs are those applied in Austria (according to the Austrian electricity regulatory office [46]). The investigated parking lot has 30 charging infrastructures with different nominal powers; 4 charging stations with a nominal power of 22 kW, 10 with a nominal power of 11 kW and 16 with a nominal power of 3.7 kW. This study aims to understand which is the most advantageous charging strategy and how convenient it is to install an 80 kWh-capacity stationary battery storage. The considered stationary battery storage consists in a battery pack of lithium-iron-phosphate batteries (model *"BYD BATTERY-BOX HV"* with an external inverter). Over the period of one year, 3739 charging processes of EVs take place with a total of 54.927 MWh. The consumption data of the EVs are actually measured data of the investigated office site. The European Power Exchange (EPEX) DA spot market prices are considered, available on the ENTSO-E transparency platform [47]. Table 1 shows the grid costs and the LCOS that are assumed in the simulations.

Table 1. Assumed grid costs and LCOS in the simulations.

Parameter	Value	Unit	Description
$C^{\text{Grid,FR}}$	1492 [46]	$\frac{€}{Year}$	Fixed flat rate of the power grid
$p^{\text{Grid,E}}$	33.1 [46]	$\frac{€}{MWh}$	Specific energy-related grid price
p^{Power}	46.725 [46]	$\frac{€}{kW_P \cdot Year}$	Specific power-related grid price
$LCOS$	20 [48]	$\frac{€ct}{kWh}$	Levelized cost of storage

The objective of this work is to compare the economic potential of four charging strategies (MC, V2G, CMC, CV2G) with the unmanaged charging of EVs for an existing office site in Austria with multiple charging infrastructures. It is assumed that the operations of the managed components are optimized through automated technologies. Furthermore, no communication problems of any kind between the operating components are considered. Moreover, since this work aims to understand the potential of the different charging strategies for EVs, the optimization problems are solved under the assumption of perfect load forecast.

5. Results

In this section, the results of the simulations are presented, and the economic potential of the four investigated EVs charging strategies of (MC, V2G, CMC, CV2G) are compared with the unmanaged charging (BL).

The results of the simulations are described and discussed, focusing on quantifying the value of different charging managements strategies of EVs. Figure 5 shows the results of the investigated case study and raises the monetary potential of four charging strategies (MC, V2G, CMC, CV2G) compared with the unmanaged charging of EVs (BL) for the studied office site in Austria.
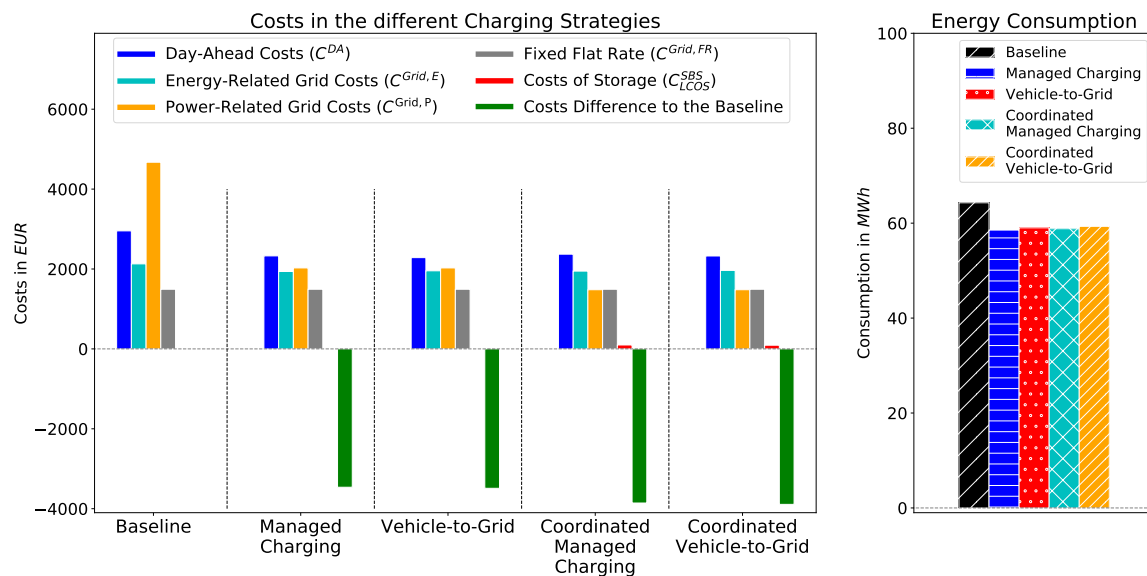
Figure 5. Costs and energy consumption in the different charging strategies.

In Figure 5, it is observable that in the BL, the overall costs (in the graph on the left) and the electricity consumption (in the graph on the right) are higher compared to the remaining four investigated charging strategies. In the BL, the electricity consumption is higher because the EVs are charged as soon as they are connected to the charging infrastructure and remain connected to the charging infrastructure until the disconnection time occurs. This leads to high standby losses. Consequently, more electricity is needed to reach the required state of charge of the EV's batteries when the disconnection time occurs. Therefore, the energy-related grid costs (light blue) are higher in the BL compared to the other four investigated charging strategies. The costs at the DA spot market (blue) are mainly higher for two reasons. Firstly, as already mentioned, more electricity is required and therefore it is necessary to buy more electricity in the DA spot market. The second reason is that the capacity of a charging process is not utilized (as already shown in Figure 3). In the BL, in fact, electricity is bought regardless of the DA spot market prices as soon as an EV connects to the charging infrastructure without applying any load shifting. Furthermore, in the BL, no peak shaving is operated for the aggregated charging infrastructures. This leads to high power-related grid costs (orange). The fixed flat rate is the same for all investigated use cases since it depends exclusively on the time of use of the grid connection, which in this study amounts to one year.

The MC achieves a reduction in overall costs of 30.7% compared to the BL. This is due to the fact that in this case, the load shifting and the peak shaving are applied with the possibility of charging EVs when the DA spot market prices are low and avoiding congestion of EVs charging processes. Congestion of EVs causes the increase in peak power, and consequently of the power-related grid costs. In fact, the power-related grid costs in the MC use case are reduced by 56.6% compared to the BL. Moreover, in this case, the electricity is bought when it is economically more convenient taking into account the grid costs, DA spot market costs and losses of the EV. This leads to a reduction in DA spot market costs of 21.2% and in the energy-related grid costs of 9% as observable in Figure 5.

Furthermore, the V2G strategy achieves overall costs reduction of 31% compared to the BL. In this case, the reinjection of electricity from the EVs into the power grid is enabled together with the possibility to operate load shifting and peak shaving, when it is economically convenient. The power-related grid costs, in this case, are reduced by 56.6%, the DA spot market costs of 22.6% and the energy-related grid costs of 8.2% compared to the BL. The possibility to reinject the electricity into the power grid, in fact, allows the resale of electricity purchased at a low price for a higher price. Hence, in this case, an increased amount of electricity is consumed, but the costs at the DA spot market are lower compared to those in the MC use case.

Moreover, in the CMC and CV2G strategies, the use of the SBS allows achieving further costs reductions compared to the other investigated use cases. As we can see in Figure 5, the overall cost reduction in both cases is more than 34%. The DA spot market costs are reduced by 19.7% applying the CMC and 21.3% in the CV2G use case. The energy-related grid costs are reduced by 8.5% in the CMC use case and 7.7% applying the CV2G strategy compared to the BL. The operation of the SBS aims mainly to reduce the power peak in order to reduce the power-related grid costs in both cases, achieving a reduction of 68.3% compared to the BL.

The high LCOS makes the SBS use very rare for load shifting. For this reason, the SBS is used more in the CMC than in the CV2G use case, since the possibility to inject the electricity directly from the EVs to the power grid makes the SBS less useful. In fact, applying the CV2G strategy, the SBS is charged with an amount of electricity equal to 489.1 kWh, while in the CMC use case the SBS is charged with 519.7 kWh. The amount of electricity flown in the SBS, as already mentioned, is very low due to the high LCOS. Section 5.1 presents a sensitivity analysis aimed to determine the effect of variations in LCOS on the overall costs and battery usage.

5.1. Sensitivity Analysis: Levelized Costs of Storage vs. Overall Costs and Stationary Battery Storage Usage

In an EVs parking lot, the SBS can contribute to the reduction of the overall costs in three ways.

- Through the buying and selling of electricity in the DA spot market, so as to be able to take advantage of price volatilities,
- applying a further load shifting by buying the electricity needed to charge the EVs when the EVs are not yet connected to the charging infrastructures,
- by doing peak shaving, thus reducing power-related grid costs. In all three cases, the LCOS costs play a key role because they determine the monetary convenience of operating the SBS.

In all three cases, the LCOS costs play a key role because they determine the monetary convenience of operating the SBS. Figure 6 presents a sensitivity analysis, aimed to determine the effect of variations in LCOS on the overall costs and the SBS usage in the CMC and CV2G use cases.
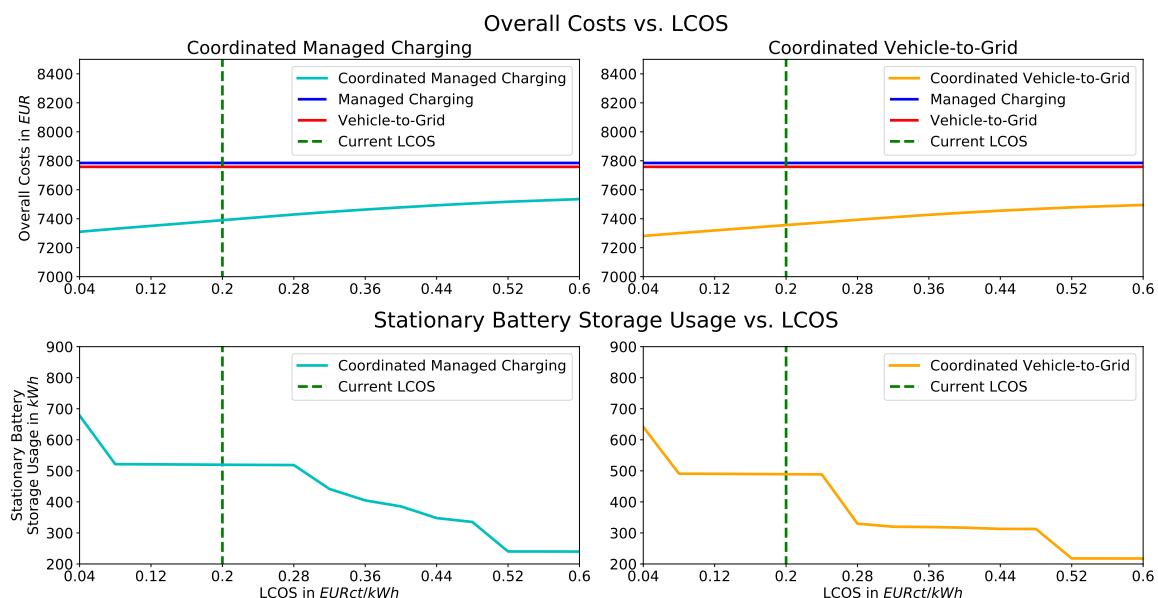

Figure 6. Levelized costs of storage vs. overall costs and stationary battery storage usage.

As shown in Figure 6, the overall costs of the CMC (light blue) and CV2G (orange) use cases decrease with the lowering of the LCOS. As the LCOS increases, the overall costs of the CMC and CV2G use cases tend to the overall costs of the MC (blue) and V2G (red) use cases, as the SBS usage decreases. The SBS in the CMC use case is utilized more than in the CV2G use case since, with high

LCOS, it is more convenient to inject and withdraw electricity from the EVs when their capacity is available. In the CV2G use case, in fact, the SBS is used mostly for peak shaving and less for electricity marketing and load shifting as we can see from the lower graphs of Figure 6. The use of the SBS, in fact, decreases with the increase of the LCOS, since it becomes no longer economically convenient to cover a high number of power peaks and that is why it is preferable not to operate peak shaving and pay a higher power-related grid rate. Moreover, in Section 5.2, a sensitivity analysis aimed to determine the effect of variations in specific energy-related grid price on the overall costs is presented.

5.2. Sensitivity Analysis: Specific Energy-Related Grid Price vs. Overall Costs

In this section, it is investigated whether increasing or reducing the specific energy-related grid price ($P^{\text{Grid,E}}$) can, in some way, incentivize the investigated Austrian office site to apply one of the studied charging strategies. Figure 7 consists of 5 graphs showing the overall costs as a function of the specific energy-related grid price for the four investigated use cases and the BL.
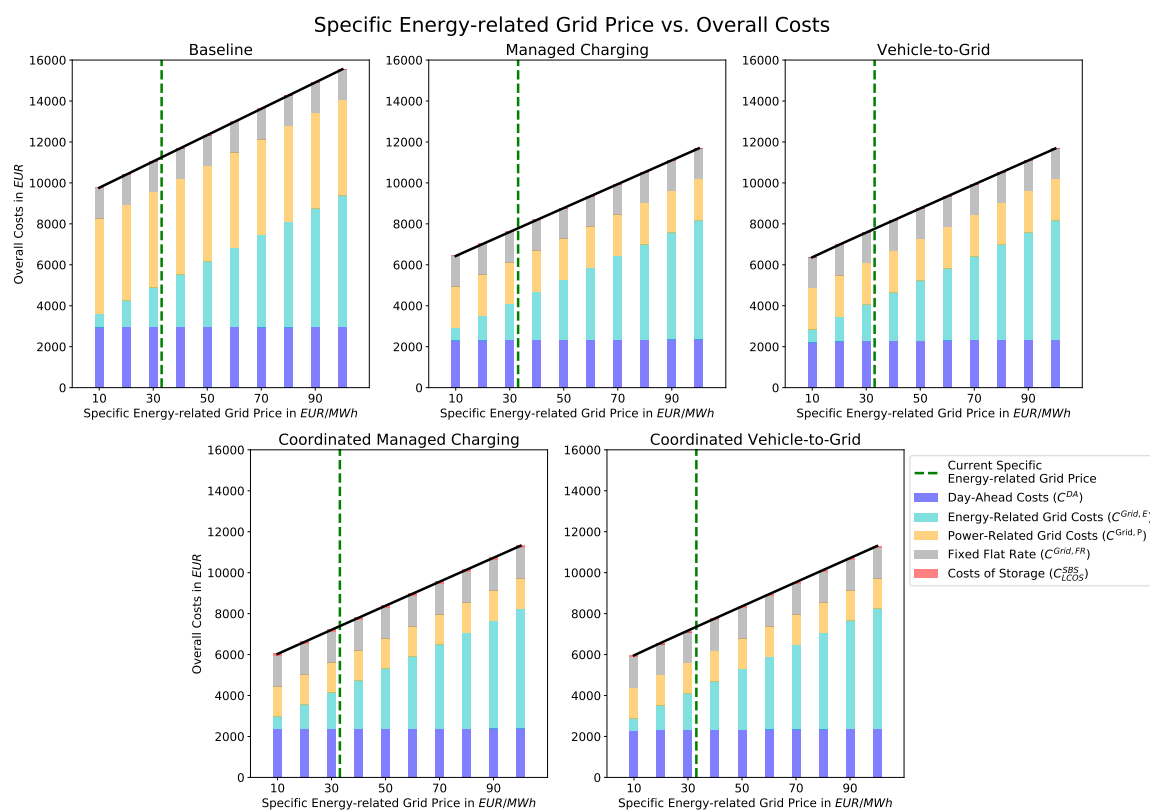

Figure 7. Specific energy-related grid price vs. overall costs.

Figure 7 shows that the changes in specific energy-related grid price have a similar influence on all investigated use cases. This is due to the fact that in all use cases studied, EVs must be charged with the same amount of electricity. This means that at high specific energy-related grid price, the optimal solution leads to minimizing the losses, so as to have the least amount of electricity flowing through the grid connection point. With the increase of the specific energy-related grid price, it does not become more economically convenient to operate electricity marketing on the DA spot market since the storage of electricity causes efficiency and standby losses, and also because the electricity purchase price increases linearly with the specific energy-related grid price. An increase in specific energy-related grid price, therefore does not make any of the four investigated charging strategies more advantageous over the other. Even at a very low specific energy-related grid price, the SBS is mostly operated for peak shaving, as current LCOSs often do not make it convenient to operate electricity marketing in the

DA spot market. Therefore, in Section 5.3 a sensitivity analysis is presented in order to determine the effect of variations in specific power-related grid price on the overall costs.

5.3. Sensitivity Analysis: Specific Power-Related Grid Price vs. Overall Costs

As already seen in Figure 5, the power-related grid costs constitute the most expensive cost component in the BL. Therefore, the four investigated charging strategies aim mainly to reduce the power-related grid costs lowering the peak power. Figure 8 presents a sensitivity analysis aimed to determine the effect of variations in the specific power-related grid price on the overall costs.

Figure 8. Specific power-related grid price vs. overall costs.

In Figure 8, it is observable that the overall costs in all investigated use cases increase almost linearly with the increase of the specific power-related grid price. However, it is evident how the slope of the total costs as a function of the specific power-related grid price changes in the studied use cases. The BL has the most significant slope, while the cases where the EVs are coordinated with the SBS the slope is minor. This is due to the fact that in the CMC and CV2G use cases, there is more capacity available to perform peak shaving. Again, the difference in overall costs between the MC and the V2G use cases and between the CMC and the CV2G use cases is minimal, confirming the fact that injecting electricity into the grid from an EV is rarely cost-effective. In conclusion, it can be demonstrated to the hand of Figure 8 that an increase in specific power-related grid price would further incentivize the investigated Austrian office to implement a smart charging strategy and invest in the SBS.

6. Conclusions and Outlook

This paper presents the monetary potential of different EVs charging strategies for an existing Austrian office site with multiple charging infrastructures. Hence, multiple optimization problems are defined in order to determine the operation of the investigated components in the different EVs charging strategies. Various diversities and potentials of different EVs charging strategies are identified

comparing four use cases for the same case study. Furthermore, the method to implement EVs and SBSs in optimization problems with the exclusive use of linear relationships is presented.

The simulations have shown that unmanaged charging of EVs leads to high power peaks, which result in high overall costs. The implementation of a managed charging strategy can lead the overall costs of the Austrian office site's parking lot to a reduction of more than 34%. In particular, the power-related grid costs can decrease by 68% if the charging of EVs is managed and coordinated with the operation of a SBS. Moreover, the simulations have shown that the charging processes management leads to less electricity consumption because of the lower standby losses. This results in reduced energy-related grid costs, which can decrease by 9%. The results highlight the fact that for an office there is no big difference in overall costs if the V2G is operated. In fact the overall costs between the V2G and MC use case and between the CV2G and CMC use cases differ only by 0.3%. This is mainly due to the fact that the connection time of EVs to the charging infrastructures at an office is not long enough to allow the capture of market price signals and charging the EV at the same time. In fact, the average connection time of EVs to the charging infrastructures during the year 2019 was 98 min. However, it should be noted that this cannot be ruled out for private end-users, where the average connection time of EVs is certainly longer and it is possible that the V2G charging is monetary convenient.

The performed sensitivity analyses show that the SBS at current LCOS operates mostly for peak shaving and not for marketing electricity in the DA spot market. Marketing electricity in the DA spot market is economically convenient for the SBS when the LCOS are lower than 0.08 $\frac{\text{€ct}}{kWh}$. It has also been shown that variations in specific energy-related grid price are unlikely to incentivize the Austrian office site to implement managed charging in their parking lot. Instead, an increase in specific power-related grid price makes EV's charging management more convenient and therefore incentivize the Austrian office site to implement it and also to invest in a SBS. Therefore, one of the future challenge is to investigate to what extent the specific power-related grid price will increase. Nowadays, the growing share of renewables in the power grid raised the specific power-related grid prices in different European countries. Therefore, it is reasonable to assume that in the future the charging process management of EVs can be further incentivized.

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Abbreviations

The following abbreviations are used in this manuscript:

BL	Baseline
CMC	Coordinated Managed Charging
CV2G	CoordinatedVehicle-to-Grid
DA	Day-Ahead
EPEX	European Power Exchange
EV	Electric Vehicle
GCP	Grid Connection Point
IPCC	Intergovernmental Panel on Climate Change

MC　　　Managed Charging
SBS　　Stationary Battery Storage
V2G　　Vehicle-to-Grid

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