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A Nature-Inspired Algorithm to Enable the E-Mobility Participation in the Ancillary Service Market

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Abstract: In the present paper, a tool is proposed to optimally schedule the charging requests of a fleet of carsharing Electric Vehicles (EVs) in an urban area, to enable their participation in the Ancillary Service Market. The centralized scheduler minimizes the imbalance of an EV fleet with respect to the power commitment declared in the Day-Ahead Market, providing also tertiary reserve and power balance control to the grid. The regulation is carried out by optimizing the initial charging time of each vehicle, according to a deadline set by the carsharing operator. To this purpose, a nature-inspired optimization is adopted, implementing innovative hybridizations of the Artificial Bee Colony algorithm. The e-mobility usage is simulated through a topology-aware stochastic model based on carsharing usage in Milan (Italy) and the Ancillary Services requests are modeled by real data from the Italian electricity market. The numerical simulations performed confirmed the effectiveness of the approach in identifying a suitable schedule for the charging requests of a large EV fleet (up to 3200 units), with acceptable computational effort. The benefits on the economic sustainability of the E-carsharing fleet given by the participation in the electricity market are also confirmed by an extensive sensitivity analysis.

Keywords: Electric Vehicle; aggregation; Ancillary Services; Artificial Bee Colony; scheduling

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1. Introduction

Environmental and technical factors are driving the transition toward a low-carbon energy scenario. Electricity and road transport, underpinned by environmental policies, are among the sectors facing the greatest transformations. As a consequence of the spreading of renewable energy sources, electric power systems are subject to an increasing variability and unpredictability of power injections and to a gradual replacement of conventional generators, historically in charge to supply Ancillary Services (ASs) to the grid, with non-dispatchable generation. To improve the power system's reliability, recently, some countries around the world envisaged the opening of their Ancillary Service Markets (ASMs) to new subjects, such as distributed energy resources, renewable power plants, controllable loads, energy storage systems and also e-mobility [1–3], with the goal of increasing the number of suppliers of the ASs needed for grid operation. In this scenario, electric networks can take advantage of synergies with the transport sector, given the deep changes the latter is facing to reduce local pollutants and increase the efficiency of urban space usage [4]. In this regard, the promotion of electric carsharing could strongly favor the shift toward a sustainable transport sector [5]. Moreover, Electric Vehicles (EVs) are a very promising flexibility resource, even though their charging requests need to be properly coordinated to avoid detrimental effects on the grid [6].

In the outlined framework, the present paper proposes a novel optimization procedure based on a hybridization of the Artificial Bee Colony algorithm aimed to schedule the charging requests of an EV carsharing fleet [7]. The initial charging time of each vehicle is coordinated by adopting a Centralized Control Architecture (CCA). To preserve batteries' lifespan, only the starting time of the charging is managed, while no preemption nor

Bidirectional Vehicle to Grid (V2G) are considered. The strategy enables the aggregated participation of e-mobility in the ASM, the supply of ASs to the grid (tertiary reserve and power balance control) and the reduction of power imbalances with respect to the market commitment defined in the Day-Ahead Market (DAM).

In the following, after a literature review in Section 2, the scenario of application and its modeling are depicted in Section 3. The description of the dynamic optimization problem studied is presented in Section 4. Section 5 introduces the enhancements proposed to adapt the Artificial Bee Colony to this large-scale optimization problem. Finally, Sections 6 and 7 present the case study and the numerical analyses carried out to assess the effectiveness of the proposed solution, while in Section 8, the techno-economic profitability of the CCA is analyzed in different case studies as well as performing a sensitivity analysis.

2. Related Works

In recent years, the exploitation of the flexibility of EVs to supply services to the power grid has shown an increasing interest in the scientific community. Regulation capabilities, scheduler architecture and optimization strategies to approach the scheduling problem are all topics widely debated today.

The capability of EVs to manage unidirectional or bidirectional power flows deeply affects the performance during the service provision to the power system. In unidirectional grid-to-vehicle (hereinafter V1G), EVs can be considered as a flexible load, since the power can flow only from the grid to the vehicle [8], whilst the bidirectional grid to vehicle (V2G) enables EVs both to absorb or inject electric power from/into the grid. As concluded in [9], the bidirectional configuration has higher performances than V1G, but battery degradation, charging infrastructure and control logics are still crucial problems [10].

From the point of view of the scheduler architecture, in the centralized control, the operator managing the regulation of EVs and offering their flexibility services on the market (in the following, also called Aggregator) collects all the information about the connected EVs, determines the optimal charging scheduling and coordinates the fleet's power exchanges with the grid to obtain the services settled on the market. The opposite of this approach is the decentralized control logic, where each EV is capable to determine its charging parameters. Most of the literature focuses on the centralized logic [11,12], since it allows usually reaching better coordination and provides a higher amount of services to the power system. However, the centralized approach could show severe scalability limits [13], since the EV scheduling is a dynamic optimization problem [14], therefore, the solution shall be available in a few seconds to start the EV charging and reiterate the procedure for the next time steps. It is not surprising that to face this issue, in most of the works adopting a centralized architecture, the size of EVs' fleet is very limited [15]. To address the scalability issues of centralized architectures, recently, Meta-Heuristic optimization techniques have met an increasing interest. Genetic Algorithms, Particle Swarm Optimization and Artificial Bee Colony (ABC) have been extensively applied to solve EV charging scheduling problems [16–18].

In this work, an innovative hybridization of the ABC algorithm is provided to dynamically schedule the charging requests of a large carsharing fleet, modeling stochastically the EVs' behavior and the ASM. Actually, ABC is suitable for challenging optimization problems since it systematically incorporates exploration and exploitation mechanisms [19]. Nevertheless, in literature, it is a common practice to overcome the disadvantages of ABC by hybridization techniques [20]: most of the works proposing changes to the ABC algorithm focus on the procedure for setting the initial populations [16] or on the local research process [21]. Starting from these considerations, the proposed approach (h-ABC) aims to efficiently solve the scheduling problem, by improving both the population initialization and the local research process compared to the standard ABC.

In this regard, in studies [7,22], the authors presented a preliminary architecture to enable the e-mobility participation in the market for the AS provision, focusing also on the undesirable effects caused to the distribution grid. However, neither the details of the implemented optimization algorithm nor the approach adopted to simulate EV usage have been reported. These aspects are described in detail in this work, also proving the effectiveness of the proposed method by comprehensive techno-economic analyses.

3. System Model

In the present paper, Ancillary Services (ASs) are supplied to the power system by scheduling the charging requests of a fleet of EVs managed by a carsharing operator, who is assumed to act also as Balancing Service Provider (BSP) [23], aggregating the regulation capacity of the fleet and offering it on the electricity market. To this purpose, the CCA optimizes the charging scheduling and communicates with the Charging Stations (CSs) enabling the recharge of car batteries. The purpose of the envisaged architecture is to enable a carsharing operator to participate in the Ancillary Service Market (ASM), thus increasing his profits, but also taking care to avoid detrimental effects on the quality of carsharing service provided to customers.

In this scenario, schematically represented in Figure 1, at day D-1, the carsharing operator (operating as an Aggregator) submits requests on the DAM to buy the energy requested the next day (D) to charge the EVs. As a result, a binding day-ahead schedule (hereinafter Power Baseline Schedule) is defined. During the relevant ASM sessions (for instance, according to the scenario in place in Italy, 4 h before the real-time), the Aggregator submits bids for up/downward reserve, which are selected by the Transmission System Operator (TSO) through a pay-as-bid approach and, if accepted, are notified to the Aggregator shortly before the real-time (i.e., 15 min in advance). The combination of DAM and ASM schedules is defined as Power Request Schedule, which represents a commitment toward the market that the Aggregator must respect; otherwise, it is penalized by imbalance fees. In the real-time, EVs are used by carsharing customers. Each user at the end of the rent could connect the car to one of the CSs over the city, or park it in a public spot without a CS. When the EV is plugged into a CS, the CCA optimizes the initial charging time to meet the market commitments, while preserving the final battery's State of Charge (SoC) according to a deadline defined by the carsharing operator.

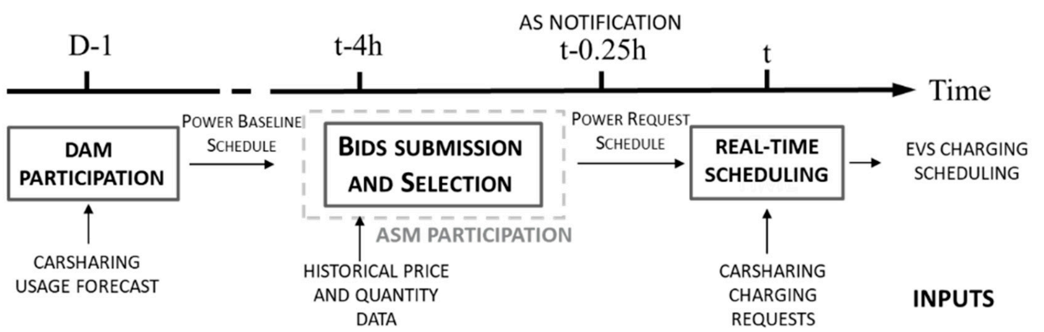

Figure 1. Scenario of application of the proposed scheduler.

To assess the performances of the proposed scheduler, in this work, suitable numerical tools have been developed to model the participation of the carsharing operator in the electricity markets (i.e., DAM and ASM) and to simulate cars' usage by users. An in-depth description of these tools is provided in the following subsections.

3.1. Electricity Market Participation

In the DAM, the Aggregator purchases the Power Baseline Schedule, which defines for every hour of the day D the amount of power $P_0(t)$ that should be absorbed to charge the EVs' fleet. An accurate forecast of energy requirements for the next day is essential since a mismatch between the power actually absorbed in real-time and the scheduled one implies an economic penalty (i.e., imbalance fee). The development of forecasting algorithms is out of the scope of this work; thus, a simplistic approach is adopted to estimate future power withdrawals from the grid, based on the persistence model [24]. In the session of the DAM on the day D-1, the Power Baseline Schedule is forecasted, assuming as a reference the profile of charging requests registered on the previous day (D-2). In particular, the Power Baseline Schedule (P_0) is defined, assuming all the charging requests at day D-2 are satisfied as soon as the EVs were connected to the CS:

$$P_0(t) = \sum_{i=1}^{N_{req}^{D-2}(t)} P_{chg}^{i,D-2}(t)\ \forall t \in \vec{\boldsymbol{T}}_{\boldsymbol{D}} \tag{1}$$

where $\vec{\boldsymbol{T}}_{\boldsymbol{D}}$ is the vector of all time steps in day D, while $N_{req}^{D-2}(t)$ and $P_{chg}^{i,D-2}(t)$ are, respectively, the number of EVs charging at time t and the power absorbed by the i-th EV.

Then, during the ASM sessions, the Aggregator submits bids for upward and downward reserve. In case of acceptance, AS requests (P_{AS}) are notified 15 min before the real-time as power variations with respect to the Power Baseline Schedule, as defined in Equation (2), where a load sign convention is adopted:

$$P_{req}(t) = P_0(t) + P_{AS}(t) \tag{2}$$

Hence, in the real-time, the CCA will adjust the power absorption of the EVs by scheduling their charging, in order to meet the corresponding Power Request Schedule (i.e., P_{req}).

3.2. Vehicle Model

The performance of the proposed CCA is evaluated by a carsharing usage model, realistically reproducing the common behavior of customers. A fleet composed by N_{fleet}^{tot} EVs is simulated, adopting a stochastic approach aware of the city topology, as in [25]. The approach, schematically presented in Algorithm 1, simulates each vehicle of the fleet, denoted by id ($\forall id \in \boldsymbol{N_{fleet}} = [1, N_{fleet}^{tot}]$), in an arbitrary number of days ($\forall d \in \boldsymbol{N_{day}} = \left[1, N_{days}^{tot}\right]$).

For each EV, firstly, the total number of daily rent requests ($n_{rent}^{id,d}$) is extracted from a normal integer distribution, with a mean value equal to 4. Then, the EV usage in each rent ($\forall r \in [1,\ n_{rent}^{id,d}]$) is defined by extracting the initial time ($t_{in}^{r,id}$), the duration of the rent ($\Delta t_{rent}^{r,id}$) and the distance covered ($\Delta d_{rent}^{r,id}$). All these data are obtained from statistics based on the actual carsharing usage in Italy, as described in Section 5. Incoherent rents are discarded (line 9 of Algorithm 1). At the end of the rent, the customer can choose to plug the EV into one of the CSs dispersed in the city or to park it in a public car park without a CS. To model this decision, a biased Boolean extraction is performed, assuming that one out of four customers will plug the EV into the CS, so that each EV is charged, on average, once per day. If the user opts to connect the EV to a CS, from the set of all CSs distributed in the city, denoted by $\boldsymbol{CS}$, only the ones far from the initial position (d^{cs-int}) less than the distance covered during the rent (i.e., $d^{cs-int} < \Delta d_{rent}^{r,id}$) are considered. Finally, one of these admissible CSs ($\boldsymbol{CS}_{adm}^{id}$) is randomly selected:

$$\boldsymbol{CS}_{adm}^{id} \in \left\{ \boldsymbol{CS} \cup (d^{csint} < \Delta d_{rent}^{r,id}) \right\} \tag{3}$$

This way, the motion of each EV in the fleet is simulated, tracking its path in the city and updating the relevant SoC:

$$SoC_{CS,con}^{r,id} = SoC_{int}^{r,id} - \Delta d_{rent}^{r,id} \bar{e}_{cons}^{id} / C_{brt}^{id} \tag{4}$$

where $SoC_{int}^{r,id}$ is the SoC of the EV before the rent, $\bar{e}_{cons}^{id}$ and C_{btr}^{id} are, respectively, the average energy consumption per kilometer and the battery capacity for the id-th EV. Once the EV is plugged in, the CS collects the relevant SoC ($SoC_{CS,con}^{r,id}$), charging power (P_{chg}^{id}) and charging deadline time ($D_{time}^{id,r}$). Coherently with the market dynamics rules, a quarter of hour resolution has been adopted (τ = 0.25 h) for simulating the car behavior: therefore, every 15 min, data of new EVs connected to the CSs are collected and sent to the CCA, which sets the initial charging time by solving the optimization process.

Algorithm 1. Fleet Modeling

1: **for** $d = 1$: N_{days}^{tot} **do**
2: **for** $id = 1$: N_{fleet}^{tot} **do**
3: $n^{id,d}{}_{rent} \leftarrow$ number of rents
4: **for** $r = 1$: $n_{rent}^{id,d}$ **do**
5: $t_{in}^{r,id} \leftarrow$ starting rent time
6: $\Delta t_{rent}^{r,id} \leftarrow$ rent duration
7: $\Delta d_{rent}^{r,id} \leftarrow$ distance covered
8: $v^{r,id} = \Delta d_{rent}^{r,id} / \Delta t_{rent}^{r,id} \leftarrow$ mean speed during rent
9: **if** $v^{r,id} > v_{MAX}$ **or** $t_{in}^{r+1,id} > D_{time}^{id,r}$
10: **go to** line 5
11: **end if**
12: $rnd_{CS} \leftarrow$ Boolean extraction (if TRUE, an EV is connected to a CS)
13: **if** $rnd_{CS} = \text{TRUE}$
14: select the arrival CS from the set of $\boldsymbol{CS}_{adm}^{id}$
15: **end if**
16: **end for**
17: **end for**
18: **end for**

4. Optimization Problem

The CCA deals with a dynamic scheduling optimization problem, because the EVs' charging requests and the relevant characteristics at the arrival are not known in advance. Therefore, at each time step ($\forall t \in \vec{\boldsymbol{t}}_{\boldsymbol{tot}} = \left[1, N_{days}^{tot} \cdot \frac{24}{\tau}\right]$), the CCA shall perform an optimization based on its best knowledge of the problem. In this work, to improve the capability of the CCA to find the optimal scheduling, a forecast is implemented to predict the charging requests in the upcoming time steps ($\vec{\boldsymbol{T}}_{\boldsymbol{f}}$) and to plan consequently the EVs' charging in the next future. The optimal solution found in the current time step (t_0) depends also on the forecasted future events (i.e., charging requests). Hence, during each optimization process, performed at the time t_0, a moving time window is considered, including the present time and the time steps in the next hour ($\vec{\boldsymbol{T}}_{\boldsymbol{f}}$):

$$\vec{\boldsymbol{t}}_{\boldsymbol{opt}} = [t_0, \vec{\boldsymbol{T}}_{\boldsymbol{f}}] = \{t_0, t_0 + \tau, \ldots, t_0 + 4\tau\} \tag{5}$$

The number of EVs expected connecting in upcoming time steps ($N_{exp}(t_f)\ \forall t_f \in \vec{\boldsymbol{T}}_{\boldsymbol{f}}$) and the relevant characteristics (SoC, rated power, etc.) are predicted based on historical data, while the same information for EVs already connected at the time t_0 is known. Finally, in each time step t ($\forall t \in \vec{\boldsymbol{t}}_{\boldsymbol{tot}}$), the instance $\boldsymbol{P}^{\boldsymbol{t}}$ is defined, including the set of all EVs (predicted or already connected) whose charging time should be optimized.

The optimization problem aims at minimizing, in each time step ($\forall t \in \vec{\boldsymbol{t}}_{\boldsymbol{opt}}$), the costs for the Aggregator:

$$F_{obj}(t) = Cost_{imb}(t) + Cost_{dln}(t) \tag{6}$$

The first term, $Cost_{imb}(t)$, models the imbalance fees applied to the Aggregator in the considered time window ($\vec{\boldsymbol{t}}_{\boldsymbol{opt}}$) in case of mismatches between the actual power absorbed from the network and the power schedule resulting from the participation in DAM and ASM sessions:

$$Cost_{imb}(t) = \sum_{t_{opt}}^{\forall t_{opt} \in \vec{t}_{opt}} c_{imb} \frac{a(t_{opt})}{\tau} \left| P_{abs}(t_{opt}) - P_{req}(t_{opt}) \right| \tag{7}$$

Imbalance costs are assumed proportional to the amount of energy imbalance, therefore, c_{imb} is a unitary imbalance fee (EUR/MWh) and the function $a(\vec{\boldsymbol{t}}_{\boldsymbol{opt}})$ is a hyper-parameter that weighs the foreseen imbalances with respect to the current one, having $a(t_o) = 1$ and $a(t_{opt}) < 1$ for $t_{opt} > t_0$ $\forall t_{opt} \in \vec{\boldsymbol{t}}_{\boldsymbol{opt}}$. Finally, P_{req} is the Power Request Schedule defined in Equation (2) and P_{abs} is the power absorbed by the CSs, calculated using:

$$P_{abs}(t_{opt}) = \sum_{ev=1}^{N_{chg}(t_{opt})} P_{chg}^{ev} \qquad \forall t_{opt} \in \vec{\boldsymbol{t}}_{\boldsymbol{opt}} \tag{8}$$

where P_{chg}^{ev} is the power absorbed by the *ev*-th vehicle and $N_{chg}(t_{opt})$ is the total number of EVs scheduled to charge in time step t_{opt}. For the sake of simplicity, a constant charging power is assumed (hypothesis usually true for the slow charging strategy commonly adopted for low-cost carsharing EVs).

The second term of the objective function (Equation (6)) is addressed to preserve the quality of the carsharing service. It assumes that the carsharing operator's loss of profit is proportional to the reduction of the EVs' range autonomy caused by an incomplete battery charging:

$$Cost_{dln}(t) = c_{dln} \sum_{ev}^{\forall ev \in \boldsymbol{P^t}} Err_{dln}^{ev} \tag{9}$$

with

$$\begin{cases} Err_{dln}^{ev} = 0 & if \;\; st^{ev} + \Delta t_{chg}^{ev} \le D_{time}^{ev} \\ Err_{dln}^{ev} = st^{ev} - t_{in}^{ev} & if \;\; st^{ev} + \Delta t_{chg}^{ev} > D_{time}^{ev} \end{cases} \tag{10}$$

$$\Delta t_{chg}^{ev} = \left(SoC_{Fin} - SoC_{CS,con}^{ev} \right) \cdot \frac{C_{btr}^{ev}}{P_{chg}^{ev}} \tag{11}$$

where c_{dln} is the cost associated with a unitary (15 min) postponement of the charging, which results in a reduction of the SoC at the CS disconnection. Err_{dln}^{ev} is a parameter different from zero if the proposed initial charging time (st^{ev}) does not allow reaching the maximum SoC expected before the disconnection in the time step D_{time}^{ev}. The charging duration (Δt_{chg}^{ev}) is calculated with Equation (11), where C_{btr}^{ev} is the battery capacity and SoC_{Fin} and $SoC_{CS,con}^{ev}$ are, respectively, the SoC to achieve during the charging (i.e., assumed equal to 1) and the battery SoC when the vehicle is plugged into the CS, obtained by means of the carsharing model described in Section 3.

It is worth noting that the adoption of the moving time windows technique in the optimization process allows obtaining a solution (optimal EVs' charging schedule) which is a function of the future events (i.e., power variations due to AS requests in the imminent future).

The optimization problem, formulated as follows, should be solved in all time steps ($\forall t \in \vec{\boldsymbol{t}}_{\boldsymbol{tot}}$), updating at each step the EVs' data and the Power Request Schedule:

$$\underset{st^{ev}}{Min} \quad F_{obj}(t) \;\; \forall t \in \vec{\boldsymbol{t}}_{\boldsymbol{tot}} \quad \forall ev \in \boldsymbol{P^t} \tag{12}$$

subject to

$$t_{in}^{ev} \le st^{ev} \le D_{time}^{ev} \;\; \forall ev \in \boldsymbol{P^t} \tag{13}$$

$$P_{abs}(t_{opt}) = \sum_{ev=1}^{N_{chg}(t_{opt})} Err_{dln}^{ev}\ \forall t_{opt} \in \vec{\boldsymbol{t}}_{\boldsymbol{opt}} \quad (14)$$

$$P_{req}(t_0) = P_0(t_o) + P_{AS}(t_0) \quad (15)$$

$$P_{req}\left(t_f\right) = P_0\left(t_f\right)\ \forall t_f \in \vec{\boldsymbol{T}}_{\boldsymbol{f}} \quad (16)$$

$$0 < SoC_{Fin} \leq 1\ \forall ev \in \boldsymbol{P^t} \quad (17)$$

The objective function in Equation (12) should be minimized by optimizing the initial charging time (st^{ev}) of each EV in the considered instance $\left(\forall ev \in \boldsymbol{P^t}\right)$. Constraint in Equation (13) specifies the lower and upper bounds of the charging time for each EV, while constraint in Equation (14) defines the power absorbed by the Aggregator during the considered time window ($\vec{\boldsymbol{t}}_{\boldsymbol{opt}}$). Equations (15) and (16) determine, respectively, the Power Request Schedule in the current time step (t_0) and in the upcoming ones ($\vec{\boldsymbol{T}}_{\boldsymbol{f}}$). Finally, the constraint in Equation (17) models the physical limits of the EV's battery.

To solve the described optimization problem, in this paper, a hybridization of the ABC algorithm (h-ABC), is proposed.

5. The h-ABC Approach

The Artificial Bee Colony is a population-based Meta-Heuristic algorithm inspired by the foraging behavior of bees. It is a swarm-based optimization method, so the N_{FS} different solutions are simultaneously evaluated and improved, thanks to the iteration of three phases: employed, onlooker and scout ones [26]. ABC is based on a random scattering of the initial solutions and then the reiteration of a searching process, which is designed without considering the nature of the problem (pseudo-random research). This can negatively affect the computational effort to find the optimal solution, a key parameter in large-scale dynamic problems. Therefore, in this work, the ABC is improved by deeply revising two phases: (1) the definition of the initial solutions; (2) the research process during the employed bee phase.

5.1. Initial Population

The standard ABC algorithm initializes each candidate solution ($\forall p \in [1; N_{FS}]$) by randomly arranging them in the allowed domain (i.e., meeting the constraints).

In the h-ABC approach, two phases are implemented to define the initial solutions: firstly, the charging order of EVs is defined in each initial solution by dispatching rules, and then, a tournament selection mechanism is applied. Indeed, Meta-Heuristic algorithms, such as ABC, have been found to be more effective if the initial population is selected by sub-optimal scheduling rules (i.e., first-in first-served approach, etc.) [27]. The dispatching rules adopted are:

1. Due to Time (DtT) in which the charge priority is computed considering the difference between D_{time}^{ev} and Δt_{chg}^{ev}.
2. Arrival Time (AT) in which the EV charge priority is determined considering a first-in first-served approach.

The charging order vector for each initial solution ($v_p\ \forall p$) is defined by the following procedure: firstly, the EVs not yet added to the initial solution are sorted using a dispatching rule (i.e., DtT or AT), then a tournament selection is applied to select h individuals from the sorted vector, adding to the charging order v_p the best of these h individuals. One-half of the initial solutions are initialized by each dispatching rule and, to further increase the population diversification, the tournament size is decreased after the definition of each charging order.

5.2. Employed Bee

After the initial population definition, both in ABC and h-ABC, an iterative process starts. The first step (employed bee) performs local research around each solution p ($\forall p \in [1; N_{FS}]$). In the ABC, the local research process initializes a new candidate solution ($\vec{e}^{\,p}$) in the neighbor of the current one ($\vec{st}^{\,p}$), adopting Equation (18) [28]:

$$e^{ev,p} = st^{ev,p} + \Phi \cdot \left(st^{ev,p} - st^{ev,k}\right) \tag{18}$$

where ev and k are randomly chosen indexes with $ev \in \boldsymbol{P^t}$ and $k \in [1; N_{FS}]$ and $k \neq p$. Φ is a random number between -1 and +1, extracted from a uniform distribution. Then, between the new candidate solution and the old one, a greedy selection process is carried out and, in case of objective function's improvement, the old solution is replaced with the new one.

The research process adopted in h-ABC relies on a more advanced heuristic research. The approach (Algorithm 2) can be subdivided into two phases. In the first phase, each term of Equation (7) is inspected and the one with the highest contribution is selected as the critical one (t_{crit}). Then, in the second phase, the algorithm evaluates if, in t_{crit}, a surplus or a lack of power absorbed with respect to the requested one occurs. If the power absorbed exceeds the requested one ($P_{abs}(t_{crit}) > P_{req}(t_{crit})$), the EV having the minimum tardiness, defined in Equation (19), among all the ones scheduled to charge in t_{crit}, is selected. Then, its recharge is postponed in a time step t_{post}, with $t_{post} > t_{crit}$, having a non-negative imbalance. In absence of a time step t_{post} satisfying both $t_{post} > t_{crit}$ and the imbalance sign constraint, the selected EV is simply postponed in t_{crit} + 1. Indeed, $a(\vec{\boldsymbol{T}}_f)$ is a decreasing function, therefore, by shifting forward in the future the imbalance, the objective function in the current time step is reduced. This approach is justified considering that in upcoming time steps, the new connected EVs and possible changes in the Power Request Schedule could eliminate foreseen imbalances. In the opposite case, if $P_{abs}(t_{crit}) < P_{req}(t_{crit})$, the tardiness of the EVs whose charging is scheduled in $t_{opt} > t_{crit}\ \forall t_{opt} \in \vec{\boldsymbol{t}}_{opt}$ is evaluated; the EV with the maximum tardiness is selected and its charging time is set to t_{crit}. Obviously, during the EV selection, the constraints defined in Equation (17) shall be respected.

$$tard_{ev} = Max\left(0; st^{ev} + \Delta t^{ev}_{chg} - D^{ev}_{time}\right) \forall ev \in \boldsymbol{P^t} \tag{19}$$

Algorithm 2. Heuristic research

for $p = 1: N_{FS}$ **do**
  $t_{crit} \leftarrow$ time step with the highest $Cost^p_{imb}$
  if $P^p_{abs}(t_{crit}) > P_{req}(t_{crit})$
    find ev such that $st^{ev,p} = t_{crit}$ and select the one with $Max(tard_{ev})$
    $t_{crit} \leftarrow P^p_{abs}(t_{post}) < P_{req}(t_{post})$ and $t_{post} > t_{crit}$
    $st^{ev,p} = t_{post}$
  else
    find ev such that $st^{ev,p} = t_{crit}$ and select the one with $Min(tard_{ev})$, so $st^{ev,p} = t_{crit}$
  end if
end for

5.3. Onlooker Bee

The onlooker bee phase is designed to further explore promising regions of the domain by the sharing of information between different solutions. This phase is implemented in the same way in ABC and h-ABC. Firstly, a fitness function is calculated for each solution ($fit_p\ \forall p$) as the inverse of the corresponding objective function. Then, the probability distribution function shown in Equation (20) is used to perform a roulette wheel selection, which associates each onlooker bee ($\forall o \in [1; N_{FS}]$) to different solutions ($\forall p \in [1; N_{FS}]$):

$$Prb_p = \frac{fit_p}{\sum_p fit_p} \quad \forall p \in [1, N_{FS}] \tag{20}$$

To initialize a new solution ($\overrightarrow{v}^{o}_{chg}$) around the corresponding solution p extracted in the roulette wheel process, Equation (18) is once again applied. Finally, the new solution and the old one are compared through a greedy selection process, keeping the best one. To better control the exploitation of the domain, the parameter Lim_p is introduced: it is initialized to zero for all the solutions and each time an onlooker bee does not improve the current solution (p), Lim_p is increased by one.

5.4. Scout Bee

The last phase in both ABC and h-ABC is the scout bee: it is activated when the parameter Lim_p reaches a fixed upper bound (Lim_{MAX}). If this occurs, the algorithm considers the area of the domain around the solution p fully exploited, discards it and the solution is replaced with a new one, randomly generated.

5.5. Convergence Criteria

In the ABC, the three phases are iteratively repeated until a maximum number of iterations (N_{main}); then, the solution with the lowest value of the objective function is selected as the optimal one. In h-ABC, a more advanced stopping criterion is introduced in addition to the one just described: after a fixed number of iterations ($N_{cyl,min}$), the objective function trend is analyzed. If the populations do not improve their objective function for a given number of iterations (empirically set to 5 in the numerical analyses that follow), the iterative process stops, avoiding the unnecessary computation of cycles not improving the solutions.

When the convergence criterion is reached, the EVs' charging schedule with the lowest objective function value is adopted: EVs with $st^{ev} = t_0$ will immediately start the charging, whilst the charging of the remaining ones ($st^{ev} > t_0$) will be rescheduled in the optimization performed in the next time steps by considering possible updates to the connected EVs and to the Power Request Schedule.

6. Case Study

In this work, the participation of a carsharing operator, acting as an Aggregator by selling the EVs' flexibility on the Ancillary Service Market, has been reproduced through the historical data collected on the Italian ASM in 2018. To this purpose, all the bids submitted to the ASM by three conventional Power Units for balancing and tertiary reserve have been considered in terms of offered and awarded power and prices. Data have been processed to remove periods without offers (maintenance stops, etc.) and scaled to match the EVs aggregate's rated power. Finally, to generalize the market requests delivered to the Aggregator, the pool of AS requests has been extended by sampling the historical market data in groups of 7 consecutive days and randomly combining them together.

For the evaluation of the economic flows deriving from the market participation, the following scheme is adopted. In the case of imbalances between the Power Request Schedule and actual absorbed power (P_{abs}), an imbalance penalty is applied to the Aggregator. If $P_{abs} > P_{req}$, the power surplus (not declared in the DAM) is paid by the Aggregator $p_{DAM} + c_{imb}$, where p_{DAM} is the price cleared in the DAM and c_{imb} is the imbalance fee. Vice versa, if $P_{abs} < P_{req}$, the power not absorbed by EVs is refunded to the Aggregator at price $p_{DAM} - c_{imb}$. Therefore, in each time step in which the power schedule (P_{req}) is not fully respected, the Aggregator is subject to an imbalance cost (C_{imb}) calculated as $C_{imb} = c_{imb}\left|P_{abs} - P_{req}\right|$. For the sake of simplicity, p_{DAM} and c_{imb} are taken constant and respectively equal to 50 EUR/MWh and 80% of p_{DAM} (c_{imb} = 40 EUR/MWh).

Concerning the AS provision, in the case of upward regulation (i.e., reduction of the power absorbed), the Aggregator is paid $p_{DAM} + p_{AS}$, to refund the energy purchased in the DAM not absorbed and to remunerate the AS supplied (p_{AS}). For downward regulations (i.e., load increase), the Aggregator pays $p_{DAM} - p_{AS}$, the difference between the cost related to the energy absorbed but not declared in the DAM (p_{DAM}) and the AS remuneration (p_{AS}). Hence, the net revenues for the Aggregator from the AS provision (R_{AS}) are calculated as a product between energy awarded in the ASM and its unitary reward (p_{AS}). Assuming the economic neutrality of the TSO, the AS remuneration (p_{AS}) has been set equal to c_{imb}, since, as general principle, the imbalance fees applied to users should reflect the costs covered by the system to purchase on the market the ASs required to correct the mismatches between expected and actual power exchanges [29].

The usage of each EV in the carsharing fleet is simulated considering the stochastic model described in Section 3. The statistical parameters adopted are based on the real data of carsharing usage in Milan collected during the weekdays of 2018, shown in Figure 2 and Table 1. EVs involved in the fleet are assumed to having P^{id}_{chg}, C^{id}_{btr} and $\bar{e}^{id}_{cons}$ respectively equal to 7 kW, 40 kWh and 0.2 kWh/km [25]. These hypotheses are coherent with the scenario under analysis: a carsharing fleet composed, for technical and economic reasons, by low-cost EVs having similar characteristics.

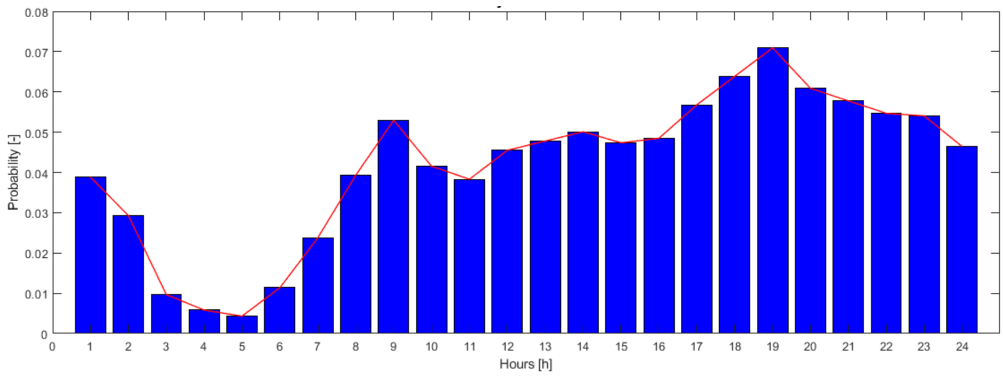

Figure 2. Hourly probability of carsharing rent requests.

Table 1. Statistics adopted to simulate the carsharing usage.

Variable Modeled	Distribution and Parameters Adopted
Rent duration (Δt_{rent}) (min)	Gamma distribution $k = 2.98$ $\theta = 5.51$
Rent turnover (n_{rent}) (rents/day)	Integer normal distribution $\mu = 4$ $\sigma = 1$
Distance covered (Δd_{ev}) (km)	Log-logistic $\mu = 1.49$ $\theta = 0.43$

The profitability of the CCA is evaluated by a holistic approach, taking into account also the possible detrimental effects on the carsharing service's quality. According to data collected about the real carsharing usage in Milan, the distance covered between two charging stops is, in 99% of cases, lower than 100 km (rng_{min}). To ensure this autonomy, considering the technical characteristics previously presented, the EVs shall leave the CSs with a SoC ≥ 0.5. Assuming that the carsharing operator revenues are proportional to the distance traveled by each EV, it is possible to conclude that each time an EV with an autonomy (rng_v) lower than the minimum autonomy (rng_{min}) is rented, the Aggregator has a loss of profit $c_{lost}(rng_{min} - rng_v)$, where c_{lost} is the operator's net profit per kilometer covered by the customer. This fee is estimated by subtracting from the carsharing tariff c_{rent}, set equal to 0.28 EUR/min [30], the operator's costs (i.e., electric bill, taxes, maintenance costs, etc.). As gross estimate, c_{lost} is set equal to $0.3 \cdot c_{rent}$. A similar approach has been applied to define c_{dln} in Equation (9). In Section 8, a sensitivity analysis on c_{rent} and c_{imb} is presented to evaluate the impact of these parameters on the Aggregator's profits.

7. ABC/h-ABC Comparison

The ABC and h-ABC algorithms require a preliminary tuning to set the value of the optimization's parameters (i.e., N_{FS}, N_{main}, Lim_{MAX}), considering the trade-off between quality of the solution reached and time required to find it [27]. To this purpose, an upper limit of 60 s has been adopted for the computational time, since in real-life when an EV is connected to a CS, its charging can start only after that the optimal schedule has been identified by the CCA. The optimal parameters for the two algorithms, obtained in output to the tuning process, are shown in Table 2.

Table 2. Optimal hyper-parameters found for the two algorithms.

Algorithm Parameter	Optimal Value Found	
	ABC	h-ABC
N° main algorithm iteration (N_{main})	200	260
N° candidate solution (N_{FS})	30	22
Scout bee limit (Lim_{max})	150	100

To test the effectiveness of the hybridizations proposed in the h-ABC, a comparison with the standard ABC approach is performed. To this purpose, the participation in the ASM of a carsharing fleet, composed of 1600 EVs, is simulated over a 3-month period. During the test, the performance of the two algorithms in finding the optimum is evaluated on almost 9000 optimization runs, using the parameters shown previously. For the comparison, in each time step, the value assumed by the objective function Equation (6) has been normalized with respect to the value obtained in the same time step at the end of the optimization process by the best performing algorithm (ABC or h-ABC). Finally, the average value of the objective function evaluated on all the populations for the two algorithms in each time interval has been calculated.

According to Figure 3, despite the lower number of initial populations (N_{FS}), the h-ABC algorithm is capable to initialize solutions having objective function, on average, 98% lower than ABC method, thanks to the dispatching rules and the tournament selection procedure implemented. Additionally, regarding the value reached by the objective function for the optimal solution, the h-ABC outperforms the standard ABC, since the former is able to approach the optimal value much faster than the latter and, on average, the best value found by h-ABC is almost 50 times lower than with ABC. The effectiveness of h-ABC approach is also proved through a statistical analysis of the minimum value of the objective function reached in each instance by the two algorithms. Firstly, a Shapiro–Wilk test is performed to confirm the non-normality of the data, then, a paired Wilcoxon signed rank test is applied to evaluate whether the proposed approach performs better than the standard ABC. Adopting a Wilcoxon test with a confidence level of 1%, the resulting p-value is lower than 1×10^{-30}. Hence, it is possible to conclude, with high statistical confidence, that the proposed methodology outperforms the standard ABC.

In order to better appreciate the complexity of the proposed charging scheduling and the number of variables involved during each optimization process, an example of charging profile optimized by h-ABC is shown in Figure 4. Each rectangle represents an EV in charge: therefore, the power absorbed in each time step is the total height of the rectangles, while the Power Request Schedule is the black dotted line. As one can observe, the power requested is almost always overlapped with the absorbed one, therefore, the imbalances experienced are nearly negligible. The black rectangles represent EVs not reaching the maximum SoC within the deadline set by the carsharing operator. It is important to point out that, even if these EVs are not fully charged, the SoC achieved is usually enough to cover the distance required by carsharing users. A further investigation on the performances obtainable by the h-ABC is provided in the next section.

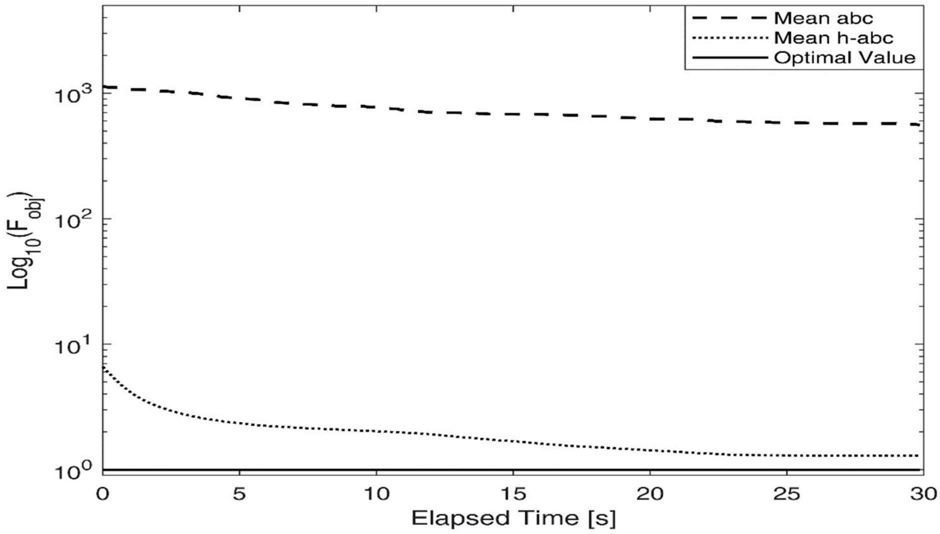

Figure 3. Mean value of the objective function in ABC and h-ABC as a function of computational time.

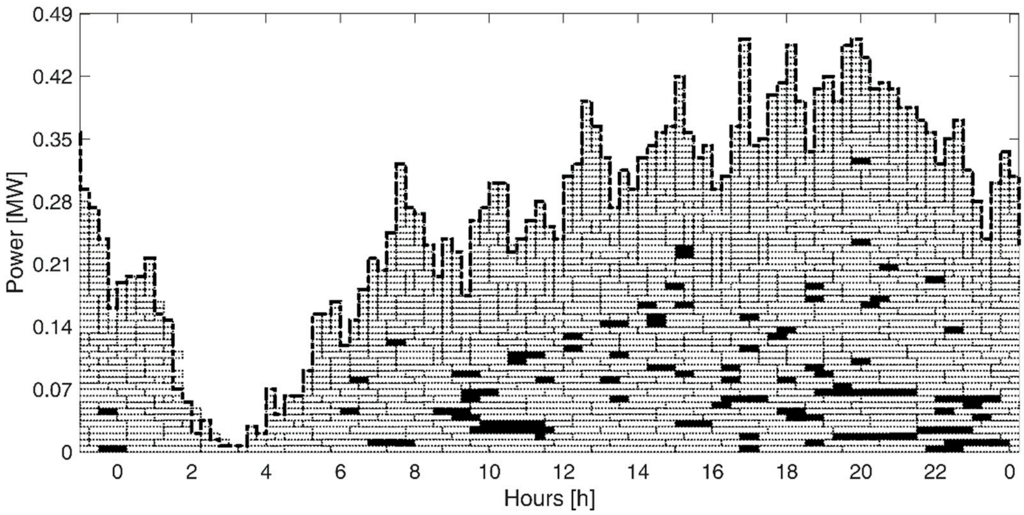

Figure 4. Charging profile obtained in the 3rd day simulated by h-ABC.

8. Numerical Results

Once having proved the better performance of h-ABC approach compared to ABC, in this section, the techno-economic feasibility of the proposed scheduler is evaluated by simulating the behavior of a carsharing fleet with 1600 EVs over a 30-day period. Simulations are repeated 18 times, randomly changing the EVs' usage and AS requests, therefore obtaining a total of 540 simulated days and 51.840 optimization runs. The scenario with the CCA (in the following, *Sch* scenario) is compared to the scenario currently in place for the e-mobility (*No Sch* scenario), in which EVs are charged as soon as they reach the CS, without neither charging scheduling nor provision of ASs to the grid. To make the *No Sch* and *Sch* scenarios fully comparable, the same EVs' behavior is applied in both cases. Thus, the average energy absorbed is the same and equal to 7.94 MWh. The comparison is performed according to three aspects: (i) imbalances; (ii) AS supplied; (iii) carsharing service quality.

Concerning the first quantity, Figure 5 presents the distribution of the normalized daily imbalance, $Imb_{\%}(D)$, defined in the two scenarios using Equation (21):

$$Imb_{\%}(D) = \sum_{t}^{T^D} \frac{|P_{abs}(t) - P_{req}(t)|}{E_{abs}(D)} \tag{21}$$

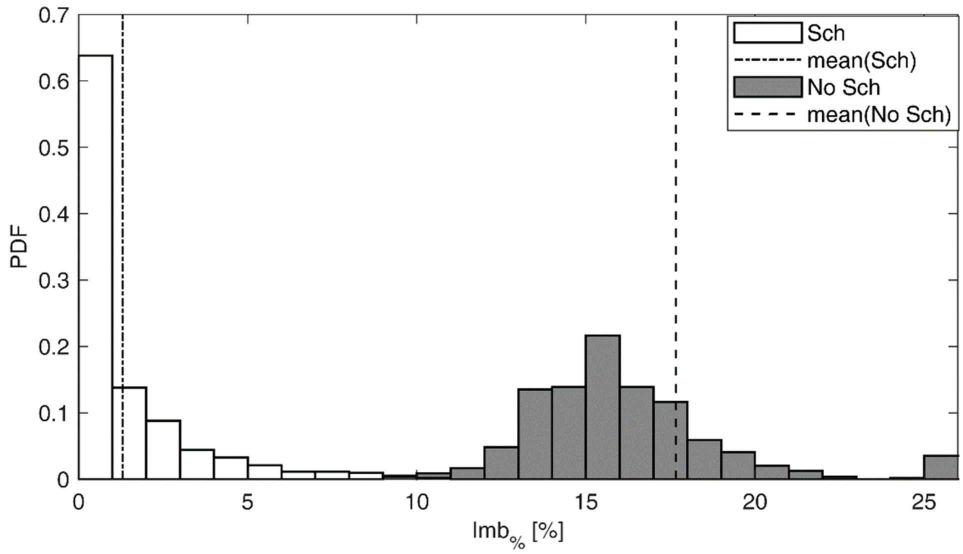

Figure 5. Comparison of the imbalance PDF in the two scenarios.

The numerator of Equation (21) represents the total imbalance in the day D, while the denominator, $E_{abs}(D)$, is the total daily energy absorbed by the aggregate. As shown in Figure 5, the CCA allows drastically cutting down the imbalance, obtaining $Imb_{\%}(D) < 1\%$ in the 64% of simulated days and reducing the average imbalance from 17.3 to 1.3% (see dotted vertical lines in Figure 5). Figure 6 shows the comparison between the Power Schedule and the powers absorbed in the *Sch* and *No Sch* scenarios. The data refer to 2 days in August. Despite the uncertainties that characterize the EV's charging requests, the proposed architecture is capable of avoiding power imbalances, exchanging with the grid the power declared in the DAM (Power Request Schedule).

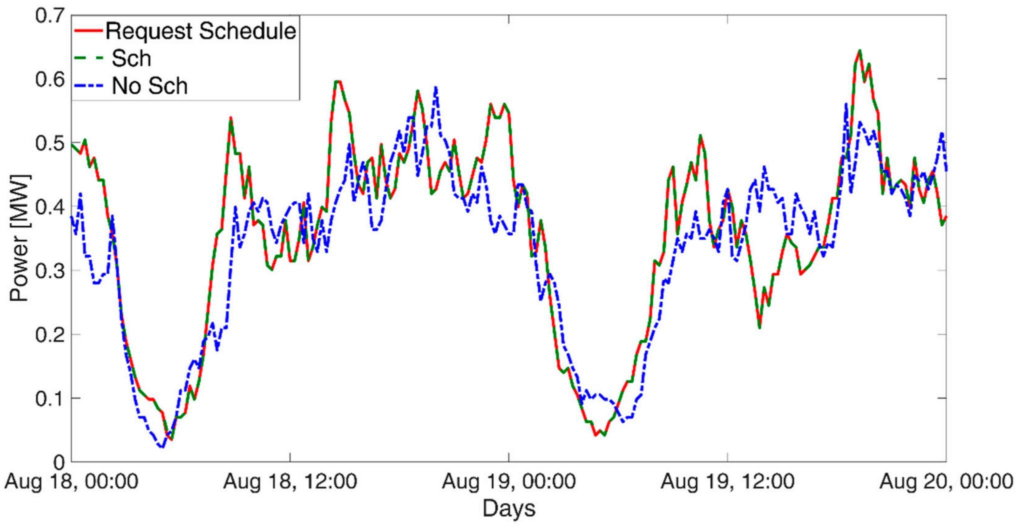

Figure 6. Comparison between the power schedule and the power absorbed, in *Sch* and *No Sch* scenarios.

The statistical distributions of simulated AS requests are presented in Figures 7 and 8. On average, ASs are requested to the Aggregator in 40.6% of time steps and in 79.2% of cases these are downward requests. Figure 7 reports the PDF of the ratio between the requested power variation due to the AS and the average power absorbed ($\overline{P}_{abs}$) by the aggregate (0.33 MW), while Figure 8 shows the PDF of the duration of dispatching orders (in hours). The ASs activated by the TSO during 3 days in August are depicted in Figure 9. It is possible to notice long upward activations (up to 8 consecutive hours) and large power variations (up to 26% of $\overline{P}_{abs}$).

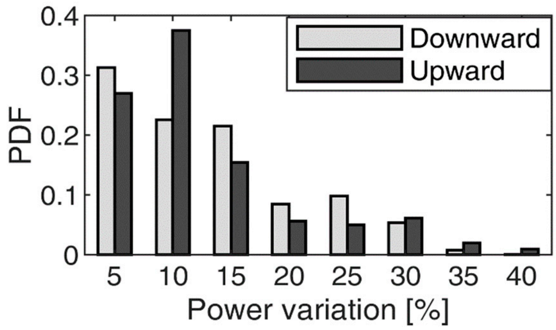

Figure 7. PDF of the power awarded for AS request with respect to $\overline{P}_{abs}$.

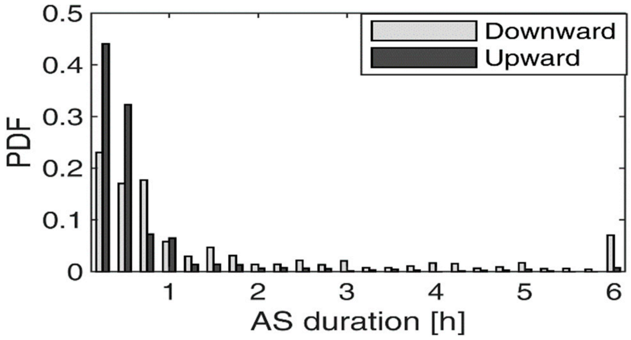

Figure 8. PDF of the AS duration requests in hours.

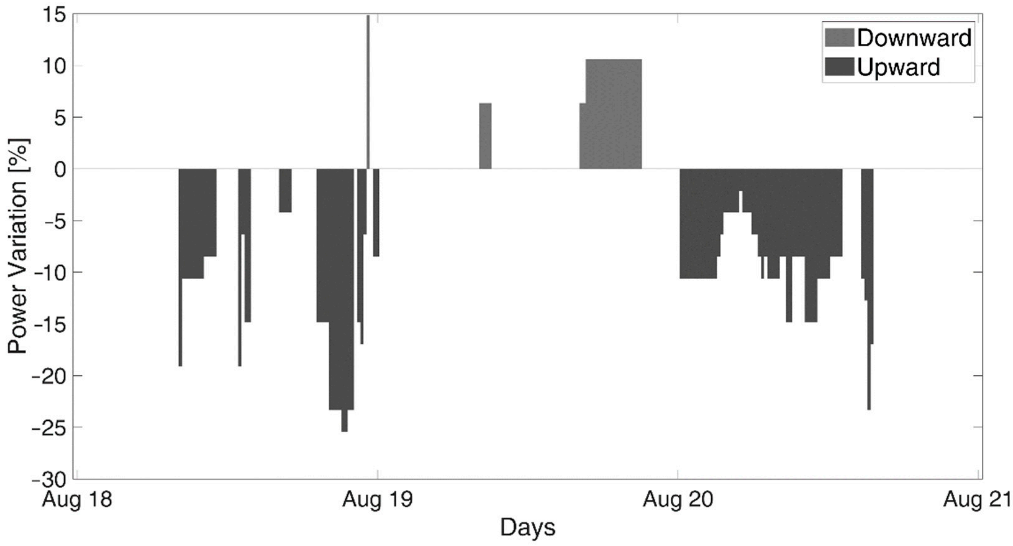

Figure 9. Trends of the AS requests during 3 days of examples.

To prove the capability of the proposed CCA to supply ASs, the amount of imbalance that occurred in time steps when the Aggregator is selected for AS provision (t_{AS}) has been also analyzed. On average, in 85.4% of cases, a zero imbalance is registered during the AS provision (median value equal to 94%) and, for the remaining time, the imbalance is higher than 5% of the corresponding AS requests ($Imb(t_{AS}) > 0.05 \cdot P_{AS}(t_{AS})$) only in 10% of cases, with a median value equal to 6%. This result has been achieved thanks to the implementation of the approach based on Equation (7), which allows to schedule the EVs' charging also according to the AS requests expected in the upcoming time steps.

The effects of EVs' scheduling on the quality of the carsharing service must be also evaluated, because an excessive postponement of the recharge could cause that the vehicles are rented before a full SoC is achieved, resulting in a lower autonomy. Table 3 reports the percentage of vehicles leaving the CS fully charged or with SoC (SoC_{out}) lower than a given threshold. It can be noticed that the CCA affects almost negligibly the quality of the carsharing service offered, since the probability to rent a vehicle with SoC < 0.5 (corresponding to the minimum autonomy threshold presented in Section 5) is only marginally increased by the scheduling.

Table 3. Cumulated PDF of EVs' SoC when disconnected from a CS.

Scenario	P (SoC_{out} = 1)	P (SoC_{out} < 0.9)	P (SoC_{out} < 0.8)	P (SoC_{out} < 0.7)	P (SoC_{out} < 0.6)	P (SoC_{out} < 0.5)	P (SoC_{out} < 0.4)
No Sch	90.1%	5.4%	2.4%	1.1%	0.5%	0%	0%
Sch	85.0%	6.5%	2.9%	1.3%	0.6%	0.04%	0.02%

The loss of profit on day D for the carsharing operator can be calculated by Equation (22), where $\vec{S^D}$ collects the EVs scheduled in the day D:

$$C_{rent}(D) = c_{lost} \cdot \sum_{v}^{v \in \vec{S^D}} max(0; rng_{min} - rng_v) \tag{22}$$

Finally, it is possible to calculate the daily electricity bill (C_{Bill}) as the product between the total energy absorbed by the EVs (E_{abs}) and the energy price (p_{DAM}). Concerning the imbalance cost (C_{imb}) and the revenues from the AS provision (R_{AS}), they are computed as presented in Section 6.

Table 4 reports the economic outcomes for the two scenarios, normalized with respect to the mean daily total cost for the Aggregator obtained without the CCA ($C_{tot}^{No-sch} = C_{Bill} + C_{imb}$), on average equal to 454.5 EUR/day. In the *No Sch* scenario, the loss of profit due to the decrease in EV autonomy (C_{rent}) and the AS remuneration are equal to zero. In the *Sch* scenario, the proposed architecture allows reducing the total daily cost by about 14.3%, thanks to the reduction of imbalance cost (56.1 EUR/day in the *No Sch* scenario and 4.14 EUR/day in the *Sch* one) and the AS revenues, roughly equal to 15 EUR/day (on average, −3.3% of C_{tot}^{No-sch}). Moreover, analyzing the impact of the CCA on the carsharing service, it is possible to conclude that it is negligibly affected, because the corresponding costs (C_{rent}) are increased only by 0.4%.

Table 4. Economic results of the *No Sch* and *Sch* scenarios (in % w.r.t. the total cost of the *No Sch* scenario; negative values are actually incomes).

		$C_{Bill,\%}$	$C_{imb,\%}$	$R_{AS,\%}$	$C_{rent,\%}$	$\Delta Cost_{\%}$
No Sch	mean (%) (Max; std)	87.7% (98.5; 14.0)	12.3% (55.7; 7.3)	-	0% (0; 0)	100%
Sch	Mean (%) (Max; std)	87.7% (97.5; 10.1)	0.9% (7.6; 1.3)	−3.3% (11.5; 2.8)	0.4% (4.0; 0.6)	85.7%

The tests are then repeated in two other case studies, characterized by different sizes of the carsharing fleet, respectively equal to 800 and 3200 EVs. The simulations were run on a computer equipped with an Intel Core i7-8700, 16 GiB of RAM, a Windows 10 operating system and MATLAB R2020a. The techno-economic profitability of h-ABC is once again evaluated, assuming as a strict requirement reaching the optimal scheduling in less than 60 s. On average, the h-ABC process took, respectively, in the two scenarios, 22.88 and 44.83 s to find the optimal schedule.

The objective function evaluation and the heuristic research (described in Algorithm 2) are the most impacting procedures in terms of both number of operations to be performed and computational times required. In the proposed h-ABC, similarly to other swarm-based optimization methods, the number of objective function evaluations tends to be high: on average 11,500 for each time step. However, this value does not grow considerably with the increase of the fleet size (10,020 in 800 EVs case study and 14,030 in 3200 EVs case study), while the heuristic research procedure is executed, on average, 3200 times for each time step, regardless of the case study analyzed. These results motivate the limited increment in computational times observed in the case studies analyzed in this paper, where the fleet size is increased by a factor of 4 (from 800 to 3200 EVs).

In the case characterized by a fleet of 3200 EVs, the higher number of optimization variables (on average 250 in each run) caused reaching the upper limit for the computational time (60 s) in 14.6% of the runs. In these runs, even if the convergence is not achieved by the h-ABC algorithm, the solution found can be considered very near to the optimal one: as highlighted by results reported in the next paragraph, obtained by considering also these suboptimal runs, the h-ABC performance in the 3200 EVs case study is still very promising.

In the *No Sch* scenario, the average normalized daily imbalance ($Imb_{\%}$) amounts, respectively, to 22.6% and 11.8% of the total absorbed energy, while with the CCA, they are reduced to 1.4% in both cases. Comparing the quality of the carsharing service offered to the users, it does not significantly change; the mean percentage of vehicles that leave the CSs with SoC < 0.5 is equal, in both cases, only to 0.17%. The economic outcomes are reported in Table 5, normalized with respect to the average daily cost obtained without the scheduler (237.2 EUR/day in the 800 EVs case study and 883.3 EUR/day in the 3200 EVs case study). The provision of AS allows saving, respectively, 3.1% and 3.6% of C_{tot}^{No-sch}. Additionally, imbalance costs, which respectively account for 16.0% and 9.7% of total costs in the scenario without CCA, are reduced to 0.5% and 1% by the scheduling. Despite a slight increase of the loss of profit ($C_{rent,\%}$) in both the scenarios equal to +0.3%, the scheduler permits a reduction of the total costs incurred by the carsharing operator of about 17.7% and 12.1% (i.e., 42.0 and 106.8 EUR/day).

Table 5. Economic profitability of the proposed CCA as a function of EV fleet size.

	800 EVs			**3200 EVs**		
	No Sch	***Sch***	**Δ**	***No Sch***	***Sch***	**Δ**
$C_{Bill,\%}$ (%)	84.0	83.9	−0.1	90.3	90.1	−0.2
$C_{imb,\%}$ (%)	16.0	0.9	−15.1	9.7	1.1	−8.6
$R_{AS,\%}$ (%)	-	−3.1	−3.1	-	−3.6	−3.6
$C_{rent,\%}$ (%)	0	0.6	+0.6	0	0.3	+0.3
$\Delta Cost_{\%}$ (%)	100	82.3	−17.7	100	87.9	−12.1

Finally, in order to evaluate the profitability of the e-mobility scheduling under different economic conditions, a sensitivity analysis of the coefficients of the objective function is performed. In particular, both the values of c_{rent} and c_{imb} used in the objective function and in Equations (7) and (9) are varied in a range of ±25% with respect to the reference value previously applied (i.e., c_{rent} = 0.28 EUR/min and c_{imb} = 40 EUR/MWh). In particular, the following steps are considered: [−25%; −15%; 0%; +15%; +25%], therefore obtaining a total of 16 different combinations. For the sake of the sensitivity analysis, a fleet composed of 1600 EVs is simulated over 200 days. The simulated days have been obtained by changing randomly the AS market requests and carsharing users' behavior. Subsequently, an economic assessment is performed according to the procedure presented in Section 6, comparing the total costs for the carsharing operator in the *Sch* and *No Sch* scenarios: to this purpose, the quantity $\Delta Cost_{\%}$ is calculated as the difference between the costs in the scheduling scenario and the base case, given by the electricity bill (C_{Bill}), the imbalances fee (C_{imb}), the loss of profit related to the worsening of carsharing service quality (C_{rent}), minus the revenues from the ASM participation (R_{AS}).

Figure 10 shows that the proposed h-ABC scheduling, in all the case studies, is able to effectively reduce the costs compared to the *No Sch* scenario, allowing for savings between 8.5% and 16% of the costs without the scheduler. It is worth noting that these results marginally depend on the cost of the carsharing rent (c_{rent}); actually, as one can observe in Figure 10, assuming a given imbalance cost, the economic profitability of the h-ABC scheduler reduces only by about 2%, even when assuming a rent's unitary cost increase of 50% (e.g., with c_{imb} equal to 40 EUR/MWh, by increasing the rent cost from 0.22 EUR/min to 0.34 EUR/min, the cost reduction changes from 13% to 11.2%). Another interesting result is related to the dependence of the economic profitability (i.e., $\Delta Cost_{\%}$) on the unitary imbalance cost: an increase of c_{imb} allows the proposed CCA to be more profitable, even if the rent cost is kept unchanged. This fact, combined with the capability of the proposed algorithm to manage a large EV fleet, highlights how the h-ABC scheduling method could provide even more interesting results in the future, when the penetration of non-controllable renewable energy sources is expected to increase and, consequently, an increase of AS remuneration and imbalance costs is also expected, pushed by greater requests of the Ancillary Services needed to guarantee the power balance on the grid [31].

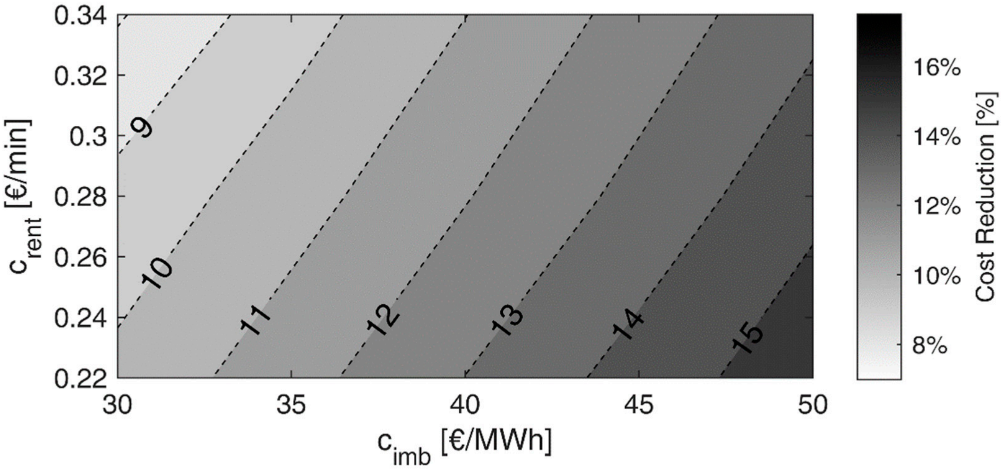

Figure 10. Map of cost reduction of the proposed scheduler, normalized w.r.t the *No Sch* total cost, for different coefficient combinations.

9. Conclusions

In the present paper, a hybridization of the ABC algorithm (h-ABC) has been presented to optimize the scheduling of the charging requests of an electric carsharing fleet. The centralized architecture, in perspective, will enable a carsharing operator to participate in the Ancillary Service Market by exploiting the flexibility of the EVs' charging. This way the economic sustainability and competitiveness of the electric carsharing service will improve, without detrimental impacts on the quality of service provided to users. The numerical analyses performed highlighted that the h-ABC architecture is effective in reducing the power imbalance with respect to the commitments to the market, also enabling a reliable provision of Ancillary Services to the grid. Additionally, considering binding requirements for the computational time (a time limit of 60 s has been assumed), a cost reduction (electricity bill + imbalances) between 12.1% and 17.7% has been achieved, depending on the size of the EVs' fleet and the forecasting error committed in estimating the DAM power schedule. A pivotal result is also the effectiveness shown by the method to preserve the quality of the carsharing service: a loss of profit, related to an unwanted decrease in the EVs' autonomy caused by the scheduling, lower than or equal to 0.6%, has been estimated in the analyzed scenarios; therefore, it has been largely compensated by the benefits of the approach in terms of reduction of the amount of imbalance fee and the revenues from the AS provision.

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Nomenclature

Acronyms:	
ABC	Artificial Bee Colony
AS	Ancillary Service
ASM	Ancillary Services Market
AT	Arrival Time
BSP	Balancing Service Provider
CCA	Centralized Control Architecture
CS	Charging Station
DAM	Day-Ahead Market
DtT	Due to Time
EV	Electric Vehicle
h-ABC	Hybrid-Artificial Bee Colony
HP	Hydro Power
SoC	State of Charge
TSO	Transmission System Operator
V1G	Unidirectional Grid to Vehicle
V2G	Bidirectional Vehicle to Grid
Parameters and Variables:	
C_{btr}	Vehicle's battery capacity
C_{Bill}	Daily electricity bill cost
C_{imb}	Daily imbalance cost
C_{rent}	Daily cost of non-fulfillment of the charging
$\boldsymbol{CS}$	Matrix containing the topology data of Charging Stations
c_{imb}	Imbalance fee
c_{lost}	Fee in case of non-fulfillment of the charging
c_{rent}	Carsharing tariff for the users
D^{id}_{time}	Charging deadline for the *id*-th vehicle
E_{abs}	Total daily energy absorbed
$\bar{e}_{cons}$	Mean energy consumption of the EV
fit_p	Fitness function of the *p*-th solution
$Imb_{\%}$	Normalized daily imbalance
Lim_p	Exploitation value of the *p*-th solution
Lim_{MAX}	Maximum exploitation limit
N^{tot}_{days}	Number of simulated days
N_{exp}	Number of expected EV connections in the following time steps
N^{tot}_{fleet}	Number of EVs in the fleet
N_{FS}	Number of solutions simultaneously evaluated by the optimization algorithm
N_{main}	Maximum number of optimization iterations
$n^{id,d}_{rent}$	Number of rents during the *d*-th day for the *id*-th EV
$\boldsymbol{P^t}$	Matrix containing the connected EVs' information
P_0	Power Baseline Schedule
P_{AS}	Power accepted in the ASM
P_{abs}	Power absorbed by the carsharing operator
${P^i}_{chg}$	Charging power of the *i*-th vehicle

P_{req}	Power Request Schedule
p_{AS}	Remuneration for the AS provision
p_{DAM}	DAM price
R_{AS}	Daily remuneration from the AS provision
rng_{min}	Minimum range required by the carsharing operator
$SoC_{int}^{r,id}$ / $SoC_{CS,con}^{r,id}$	State of Charge before/after the rent
st^{id}	Initial charging time for the *id*-th EV (optimization variable)
$\vec{T}_D$	Vector containing the time steps in day D
$\vec{T}_f$	Upcoming time steps considered during the optimization process performed in t_0
t	Generic time step
t_{AS}	Time steps with an AS request
t_{in}	Rent starting time
t_0	Current time step
$\vec{t}_{tot}$	Vector containing all the simulated time steps
$tard$	Tardiness function
$\Delta Cost$	Cost variation w.r.t. the benchmark scenario
Δt_{rent}^{r}	Duration of the *r*-th rent
Δd_{rent}^{r}	Distance covered during *r*-th rent
Δt_{chg}^{id}	Charging time of the *id*-th EV
τ	Time step resolution adopted

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