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Carbon emission evaluation for stationary storage systems in EV parking lots

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ABSTRACT

With the wide spread of electric vehicles and relevant grid-powered charging infrastructures, a safe and low-carbon integration in power systems is particularly challenging, due to variation of electricity generation mix over different time frames. As moving towards a fully green energy system, optimizing energy consumption during low-carbon periods, especially with suitable energy storage systems, can have substantial environmental advantages. In this article, the influence of stationary storage inclusion into electric vehicle parking lots on weekly operation is assessed by means of optimal daily schedule considering economic (cost minimization) and environmental (indirect carbon emission minimization) targets. Different storage sizes and EV charging rates are examined for assessing better exploitations in different weeks of operation. The evaluation of EV smart charging in combination with storage is considered as well. Results show the advantage of integrating battery storage system into the parking lot, achieving cost reduction as well as carbon emission reduction for most of charging rates considered. Further contributions in economic and environmental benefits are reached by implementing EV smart charging scheduling.

1. Introduction

The expansion of electric vehicles (EVs) ownerships [1] is challenging for electrical network safe operation due to increasing demand for EV charging, also at increasing rates. Smart charging solutions show that the possibility to control EV charging leads to several economic and technical benefits [2]. In particular, different tariff schemes [3,4] could imply economic goal achievements, still ensuring a grid safe operation in distribution networks [5,6]. Moreover, vehicle-to-grid exploitation represents a viable solution for grid service provision, as voltage support during peak demand periods [7]. However, the environmental impact of EVs is still under discussion, in terms of emissions produced during EV charging. The study presented in [8] deals with the evaluation of electricity generation emissions produced due to EV charging, highlighting that smart charging technologies could unintentionally lead to an increase in emissions production, as marginal emissions could have different patterns from average emission, as shown also in [9]. The multi-objective procedure proposed in [10] is used to compare the cost and emission benefits of smart charging with a higher grid capacity limit with the costs and emissions of grid reinforcements, proving that costs and emissions for grid reinforcements outweigh the benefits in costs and emissions in EV charging optimization resulting from increased grid capacity. However, substantial reductions in EV charging costs and emissions can be achieved under the current transformer capacity. The minimization of greenhouse gas emissions from EV charging is the main objective of [11], where the marginal emission factor and total EV charging demand are considered to find the optimal spatio-temporal distribution of EV charging activities to minimize emissions from electricity generation. The trade-off between emission reduction and peak power demand shaving is an important aspect in EV charging coordination. Coordinated charging has been shown in [12] to reduce CO_2 emissions by 18 % annually while also decreasing peak power demand by 33 %. However, further reducing emissions by around 1 % necessitates a significant increase in peak power demand by 84 %, which is 23 % higher than the peak power demand without coordination. This trade-off highlights the need to balance emissions reduction and grid stabilization goals when coordinating EV charging.

In this context, the studies in [13,14] investigate possible optimal EV charging/discharging strategies for minimizing carbon emissions,

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Nomenclature

Acronyms

BS	Battery Storage
CO_2	Carbon dioxide
EV	Electric Vehicle
PV	Photovoltaic
SOC	State-of-charge

Objective functions

f^{CO2}	Total CO_2 emission due to parking lot operation over the optimization time horizon
f^{Cost}	Total cost for energy purchasing due to parking lot operation over the optimization time horizon

Variables

x	State variable vector
$P_t^{g,in}$	Imported power from the external grid in the t-th time-step [kW]
Pc_t^{BS}	BS charging power in the t-th time-step [kW]
Pd_t^{BS}	BS discharging power in the t-th time-step [kW]
S_t^{BS}	BS SOC in the t-th time-step [kWh]
xc_t^{BS}	Binary variable for BS charging in the t-th time-step
xd_t^{BS}	Binary variable for BS discharging in the t-th time-step
P_t^{EVs}	Total EV power demand in the t-th time-step (only in smart charging procedure) [kW]

Parameters

CI_t	Carbon Intensity index in the t-th time-step [gCO_2/kWh]
$P_{buy,t}$	Purchase energy price from the grid in t-th time-step [£/MWh]
P_t^{EVs}	Total EV power demand in the t-th time-step (only in uncontrolled charging procedure) [kW]
Pc_{min}^{BS}	BS minimum charging power [kW]
Pc_{max}^{BS}	BS maximum charging power [kW]
Pd_{min}^{BS}	BS minimum discharging power [kW]
Pd_{max}^{BS}	BS maximum discharging power [kW]
S_{min}^{BS}	BS minimum SOC level [kWh]
S_{max}^{BS}	BS maximum SOC level [kWh]
Cap^{BS}	BS capacity [kWh]
Cap_{IN}	BS initial capacity ($t = 1$) [kWh]
Cap_{FIN}	BS final capacity (t=N_T) [kWh]
η_c^{BS}	BS charge efficiency
η_d^{BS}	BS discharge efficiency
P_t^v	Charging power required by the v-th EV in the t-th time-step [kW]
P_{MAX}^{EV}	EV maximum charging power [kW]
$P_t^{v,M}$	Modulated charging power required by the v-th EV in the t-th time-step [kW]
S_t^v	SOC of the v-th EV in the t-th time-step [kWh]
$S^{v,MAX}$	Maximum SOC of the v-th EV [kWh]
η_c^v	Charge efficiency of the v-th EV
E_{target}^{EVs}	Daily energy need required by EVs (only in smart charging procedure) [kWh]
t_{in}^v/t_{out}^v	Arrival/departure times of the v-th EV [h]
N^{EVs}	Number of total EVs included in the parking lot
N_t^{EVs}	Number of plugged-in EVs in the t-th time-step
N_T	Number of total time-steps
ΔT	Time-step duration in hour

Indicators

ΔCO_2	Weekly carbon emission variation [gCO_2]
CO_2^{BS}	Weekly carbon emission in the presence of BS [gCO_2]
$CO_2^{no\ BS}$	Weekly carbon emission in the absence of BS [gCO_2]
$\Delta cost$	Weekly cost variation [£]
$Cost^{BS}$	Weekly cost in the presence of BS [£]
$Cost^{no\ BS}$	Weekly cost in the absence of BS [£]
$Y\Delta CO_2$	Yearly carbon emission variation [gCO_2]
$Y\Delta cost$	Yearly cost variation [£]
W_k	Number of occurrences of the represented time horizon in the generic k-th period
n_{disch}^{BS}	BS equivalent discharging cycle number

underlying the advantage of vehicle-to-grid exploitation in CO_2 reduction, not in all scenarios though, as energy efficiency rating can widely influence emission evaluations. In particular, vehicle-to-grid exploitation could imply significant reduction in emissions, however accelerating battery degradation [15].

The inclusion of renewable energy sources, as the possibility to minimize wind curtailment with EV charging [16], or photovoltaic in dedicated infrastructures for EV charging, represents an important aspect of the safe integration of charging stations into the distribution networks, as reported in [17] where a technical-economic-environmental assessment methodology is implemented for photovoltaic-powered charging stations, which is demonstrated to produce less emissions with respect to power-connected charging stations, and [18], where a bidding model of a power grid involving PV and EVs is proposed in order to reach low-carbon grid operation. Energy storage inclusion in parking lot could improve system performances [19], depending on technology features: as reported in [20], battery-based energy storage (BS) systems have the advantages of quick response to peak demand and low dependence from the utility grid with respect to other technology with lower energy density, such as mechanical and thermal energy storage systems. As a matter of fact, BS systems could be involved in optimal scheduling procedures in order to investigate economic benefits [21], or to allow the minimization of annual equivalent carbon emissions, as in [22,23], especially considering second-life batteries, or to provide reserve to cope with uncertainties of intermittent renewable sources [24]. Off-grid PV-BS system for EV charging is shown to be a profitable project to deal with carbon emissions reduction [25].

The focus of this study is on examining how the integration of BS into EV charging infrastructure can contribute to the reduction of carbon emissions and enhance the overall sustainability of the energy system by exploring the potential synergies between BS, type of EV charging and carbon intensity. In particular, in order to assess the influence on techno-economic targets of both installation and operation aspects, such as BS sizes and EV usage, an optimal operation programming procedure is carried out on weekly time frame, accounting for costs and emission objectives and considering technical operation features. Proper technical and economic indicators are defined and contribute to effective comparison of the analyzed factors and to evaluate a preliminary BS techno-economic feasibility. A sensitivity analysis of procedure outcomes with realistic evolution of carbon intensity is carried out.

The main contributions can be summarized as in the following:

- Differently from [23], the impact of BS is assessed by means of optimal weekly scheduling procedure considering economic (cost minimization) and environmental (indirect carbon emissions minimization) targets.
- Different BS sizes are examined for evaluating possible better exploitation, and different weeks of operation as well.

- Slow and fast EV charging rates are considered, in order to assess the impact of uncontrolled and smart fast charging stations on the operation of the system and on total carbon emissions.

Section 2 describes the proposed optimization methodology, the case study is described in Section 3, whereas Section 4 is dedicated to results and discussion. Conclusions are drawn in Section 5.

2. Methodology

2.1. Overview and assumptions

The proposed methodology employs a deterministic linear mixed-integer optimization problem to control the BS operation finalized to provide energy for EV charging, while minimizing economic and environmental targets, as the total daily energy costs and CO_2 emissions. A schematic layout integrating the BS is reported in Fig. 1. The assumptions underlying the procedure are described in the following:

- uncertainties concerning EV charging demand and plug-in times [29] are taken into account by generating samples from probability distributions;
- the EV station infrastructure supports only the charging of vehicles, either uncontrolled or smart;
- BS operation is deemed to supply EV power needs in the parking lot, therefore any further exploitation towards the external grid, such as frequency, voltage and power support services [30], is neglected.

2.2. Optimization problem with EV uncontrolled charging

The optimization problem aims at coordinating the exploitation of the BS with EV uncontrolled (or dumb) charging, in order to obtain a power exchange with the external electric grid $P_t^{g,in}$, for each time step t in the considered time horizon (with N_T timesteps), able to reach defined objective f subject to proper linear constraints as in Eq. (1).

$$\begin{aligned} &min[f(\boldsymbol{x})\ ]\\ &A{\cdot}\boldsymbol{x} \leq b\\ &Ae{\cdot}\boldsymbol{x} = be \end{aligned} \tag{1}$$

where $\boldsymbol{x}$ represents the state variable vector, A and Ae represent the coefficient matrices of inequality and equality constraints respectively, and b and be are the relevant vectors of known terms.

Two different objective functions are inspected, represented by total CO_2 emissions f^{CO2} and total operation cost f^{Cost}, as defined in Eqs. (2) and (3) respectively:

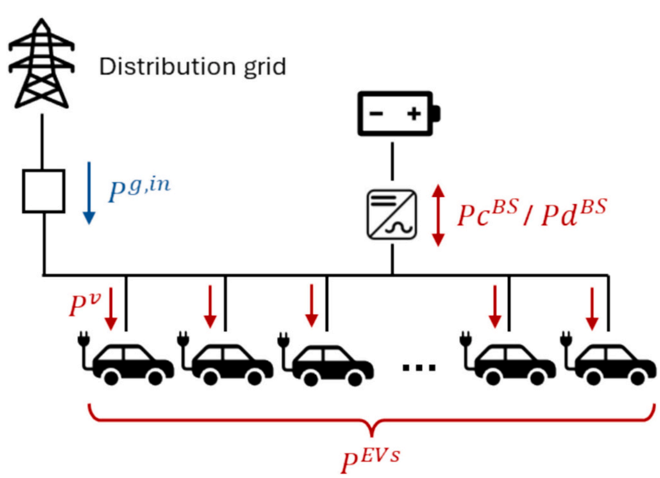

Fig. 1. System layout.

$$f^{CO2} = \Delta T{\cdot}\sum_{t=1}^{N_T} CI_t{\cdot}P_t^{g,in} \tag{2}$$

$$f^{Cost} = \Delta T{\cdot}\sum_{t=1}^{N_T} P_{buy,t}{\cdot}P_t^{g,in} \tag{3}$$

where ΔT is the time-step duration in hours, CI_t is the carbon intensity in the t-th time-step, $P_{buy,t}$ is the purchase energy price from the grid in t-th time-step.

The problem is enriched with constraints, mainly related to technical limits of the BS. In particular, Eq. (4) defines $P_t^{g,in}$ as the imported power from the external grid in the t-th time-step, which is the algebraic sum among BS active charging power (Pc_t^{BS}), discharging power (Pd_t^{BS}) and the total charging demand of EVs in the t-th time-step P_t^{EVs}. Constraints in Eq. (5) and (6) take into account technical limits of charge/discharge power of the BS for each time-step. Moreover, binary state variables xc_t^{BS} and xd_t^{BS}, introduced in Eqs. (7)–(9), account for unidirectionality of BS power exchanges, assuming value of 1 if the BS is charging (or discharging), and 0 if not. In particular, Eqs. (7) and (8) limit charging/discharging power to the maximum values when binary variables are active. Since BS discharge is only finalized to energy provision for EV charging and not for selling energy and other services to the grid to make profit, inequality in Eq. (10) allows BS discharging only in the presence of EV charging demand (Pd_t^{BS} values lower or equal to EV demand at each time step). Equality constraint in Eq. (11) represents the evolution of BS state-of-charge (SOC) S_t^{BS} for each time-step, accounting for charge/discharge efficiencies (η_c^{BS} and η_d^{BS}) as well, whereas Eq. (12) and Eq. (13) fix the initial and final SOC over the considered time horizon. Finally, in Eq. (14) proper limits on SOC evolution are posed within feasible range for the considered BS.

$$P_t^{g,in} = P_t^{EVs} - Pd_t^{BS} + Pc_t^{BS} \forall t \in N_T \tag{4}$$

$$Pc_{min}^{BS} \leq Pc_t^{BS} \leq Pc_{max}^{BS} \forall t \in N_T \tag{5}$$

$$Pd_{min}^{BS} \leq Pd_t^{BS} \leq Pd_{max}^{BS} \forall t \in N_T \tag{6}$$

$$Pc_t^{BS} \leq Pc_{t,max}^{BS}{\cdot}xc_t^{BS} \forall t \in N_T \tag{7}$$

$$Pd_t^{BS} \leq Pd_{t,max}^{BS}{\cdot}xd_t^{BS} \forall t \in N_T \tag{8}$$

$$xc_t^{BS} + xd_t^{BS} \leq 1 \forall t \in N_T \tag{9}$$

$$Pd_t^{BS} \leq P_t^{EVs} \forall t \in N_T \tag{10}$$

$$S_t^{BS} = S_{t-1}^{BS} + \Delta T{\cdot}\eta_c^{BS}{\cdot}Pc_t^{BS} - \Delta T{\cdot}\frac{1}{\eta_d^{BS}}{\cdot}Pd_t^{BS} \forall t \in N_T \tag{11}$$

$$S_{t=1}^{BS} = Cap_{IN} \tag{12}$$

$$S_{t=N_T}^{BS} = Cap_{FIN} \tag{13}$$

$$S_{min}^{BS} \leq S_t^{BS} \leq S_{max}^{BS} \forall t \in N_T \tag{14}$$

The total number of state variables for the formulated problem with EV uncontrolled charging is $5xN_T$, the number of inequality constraints – including Eqs. (5)–(10) and (14) – is $10xN_T$ and the number of equality constraints – including Eqs. (4) and (11)–(13) – is $2xN_T + 2$.

The main input of the proposed procedure is represented by the total EV charging demand in t-th time step P_t^{EVs}. For a total number of N^{EVs}, and under the assumption of uncontrolled charging, based on proper forecasts on EV maximum power rate P_{MAX}^{EV} and arrival/departure time t_{in}^{v}, t_{out}^{v} and EV SOC, P_t^{EVs} is determined as follows:

$$P_t^{EVs} = \sum_{v=1}^{N^{EVs}} P_t^v \forall t \in N_T \tag{15}$$

$$P_t^v = \begin{cases} 0 & t \notin \left[t_{in}^v, t_{out}^v\right] \\ min\left(P_t^{v,M}, P_{MAX}^{EV}\right) & t \in \left[t_{in}^v, t_{out}^v\right] \end{cases} \tag{16}$$

$$S_t^v = S_{t-1}^v + \Delta T \cdot \eta_c^v \cdot P_t^v \forall t \in N_T \tag{17}$$

$$P_t^{v,M} = \frac{S^{v,MAX} - S_t^v}{\Delta T \cdot \eta_c^v} \forall t \in N_T \tag{18}$$

2.3. Optimization problem with EV smart charging

In order to investigate the effects of EV smart charging on CO_2 emissions and costs, the problem described in the previous Section 2.2 is slightly modified, considering as additional state variable P_t^{EVs}, representing the aggregated power requested by EVs for each time step. This aggregated power is limited to a maximum value in Eq. (19), that depends both on the number of plugged-in EV for each time-step N_t^{EVs} and maximum power of the EV charging point P_{MAX}^{EV} as reported in Eq. (20). Furthermore, the same daily charging energy (as in dumb-charging problem) is guaranteed by constraints in Eq. (21) for each day of the week.

$$0 \le P_t^{EVs} \le P_{t,MAX}^{EVs} \forall t \in N_T \tag{19}$$

$$P_{t,MAX}^{EVs} = N_t^{EVs} \cdot P_{MAX}^{EV} \forall t \in N_T \tag{20}$$

$$\sum_{t=1}^{ntd} \Delta T \cdot P_t^{EVs} = E_{target}^{EVs} \tag{21}$$

The aforementioned constraints are still included in the problem formulation. In particular, with EV smart charging P_t^{EVs} is considered as a state variable in Eqs. (4) and (9) instead of the known value obtained for dumb charging as described before.

The total number of state variables for the formulated problem with EV smart charging is $6xN_T$, the number of inequality constraints – including Eqs. (5)–(10), (14) and (19) – is $12xN_T$ and the number of equality constraints – including Eqs. (4), (11)-(13), (15) and (20)-(21) – is $4xN_T + 3$.

2.4. Techno-economic indicators

The definition of proper economic and technical indicators is important for comparing results, in order to assess which strategy achieves better performances with respect to the base case, represented by the EV dumb charging without the stationary BS, e.g. considering $Pd_t^{BS} = Pc_t^{BS} = 0$, at the same EV charging rate of the optimized cases with EV uncontrolled charging. Thus, for each weekly time horizon of the simulation the CO_2 emission variation of the optimized value reported in Eq. (2) with respect to the base case represent the technical indicator, and it is evaluated as in Eq. (22). Moreover, variation of costs for energy purchasing evaluated in Eq. (3) with respect to the base case represents the economic indicator, as reported in Eq. (23).

The analysis is carried out on time horizons representing different periods of the year, therefore the annual values of the indicators are derived as well in Eqs. (24) and (25), being k the general period and W_k the number of occurrences of the represented time horizon in each period.

Furthermore, the usage of BS is assessed by means of the equivalent discharging cycle number n_{disch}^{BS}, evaluated as in Eq. (26), where η_d^{BS} is the BS discharge efficiency, while Cap^{BS} is the BS capacity.

$$\Delta CO_2 = CO_2^{BS} - CO_2^{no\ BS} = \Delta T \cdot \left(\sum_{t=1}^{N_T} CI_t \cdot P_t^{g,in} - \sum_{t=1}^{N_T} CI_t \cdot P_t^{EVs} \right) \tag{22}$$

$$\Delta cost = Cost^{BS} - Cost^{no\ BS} = \Delta T \cdot \left(\sum_{t=1}^{N_T} P_{buy,t} \cdot P_t^{g,in} - \sum_{t=1}^{N_T} P_{buy,t} \cdot P_t^{EVs} \right) \tag{23}$$

$$Y\Delta CO_2 = \sum_{k=1}^{Nk} W_k \cdot \Delta CO_{2,k} \tag{24}$$

$$Y\Delta cost = \sum_{k=1}^{Nk} W_k \cdot \Delta cost_k \tag{25}$$

$$n_{disch}^{BS} = \sum_{t=1}^{N_T} \frac{\Delta T \cdot Pd_t^{BS}}{\eta_d^{BS} \cdot Cap^{BS}} \tag{26}$$

3. System under study

The case study refers to a parking lot of 83 EV charging stations. In order to construct an insightful case study reflecting practical scenarios, a survey of three distinct parking locations is conducted by physically observing and recording vehicle activities within the Cardiff area multiple times daily over a two-week period in two separate months. Among these sites, two are linked to workplaces, while the third served as a general-use parking facility primarily catering to individuals visiting the city center or engaging in shopping activities. Notably, the workplace parking areas exhibited substantial variability, attributed largely to the presence of contractors, and visiting vehicles. According to the obtained data, the EV usage is modelled through a probabilistic approach that involves Normal distribution probabilities of plug-in start time and plug-in duration, and relevant parameters are reported in Table 1.

Moreover, EVs are assumed to be charged considering separately a slow fixed rate of 7.4 kW, an accelerated 24 kW (over all the parking time), fast 50 kW and ultra-fast 150 kW (attaining a total energy amount of the charge E_{target}^{EVs} equal to a medium-speed charge at 24 kW throughout the parking time interval).

The carbon intensity data utilized in the evaluation are sourced from [31] and are related to the year 2022 for UK system. Fig. 2 shows the average CI_t evaluated monthly from 2018 to 2024. It can be seen that the overall trend is decreasing through years, with a minimum annual average in 2020 (due to the pandemic), while 2021 average is 25 % lower than in year 2018 and 12 % lower than in year 2019. The 2022 average is 27 % lower than in year 2018 and 15 % lower than in year 2019.

The considered time horizon spans 1 week, which is further divided into $N_T = 336$ time-steps with 30-min duration ($\Delta T = 0.5$ h). System operation over a year is evaluated by the combination among one week per season (considering $Nk = 4$ seasons with average week number $W_k = 13.04$). Relevant data for carbon intensity by time step in four representative weeks of 2022 (one per each season) are represented in Fig. 3.

Furthermore, Fig. 4 reports energy costs that are determined by elaborating 2022 UK price system analysis report data [32]. In particular, energy prices are evaluated considering average system price distinguished in values for short and long system, along with percentage of system length, reported by day of the season and by settlement period (30-minute period) over the season.

Table 1
Distribution probability parameters for EV usage.

Plug-in times	Mean	Standard Deviation
Start time [hh:mm]	12:15	02:45
Duration [h]	2.13	0.38

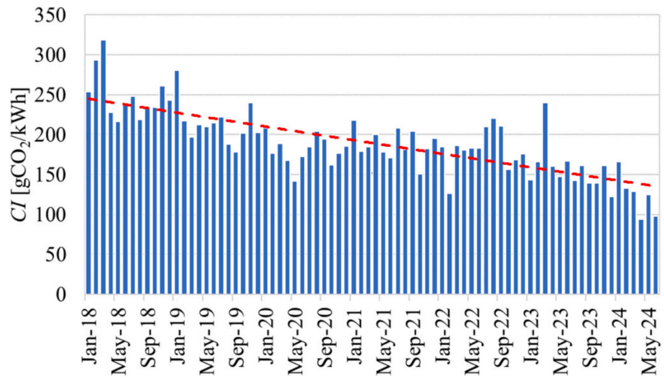

Fig. 2. Monthly average CI from 2018 to 2024. [31].

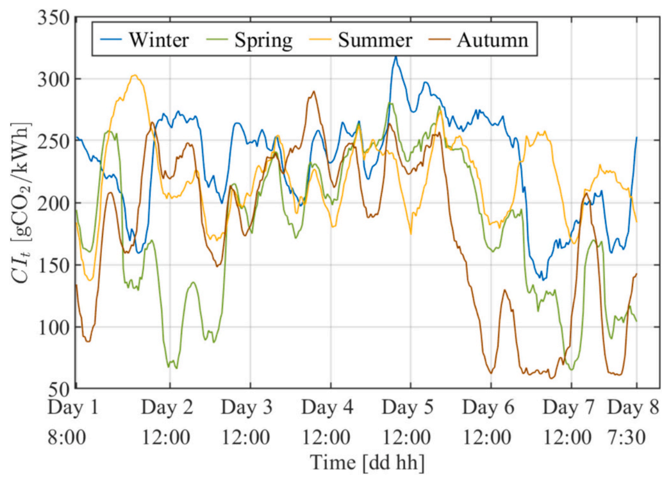

Fig. 3. Carbon intensity index over a week for each season over 2022.

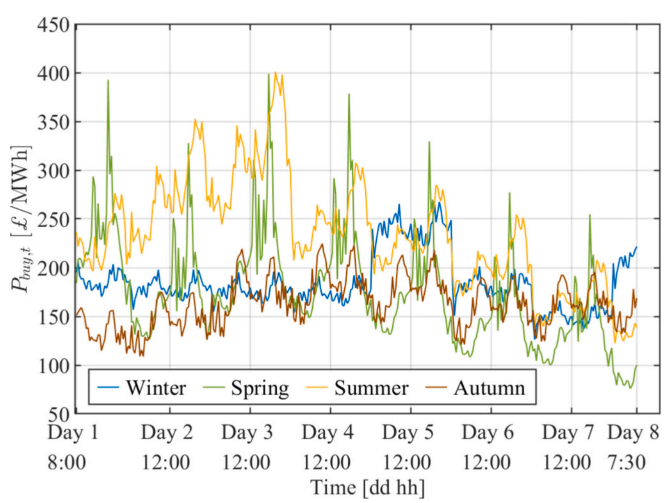

Fig. 4. Energy prices over a week for each season over 2022.

The inclusion of a $LiFePO_4$ stationary BS in the system is evaluated through the simulation of two configurations, assuming charge/discharge efficiency of 0.95, initial and final SOC (Cap_{IN} and Cap_{FIN}) at 90 % of maximum capacity Cap^{BS} and minimum/maximum SOC levels (S^{BS}_{min} and S^{BS}_{MAX}) of 20 % and 90 % of the capacity, respectively.

- BS 1: Capacity Cap^{BS} of 1 MWh, with maximum charging/discharging power (Pc^{BS}_{max} and Pd^{BS}_{max}) of 300 kW, with capital expenditure cost of 500 k£ (considering 500 £/kWh [26]) and space occupancy of 7 m^3 [27].
- BS 2: Capacity Cap^{BS} of 4 MWh, with maximum charging and discharging power of namely 500 kW and 1.2 MW, with capital expenditure cost of 2000 k£ (considering 500 £/kWh [26]) and a space occupancy of 42.77 m^3 [28].

Simulations are carried out, in uncontrolled and smart charging, for four weeks (one per season), two BS sizes, and four EV charging rates, and considering economic and technical targets. Therefore, the optimization problems described in Section 2.2 and 2.3 are run in 64 different combinations, respectively.

4. Results

In this section the main results are presented and discussed. For the purpose of brevity, the trends of power exchanges – see Eq. (4) – are shown only for winter week in various inspected combinations.

4.1. EV uncontrolled charging results

Concerning the operation with slow 7.4 kW charging rate, the power exchanges during winter week with technical objective (Eq. (2)) are shown in Fig. 5, where it can be seen that BS contribute to charge EVs when CO_2 minimization strategy is implemented, especially considering a 4 MWh capacity in BS 2 (Fig. 5b) where the battery storage is able to cover most of EV charging energy requirements during the week, deferring charging from the external electric grid in most suitable time intervals, that could be correspondent, especially during Summer, to the intervals with more renewable energy production. With the objective of energy cost minimization (Eq. (3)) the observed results are different: most of energy required for EV charging is purchased from the external grid in both BS 1 and BS 2 cases. However, highest purchased power peaks are detected for CO_2 minimization in all scenarios, but especially for 24 kW charging rate and BS 2 configuration (nearly 1.4 MW peak), since energy from utility grid (requested when CI_t is low) is used for charging both EVs and BS. The lowest peak (485 kW) is detected for 7.4 kW during winter week, as expected since it is the lowest charging rate considered.

The fast-charging rate of 150 kW leads to higher EV power peaks (1.7 MW peak in BS 2 configuration in spring and summer weeks considering f^{CO2}, and winter weeks considering f^{Cost}). Moreover, higher energy requirements for EV charge cannot be fully provided by BS, even considering BS 2 configuration. With technical objective, charging events of BS occur during night hours in winter season, according to low CI_t (Fig. 6), while in summer the BS is charged during the central hours of the day exploiting higher renewable contribution reducing carbon intensity. Considering economic target (Fig. 7), BS charging is always located in night hours, due to lower energy purchase costs. However, independently on configurations, battery storage is not fully exploited when economic target is optimized, since the problem solution tends to reduce energy costs related to its recharge.

4.2. EV smart charging results

Results related to EV smart charging procedure considering economic and environmental targets are reported for BS 1 and BS 2 in Figs. 8 and 9, respectively, referring to winter week. It can be noted that EV smart charging profiles are different with respect to the uncontrolled-charging cases. With BS 1, when optimizing f^{CO2}, charging processes of EVs are concentrated during periods of low carbon intensity, around 12:00, as in Fig. 8a, while minimizing f^{Cost} it is concentrated in the early afternoon when energy costs are low as well, see Fig. 8b. Configuration

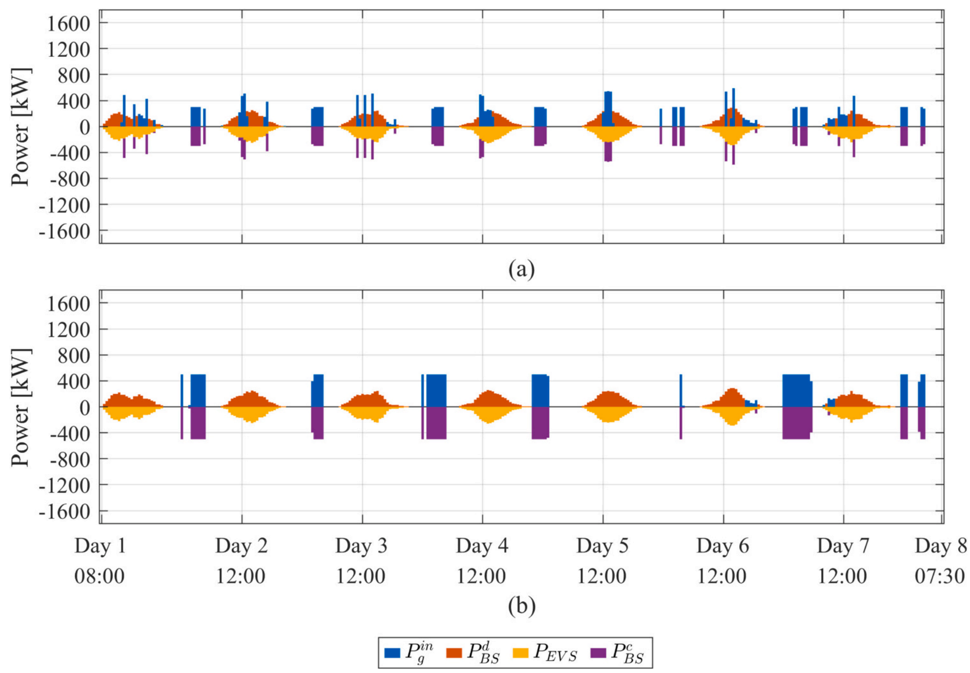

Fig. 5. Power exchanges during winter for EV uncontrolled charge at 7.4 kW charging rate, considering technical target with BS 1 (a) and BS 2 (b) configuration.

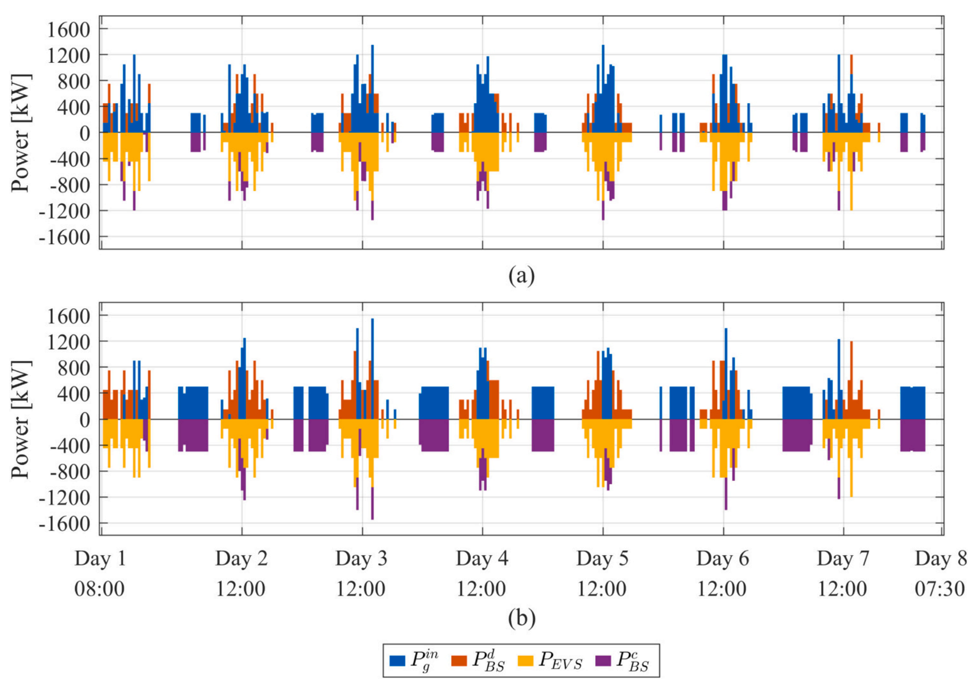

Fig. 6. Power exchanges during winter for EV uncontrolled charge at 150 kW charging rate, considering technical target with BS 1 (a) and BS 2 (b) configuration.

BS 2 shows significant exploitation for energy provision to the parking lot, especially with f^{CO2} minimization (Fig. 9a). BS charging processes occur during night hours of the day, for both technical and economic targets. Power peaks registered do not exceed the value of 1.8 MW in all scenarios, similarly to the peaks depicted in the case of uncontrolled charging, thus avoiding line overloading conditions with higher peak values.

4.3. Indicator evaluation and BS feasibility assessment

The evaluation of indicators formulated in Section 2.4 is carried out and reported in Fig. 10–11 and in Tables 2–3.

Significant CO_2 reductions with respect to the base case are achieved with the environmental target and considering BS 2 configuration for all charging rates (Fig. 10c), since the presence of stationary storage can provide energy to EVs when CI_t is high, whereas charging during low levels of carbon intensity. However, the attainment of environmental target implies an increase of operation costs, that is more evident with fast charging rates (Fig. 10a). As regards smart charging the advantage is more evident with 150 kW size, whereas 50 kW smart charging does not perform well in the BS 2 configuration.

When considering economic target, lower costs are evaluated in all

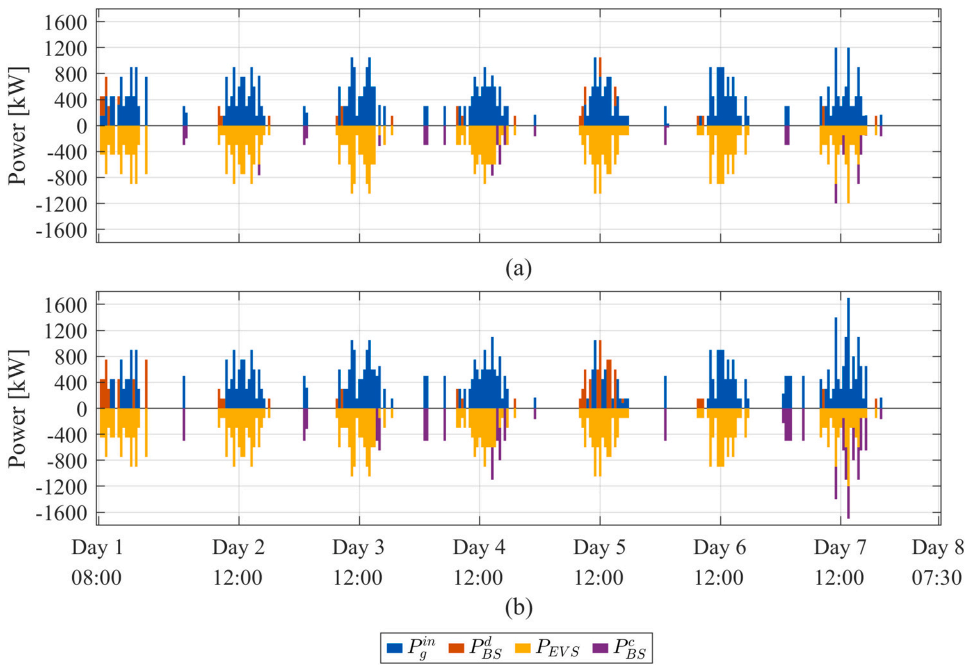

Fig. 7. Power exchanges during winter for EV uncontrolled charge at 150 kW charging rate, considering economic target with BS 1 (a) and BS 2 (b) configuration.

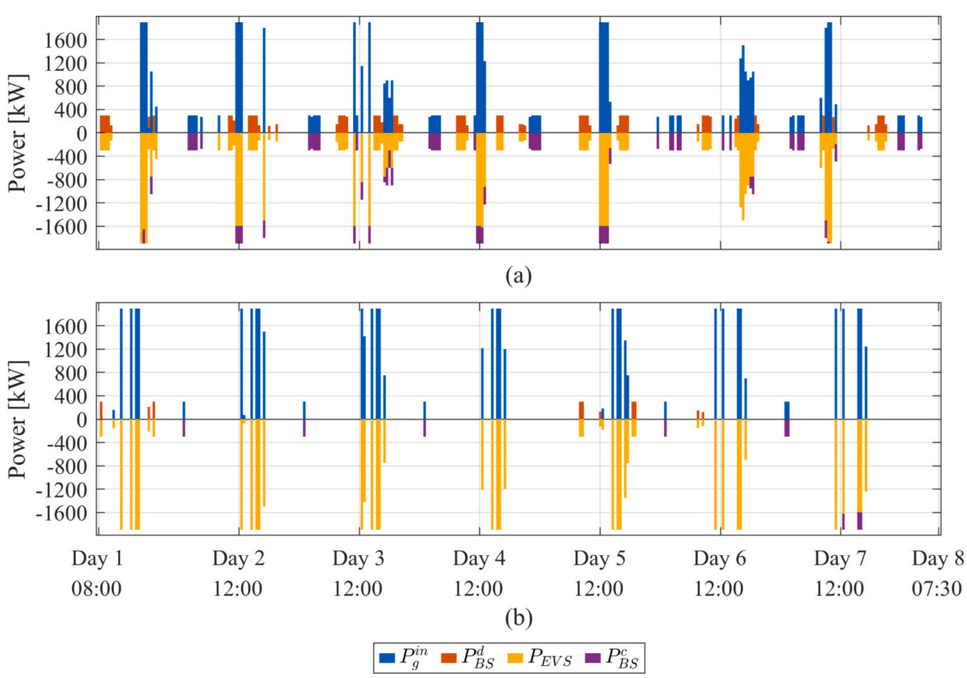

Fig. 8. Power exchanges during winter for EV smart charge at 150 kW charging rate, considering technical (a) and economic target (b) with BS 1 configuration.

scenarios considering BS 2 with respect to BS 1 for each charging rate. The adoption of charging rates higher than 24 kW with uncontrolled charging implies little improvement of the cost indicator. Moreover, the highest cost reductions with economic target are depicted considering EV smart charging with 150 kW rate (Fig. 10b), while CO_2 increase is detected especially for BS 2 and fast charging rate scenarios, except for winter season where CO_2 reduction is still detected for both sizes of storage and all charging rates (Fig. 10d), pointing out a combined optimal solution for both indicators.

Tables 2 and 3 collect indicators considering yearly operation for all scenarios. Considering the environmental target (Table 2), BS 2 guarantees both cost and CO_2 reductions over the year, except for a 50 kW EV smart charging (SC), whereas for BS 1 configuration and high charging rates (from 50 kW to 150 kW smart charging), an increase in operation costs is detected. It could be pointed out that EV smart charging procedure achieves higher CO_2 reduction already in BS 1 configuration (with respect to the uncontrolled charging), also avoiding the usage of bigger storage systems: as a matter of fact, 26,958 kg CO_2 reduction with 150 kW SC rate with BS 1 are quite close to 31,438 kg CO_2 reduction with 150 kW uncontrolled charging with BS 2 configuration. However, environmental target leads to higher number of equivalent discharging cycles, especially with 50 kW SC rate (483.4 cycles, more than one full cycle per day), whereas BS 2 configuration leads to lower discharge cycles over one year operation (44 % average

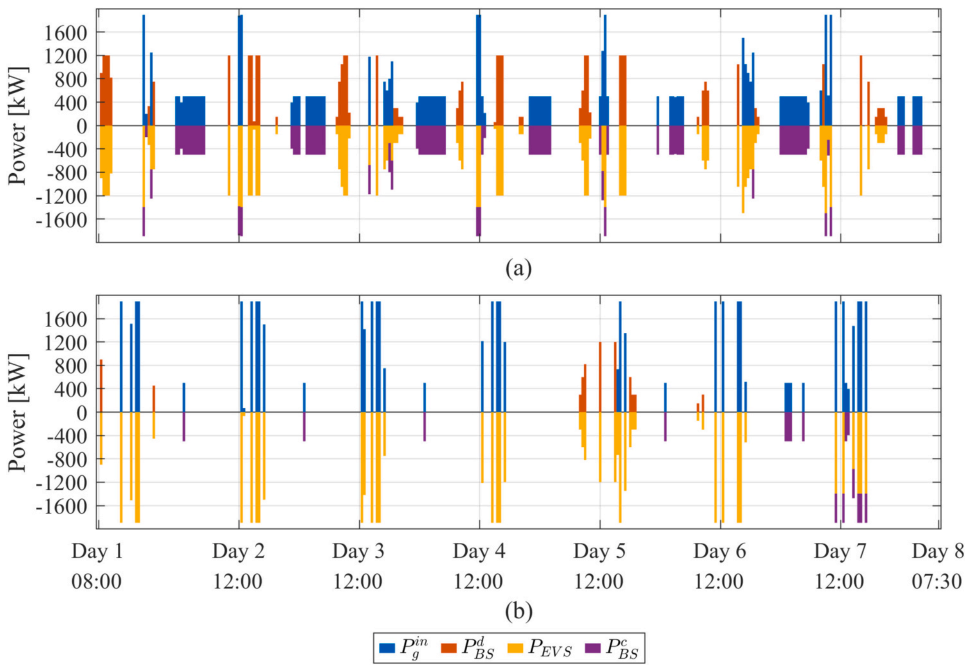

Fig. 9. Power exchanges during winter for EV smart charge at 150 kW charging rate, considering technical (a) and economic target (b) with BS 2 configuration.

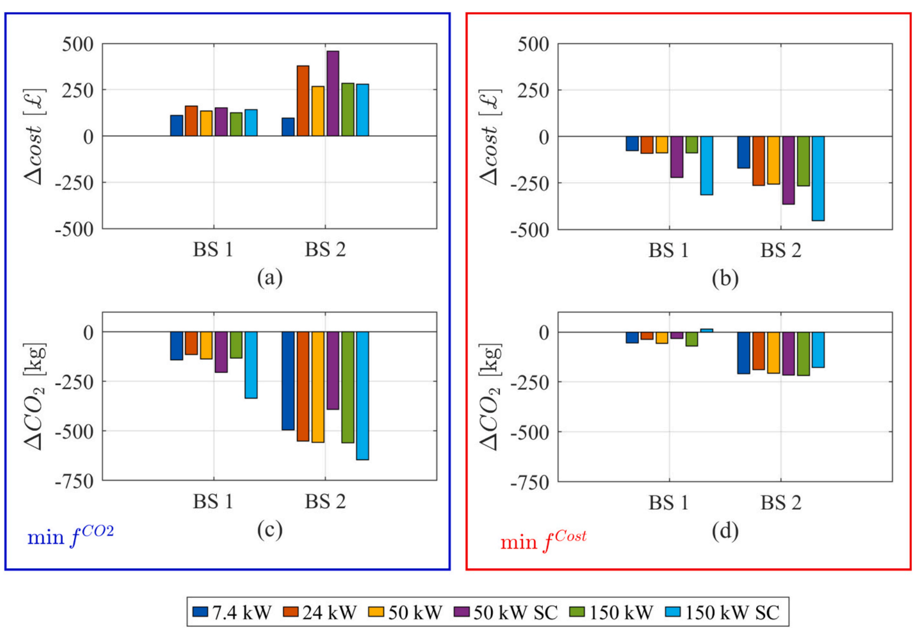

Fig. 10. Winter week. Total daily cost variation (a)-(b) and CO_2 variations (c)-(d) for both BS configurations and optimal strategies: CO2 minimization (blue box) and cost minimization (red box). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

reduction).

Regarding economical target, reported in Table 3, significant cost reduction is achieved when stationary storage supports EV charge, especially considering BS 2 configuration. As observed for environmental target, EV smart charging procedure achieves higher cost reduction already in BS 1 configuration, also avoiding the exploitation of bigger storage systems. For instance, 32,302 £ reduction considering 150 kW SC rate and BS 1 is close to the 36,511 £ reduction with BS 2 and EV uncontrolled charging. Generally, CO_2 increase is depicted in the economic optimal procedure. However, smart charging mode allows to achieve lower CO_2 increases with the respect to the uncontrolled charge in BS 2 configuration (for 50 kW and 150 kW). Furthermore, discharge cycle numbers are lower than in the case of environmental target, and smart charging mode for 50 kW and 150 kW leads to lower discharge cycles than uncontrolled charging at the same EV charging rate. Analogously to environmental target, BS 2 configuration allows even lower discharging cycles (less than one cycle per day), avoiding excessive battery storage usage and life reduction.

Fig. 11 shows the number of BS equivalent discharging cycles over a weekly operation for all the seasons and charging rates. It can be noted that, with CO_2 minimization target, higher cycles are reached in winter week, while in spring and autumn weeks higher cycles occur with economic target. Considering BS 1 configuration, cost minimization employs lower BS discharge cycles with respect to the economic target,

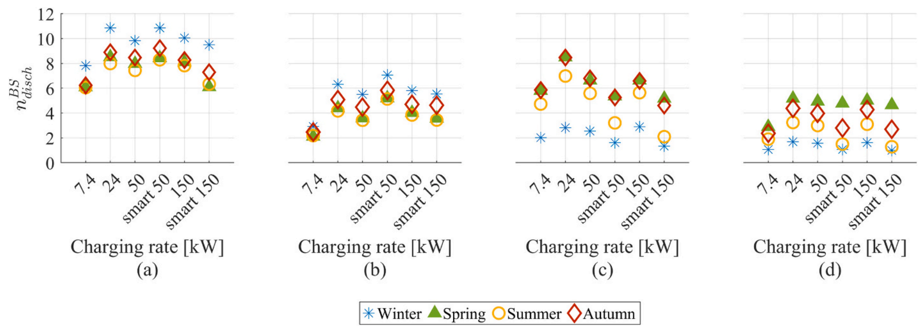

Fig. 11. BS equivalent weekly discharging cycles per seasons, evaluated in scenarios of emission minimization with BS 1 (a) and BS 2 (b) configuration and in scenarios of cost minimization with BS 1 (c) and BS 2 (d) configuration.

Table 2
Indicator evaluation over a year – CO_2 minimization.

	P_{MAX}^{EV}	7.4 kW	24 kW	50 kW	50 kW SC	150 kW	150 kW SC
$\Delta cost$ [£]	BS 1	−132	−1932	+906	+ 1174	+1128	+ 1474
	BS 2	−3790	−1770	−1228	+ 4363	−641	−779
ΔCO_2 [kg]	BS 1	−9317	−10,428	−9928	−16,951	−9628	−26,958
	BS 2	−25,186	−35,059	−30,849	−22,846	−31,438	−40,985
BS cycles	BS 1	344.3	476.5	337.9	483.4	450.0	384.1
	BS 2	127.4	262.4	223.0	305.3	241.7	225.6

Table 3
Indicator evaluation over a year – Cost minimization.

	P_{MAX}^{EV}	7.4 kW	24 kW	50 kW	50 kW SC	150 kW	150 kW SC
$\Delta cost$ [£]	BS 1	−12,082	−17,007	−14,558	−24,872	−14,414	−32,302
	BS 2	−22,494	−39,695	−33,783	−38,257	−36,511	−44,878
ΔCO_2 [kg]	BS 1	+2608	+2452	+2999	+ 2439	+2809	+ 4537
	BS 2	−718	+5652	+7446	+ 1873	+8135	+ 5280
BS cycles	BS 1	241.6	351.7	283.2	202.8	285.9	173.5
	BS 2	107.9	190.3	177.8	133.1	184.1	126.4

Table 4
Feasibility analysis – CO_2 minimization.

	P_{MAX}^{EV}	7.4 kW	24 kW	50 kW	50 kW SC	150 kW	150 kW SC
BS 1	Payback [y]	≫	≫	ND	ND	ND	ND
	Cycle operation time [y]	13.1	9.4	13.3	9.3	10.0	11.7
	Feasibility	NO	NO	NO	NO	NO	NO
BS 2	Payback [y]	≫	≫	≫	ND	≫	≫
	Cycle operation time [y]	35.3	17.1	20.2	14.7	18.6	19.9
	Feasibility	NO	NO	NO	NO	NO	NO

Legend:
≫: the payback is >50 years
ND: in the absence of economic profit, it is not possible to define the number of years for investment return

since lower exploitation is detected. Moreover, with cost minimization and BS 1, EV smart charging allows better exploitation of storage, with respect to the uncontrolled charging, with cycle numbers similar to the BS 2 ones. With cost minimization, BS 2 implies higher advantage on cycles in autumn and in summer.

The BS feasibility is assessed by comparing simplified payback with the operational cycle lifetime. The simplified payback is evaluated dividing the total investment cost by the annual cost reduction (see Δ *cost* in Tables 2 and 3), neglecting discount rate [34], whereas the operational cycle lifetime is the ratio of the total cycle BS life to the number of yearly operation cycles obtained from the optimal scheduling (see Tables 2 and 3). The feasibility is confirmed if the payback is lower than the cycle life of BS, meaning that the BS technical operation is longer than the investment return period.

To this purpose, the following assumptions are considered: unitary investment cost of 500 £/kWh and 4500 cycles at 80 % depth-of-discharge [26,33].

Results reported in Table 4 for CO_2 minimization put in evidence unfeasible economic return for BS in all configurations, due to yearly cost increase (payback is not defined) or limited cost reductions (payback is longer than 50 years), arising the need for additional remuneration schemes. Whereas, the total cycle lifetime is attained in a period ranging from 9.3 to 35.3 years with CO_2 minimization.

Cost minimization (see Table 5) leads to admissible payback values for BS 1 (best case P_{MAX}^{EV} =150 kW in SC), whereas for BS 2 payback shorter than 50 years is attained only with high power SC. The cycle lifetime is wider than in CO_2 minimization, ranging from 13 to 26 years for BS 1 and from 24 to 42 years for BS 2. The comparison yields positive

Table 5
Feasibility analysis – Cost minimization.

	P_{MAX}^{EV}	7.4 kW	24 kW	50 kW	50 kW SC	150 kW	150 kW SC
BS 1	Payback [y]	41.4	29.4	34.3	20.1	34.7	15.5
	Cycle operation time [y]	18.6	12.8	15.9	22.2	15.7	25.9
	Feasibility	NO	NO	NO	YES	NO	YES
	Payback [y]	≫	≫	≫	≫	≫	44.6
BS 2	Cycle operation time [y]	41.7	23.6	25.3	33.8	24.4	35.6
	Feasibility	NO	NO	NO	NO	NO	NO

Legend:
≫: the payback is >50 years

feasibility evaluation for BS 1 in the presence of SC, confirming that the optimal BS scheduling for cost minimization in combination with SC allows to reach suitable performances from several viewpoints.

The technology evolution, in terms of investment decrease and/or lifetime increase, could provide better outcomes, increasing the advantage of BS 2 with cost minimization.

4.4. Sensitivity on carbon intensity

With the aim of evaluating the effect of realistic *CI* evolution on the BS performances in the EV parking lot, a sensitivity analysis is performed. Based on the observed reduction of carbon intensity index in the last years, as reported in Fig. 1, where a 5 % annual average reduction can be pointed out thanks to decarbonization policies, the analysis is carried out on expectable carbon index level at 2025, assuming an average reduction of 15 % with respect to 2022 values (see Fig. 2) with further noise with normal distribution having zero mean and 1.5 % deviation.

Winter season and 50 kW EV power rate in uncontrolled charging and SC are analyzed with sensitivity assumptions, and relevant results in terms of weekly variations of CO_2 and cost with respect to the base case (without BS), along with BS weekly cycles, are reported in Table 6. For purpose of comparison, the respective results of the original analysis performed in the previous section, as already shown in Fig. 9, are reported in Table 6 as well. It can be noted that when minimizing carbon emissions, the sensitivity implies a significant decrease in CO_2 variation ΔCO_2 for both charging strategies and BS configurations, even exceeding the average 15 % reduction of the sensitivity assumptions, while $\Delta cost$ and cycles show a generally higher increase for BS 1, therefore lower *CI* values allow BS operation to take more advantage on emission reduction. When minimizing costs, cost variation and cycles keep the same of original analysis as expectable, whereas CO_2 reduction is lower than the original analysis, while keeping decrease except for BS 1, further underpinning the suitability of cost minimization with BS 2 for both indicators.

5. Conclusions

In this paper, the economic and environmental impacts of stationary energy storage system installation into EV charging infrastructures have been assessed by means of optimal procedures aimed at minimizing operational costs or carbon emissions. Scenarios of investigations have been chosen combining seasonal weekly operations with different EV charging rates (from slow to ultra-fast), and two BS configurations with different capacities. Moreover, the association of BS configuration with EV smart charging in fast and ultra-fast station has been inspected as well. EV usage uncertainties have been accounted by sampling probability distributions over a weekly time-horizon, based on data from a campus installation with EV charge in the central hours of the day when carbon intensity and energy costs are more critical.

Results have shown that BS operation has been significant to reduce EV carbon intensity and charging costs. In particular, when considering environmental target carbon emission reduction has been achieved, especially for high BS capacity levels and in scenarios of EV fast charging rates, and operational costs are higher in fast charging scenarios than in low charge ones, irrespective of the BS size and the season. Some significant cost reductions are possible considering economic target and high-capacity BS. However, this leads to an increase of carbon emissions, since variations are positive, with the only exception of winter week. The exploitation of EV smart charging has allowed a less intense exploitation of BS, ensuring longer life, and the attainment of objective values similar to higher BS sizes with uncontrolled charging. In addition, preliminary feasibility of BS has been assessed in terms of payback and cycle lifetime, pointing out that cost minimization allows to attain techno-economic feasibility in combination with SC. A sensitivity analysis on carbon index evolution has revealed that CO_2 minimization can take more advantage on environmental impact although yielding cost increase, therefore cost minimization with higher BS size has resulted as the combined suitable solution.

The procedure results flexible for analyzing different EV utilization frameworks and time distribution of charging events, in order to assess the inspected environmental, economic and technical aspects in several practical approaches where the BS management could be implemented. This study lays the basis for further investigations that could combine both economic and environmental target, along with the possibility to extend the procedure considering bidirectional EV exploitation for vehicle-to-grid applications and the effects on distribution network operation.

Table 6
Sensitivity evaluation of carbon index. Indicators over the Winter week.

	P_{MAX}^{EV}	CO_2 minimization				Cost minimization			
		Original		Sensitivity		Original		Sensitivity	
		50 kW	50 kW SC	50 kW	50 kW SC	50 kW	50 kW SC	50 kW	50 kW SC
$\Delta cost$ [£]	BS 1	+136	+152	+192	+248	−88	−221	−88	−221
	BS 2	+267	+458	+307	+427	−256	−365	−256	−365
ΔCO_2 [kg]	BS 1	−136	−205	−404	−671	−58	−32	−34	+29
	BS 2	−558	−392	−939	−749	−208	−215	−215	−176
BS cycles	BS 1	1.40	1.54	1.64	1.91	0.36	0.23	0.36	0.23
	BS 2	0.78	1.01	0.79	1.01	0.22	0.15	0.22	0.15

CRediT authorship contribution statement

Francesca Marasciuolo: Writing – original draft, Visualization, Software, Methodology, Investigation, Data curation. **Konstantinos Stamatis:** Writing – original draft, Validation, Resources, Investigation, Data curation, Conceptualization. **Giuseppe Forte:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis. **Maria Dicorato:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Liana M. Cipcigan:** Writing – review & editing, Validation, Supervision, Investigation, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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