Optimal Charging of Electric Vehicles in Incentive-Based Energy Communities

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***Abstract*—Renewable energy communities are expected to play a fundamental role in the green energy transition. In this study, an optimization framework for the optimal operation of energy communities under high penetration of electric vehicles is proposed. Specifically, we consider an energy community composed of different entities featuring loads, renewable generators, energy storage systems, and electric vehicle charging stations. The main goal is to coordinate vehicle charging and storage operation so as to minimize the overall community costs. In particular, an incentive-based remuneration scheme is considered, promoting community self-consumption. The final optimization problem is cast as a linear program, thus able to deal with a large number of entities and vehicles. Numerical results show the effectiveness of the proposed procedure in terms of cost reduction and community self-consumption.**

I. Introduction

Renewable Energy Communities (RECs) are a strategical tool for assisting in the green energy transition. A REC is an association of consumers and renewable energy producers whose goal is to bring environmental, economic, and social benefits to community members and to the area in which they operate [1]. The formation of energy communities is governed by various national legislation, promoting people participation. Several studies have demonstrated the importance of aggregation and collaboration for the benefit of both members and the environment [2], [3], [4].

In this work, we focus on incentive-based RECs, like those considered in the Italian regulation [5], [6], [7]. Within this framework, the incentive granted to the REC is proportional to the community virtual self-consumption, defined as the minimum between the energy fed into the network and the overall energy consumed by the community, in a given time period. Techniques for fair distribution of the incentive among members are usually designed in order to foster the collaboration among the participants [8]. As a consequence, one of the aim of a REC management system is the maximization of the community self-consumption, so as to achieve a greater incentive and environmental benefit. To this purpose, community members must try to synchronize their generation and consumption profiles. Producers and consumers equipped with battery energy storage systems (BESSs) can effectively contribute to the community self-consumption by coordinated storage operation [9]. Similarly, a suitable management of electric vehicle (EV) charging stations can provide a substantial increase of the incentive, especially in the presence of high penetration of EVs.

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A. Paper contribution

In this paper, we consider a REC operating within an incentive-based remuneration scheme, the incentive being proportional to its virtual self-consumption. Every member of the community (*entity* in the following) is connected to the main grid in which the actual energy exchange takes place. Different kinds of entities are considered: consumers, producers and prosumers which can be equipped with BESSs. In addition, we assume that one entity runs a charging station serving a fleet of EVs for rent. Such an entity receives a number of rent requests the day ahead and performs a request-to-vehicle assignment according to the request departure time, return time and estimated energy consumption [10]. The community is managed by a centralized administrator (*REC manager* in the following) that receives load and consumption profiles of the entities one day ahead, as well as the request-to-vehicle assignment. The REC manager coordinates the entity operation and returns the optimal schedules for BESSs and EV charging for the next day. The objective is to maximize the community profit taking into account costs and revenues associated with energy exchange with the grid, as well as the incentive based on virtual self-consumption.

The main contribution of this work consists in the formulation and solution of the above-mentioned optimization problem, where the optimization variables are the operational commands of the BESSs and the charging profiles of the electric vehicles. The optimization time horizon is set to one day and time-varying electricity prices are assumed during the day. The optimization problem is cast as a Linear Program (LP), which allows one to manage a large number of electric vehicles. Comparisons between the proposed approach and a selfish solution where entities act individually trying to maximize their profit are carried out. Results show a substantial profit increase when adopting the devised coordinated strategy.

B. Paper organization

The paper is structured as follows. In Section II, the optimization problem is formulated. Two numerical examples are reported in Section III, while in Section IV some conclusions are drawn.

II. Problem formulation

We consider an energy community composed of $U+1$ entities, one of which is an EV charging station. Each entity $u \in \mathcal{U} = \{1, \dots, U\}$ is represented by a grid-connected prosumer encompassing a load, a generator and/or a BESS. However, the model can be easily extended to incorporate entities with more complex structure, as well as multiple EV charging stations.

Next, we introduce the constraints describing the prosumers and the EV charging station, and we define the community virtual self-consumption according to the Italian regulation. Then, we formulate the considered optimization problem, consisting in the maximization of the profit of the community including the incentive, subject to the constraints of the single entities and the EV charging station. In the following, a discrete time horizon $\mathcal{T} = \{1, \dots, T\}$ is considered, with time step Δ_T.

A. Prosumers

We assume that energy production $e_{u,t}$ and energy demand $i_{u,t}$ of entity u at time t are non-flexible.

For the BESS of entity u, let $s_{u,t}$ be the energy stored in the battery at the end of sample period t, and $p_{u,t}^{cha}$ and $p_{u,t}^{dis}$ be the charging and discharging power over sample period t. Moreover, let η_u^{cha} and η_u^{dis} denote the charging and discharging efficiencies. The battery dynamics is described by the difference equation:

$$s_{u,t} = s_{u,t-1} + \eta_u^{cha} p_{u,t}^{cha} \Delta_T - \frac{1}{\eta_u^{dis}} p_{u,t}^{dis} \Delta_T, \tag{1}$$

with the initial and terminal conditions:

$$s_{u,0} = S_u^{ini} \tag{2}$$

$$s_{u,T} = S_u^{end}. \tag{3}$$

The charging and discharging power, as well as the battery energy level, are bounded as follows:

$$0 \leq p_{u,t}^{cha} \leq P_u^{cha} \tag{4}$$

$$0 \leq p_{u,t}^{dis} \leq P_u^{dis} \tag{5}$$

$$S_u^{min} \leq s_{u,t} \leq S_u^{max}, \tag{6}$$

where P_u^{cha} and P_u^{dis} are the maximum charging and discharging power, while S_u^{min} and S_u^{max} are the minimum and maximum energy that can be stored in the battery.

To prevent charging the BESS from the grid, the following constraint is enforced:

$$p_{u,t}^{cha} \Delta_T \leq e_{u,t}, \tag{7}$$

implying that the battery is always charged with energy generated by the entity.

The energy balance for entity u at time t is given by the equation:

$$e_{u,t}^{gri} - i_{u,t}^{gri} - e_{u,t} + i_{u,t} - p_{u,t}^{dis} \Delta_T + p_{u,t}^{cha} \Delta_T = 0, \tag{8}$$

where $e_{u,t}^{gri}$ and $i_{u,t}^{gri}$ are the energy exported to the grid and the energy imported from the grid by the entity. These two quantities are bounded by contractual limits:

$$0 \leq e_{u,t}^{gri} \leq E_{u,t}^{cap} \Delta_T \tag{9}$$

$$0 \leq i_{u,t}^{gri} \leq I_{u,t}^{cap} \Delta_T. \tag{10}$$

B. EV charging station

We assume that entity $U+1$ is a charging station used by an EV rental service to charge its fleet of V vehicles. To avoid cumbersome notation, we drop the subscript $U+1$ from all the quantities related to this entity. Moreover, we assume that the entity is composed of vehicles only, which are modelled as batteries.

On a day-ahead basis, the EV rental service receives H requests from customers. Each request $h \in \mathcal{H} = \{1, \dots, H\}$ specifies the departure time t_h^l, the return time t_h^r and the energy amount E_h which is required for the planned trip. Given the set $\mathcal{H}$ of requests, the following quantities can be computed for each $h \in \mathcal{H}$ and $t \in \mathcal{T}$:

$$\sigma_{h,t} = \begin{cases} 1 & \text{if } t = t_h^r \\ 0 & \text{else,} \end{cases} \qquad \omega_{h,t} = \begin{cases} 1 & \text{if } t = t_h^l \\ 0 & \text{else,} \end{cases} \tag{11}$$

$$\delta_{h,t} = \begin{cases} 1 & \text{if } t_h^l \leq t < t_h^r \\ 0 & \text{else.} \end{cases} \tag{12}$$

In (11), $\sigma_{h,t}$ and $\omega_{h,t}$ are equal to 1 only when the time index t coincides with the return time and the departure time of request h, respectively. On the other hand, $\delta_{h,t}$ in (12) is equal to 1 if request h is active at time t.

The first problem that the manager of the EV rental service has to deal with, is the assignment of requests to vehicles. Such an assignment problem can be tackled *a priori* by means of efficient heuristics, like the one proposed in [10]. The assignment returns binary quantities $z_{h,v} \in \{0, 1\}$, $\forall h \in \mathcal{H}$, $\forall v \in \mathcal{V}$, where $\mathcal{V} = \{1, \dots, V\}$ is the set of vehicles, and $z_{h,v} = 1$ if and only if request h is assigned to vehicle v. Feasibility of the assignment[1] requires that the following constraints are satisfied:

$$\sum_{v \in \mathcal{V}} z_{h,v} = 1 \qquad \forall h \in \mathcal{H}, \tag{13}$$

$$\sum_{h \in \mathcal{H}} \delta_{h,t} z_{h,v} \leq 1 \qquad \forall v \in \mathcal{V},\ \forall t \in \mathcal{T}, \tag{14}$$

where (13) imposes that each request is fulfilled by a single vehicle, while (14) imposes that a vehicle cannot fulfil multiple requests simultaneously.

Once the assignment of requests to vehicles has been accomplished, EV charging is to be scheduled with the constraint that enough energy is stored in each EV battery at the departure time of the assigned requests. This is done by modeling the EVs as batteries connected to the grid only during time periods when vehicles are parked

[1] We assume that EV rental requests are such that there always exists a feasible assignment.

in the charging station. The EV charging schedule is then determined in the framework of the optimization performed at the community level.

To model the dynamics of EV batteries, let $s_{v,t}$ denote the energy stored in the battery of vehicle v at the end of time period t. Moreover, let $p_{v,t}^{cha}$ be the charging power over time period t and η_v^{cha} be the charging efficiency. The battery dynamics for vehicle v is described by the difference equation:

$$s_{v,t} = s_{v,t-1} + \eta_v^{cha} p_{v,t}^{cha} \Delta_T - \sum_{h\in\mathcal{H}} \sigma_{h,t} z_{h,v} E_h \tag{15}$$

with the initial and terminal conditions:

$$s_{v,0} = S_v^{ini} \tag{16}$$

$$s_{v,T} = S_v^{end}. \tag{17}$$

Compared to (1), which describes a BESS, the discharge term $p_{u,t}^{dis}\Delta_T/\eta_u^{dis}$ is replaced in (15) with the impulsive term $\sum_{h\in\mathcal{H}} \sigma_{h,t} z_{h,v} E_h$, which discharges the battery of a quantity E_h in the case request h is assigned to vehicle v and time t coincides with the return time t_h^r. Like in (6), the energy level of the battery of vehicle v is bounded as follows:

$$S_v^{min} \le s_{v,t} \le S_v^{max}. \tag{18}$$

Regarding the charging power $p_{v,t}^{cha}$, it must be clearly 0 when the vehicle is away, while it may vary between 0 and the maximum charging power P_v^{cha} when the vehicle is parked in the charging station. This is imposed by the constraints:

$$0 \le p_{v,t}^{cha} \le \left(1 - \sum_{h\in\mathcal{H}} \delta_{h,t} z_{h,v}\right) P_v^{cha}, \tag{19}$$

where the right-hand side is 0 when request h is assigned to vehicle v and time t is between the departure and the return time of the request; and it is P_v^{cha} otherwise. Finally, if request h is assigned to vehicle v, the battery capacity of the vehicle at departure time t_h^l must not be less than the energy E_h required by the request. This constraint is expressed in the form:

$$s_{v,t} \ge \sum_{h\in\mathcal{H}} \omega_{h,t} z_{h,v} E_h. \tag{20}$$

C. Community virtual self-consumption

The Italian REC incentive scheme is based on the concept of community virtual self-consumption. This is defined as "the minimum between the energy fed into the network and the energy consumed by the community members" in a given time period [11]. Using the notations of this paper, it turns out that the community virtual self-consumption at time t is expressed as:

$$\zeta_t = \min\left\{\sum_{u\in\mathcal{U}} e_{u,t}^{gri},\ \sum_{u\in\mathcal{U}} i_{u,t}^{gri} + \sum_{v\in\mathcal{V}} p_{v,t}^{cha}\,\Delta_T\right\}. \tag{21}$$

The incentive granted to the REC is obtained multiplying (21) by the unitary incentive π_t^{inc}, and then summing over the whole time horizon $\mathcal{T}$.

D. Optimization problem

We consider the optimal operation of a REC in terms of the maximization of an objective function J, which represents the aggregated profit of the community, including the incentive for virtual self-consumption. The objective function J is defined as:

$$\begin{aligned} J = \sum_{t\in\mathcal{T}} \Bigg\{ \sum_{u\in\mathcal{U}} \Big[& \pi_{u,t}^{egr} e_{u,t}^{gri} - \pi_{u,t}^{igr} i_{u,t}^{gri} \\ & - \pi_{u,t}^{sto} \left(\eta_u^{cha} p_{u,t}^{cha} + \frac{1}{\eta_u^{dis}} p_{u,t}^{dis} \right) \Delta_T \Big] \\ & - \sum_{v\in\mathcal{V}} \pi_t^{igr} p_{v,t}^{cha}\,\Delta_T + \pi_t^{inc} \zeta_t \Bigg\}, \end{aligned} \tag{22}$$

where $\pi_{u,t}^{egr}$ and $\pi_{u,t}^{igr}$ are the unitary selling and purchase energy prices, $\pi_{u,t}^{sto}$ is the unitary cost for BESS usage of entity u at time t, and π_t^{igr} is the unitary purchase energy price for the charging station.

The optimization problem to be solved reads as follows:

$$\begin{aligned} \max \quad & J \\ \text{s.t.} \quad & (1) - (10) \quad \forall u \in \mathcal{U},\ \forall t \in \mathcal{T} \\ & (15) - (20) \quad \forall v \in \mathcal{V},\ \forall t \in \mathcal{T} \\ & (21) \quad \forall t \in \mathcal{T}, \end{aligned} \tag{23}$$

where the maximization is performed with respect to the optimization variables:

- $p_{u,t}^{cha}, p_{u,t}^{dis}, s_{u,t}, e_{u,t}^{gri}, i_{u,t}^{gri}$ $\quad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}$,
- $p_{v,t}^{cha}, s_{v,t}$ $\quad \forall v \in \mathcal{V}, \forall t \in \mathcal{T}$,
- ζ_t $\quad \forall t \in \mathcal{T}$.

Problem (23) is nonlinear due to the min term in (21). However, an equivalent linear form can be obtained by replacing (21) with the pair of constraints:

$$\zeta_t \le \sum_{u\in\mathcal{U}} e_{u,t}^{gri} \tag{24}$$

$$\zeta_t \le \sum_{u\in\mathcal{U}} i_{u,t}^{gri} + \sum_{v\in\mathcal{V}} p_{v,t}^{cha}\,\Delta_T. \tag{25}$$

The resulting problem is a linear program (LP), which can be solved very efficiently using state-of-the-art solvers, even for very large problem sizes. This makes it possible to address real-world case studies with large community participation in highly EV mobility penetrated scenarios. It is stressed that, when (21) is replaced with (24)-(25), equality (21) holds at the optimum of (23).

Remark 1: In our problem formulation, there is no need to impose complementarity constraints $p_{u,t}^{cha}\,p_{u,t}^{dis} = 0\ \forall u \in \mathcal{U},\ \forall t \in \mathcal{T}$, to avoid simultaneous battery charging and discharging. Indeed, these constraints are automatically satisfied at the optimum of (23), thanks to the presence of the BESS cost term in the objective function (22).

Remark 2: Regarding energy exchanges with the grid, complementarity constraints $e_{u,t}^{gri}\,i_{u,t}^{gri} = 0\ \forall u \in \mathcal{U},\ \forall t \in \mathcal{T}$, should still be enforced, instead, to avoid simultaneous export and import. Unfortunately, these constraints are non-convex, and make the optimization more involved. As shown in [12], [13], they can be replaced by introducing binary variables, leading to a mixed integer linear program (MILP), which can be solved only for small instances. Notice that we do not consider complementarity constraints $e^{gri}_{u,t}\, i^{gri}_{u,t} = 0$ in the problem formulation of this paper. However, if $\pi^{igr}_{u,t} > \pi^{egr}_{u,t} + \pi^{inc}_{t}$, then $e^{gri}_{u,t}\, i^{gri}_{u,t} = 0$ is automatically satisfied at the optimum of (23), because selling and buying the same amount of energy at time t would imply a net loss. Otherwise, should both $e^{gri}_{u,t}$ and $i^{gri}_{u,t}$ be non-zero at the optimum of (23), it is always possible to recover a feasible solution (i.e. satisfying the complementarity constraints) by considering the net export or import.

Remark 3: In this work, the assignment of requests to vehicles is accomplished prior to the REC optimization by means of the heuristic proposed in [10]. Indeed, the maximization of (22) would include the assignment of requests to vehicles as an additional tuning knob. However, this would lead again to a MILP formulation due to the binary decision variables $z_{h,v}$, thus making it unsuitable to deal with communities involving high EV penetration.

III. Numerical results

In this section, we first illustrate a toy-example in order to show how the proposed approach works. Then, we evaluate the performance by simulating a large community over a time period spanning more than three months.

To carry out suitable comparisons, the following two strategies are considered:

- **Coordinated Strategy**: the policy obtained by the REC manager when coordinating the community, i.e., the proposed approach;
- **Selfish Strategy**: the policy obtained by the entities when acting selfishly, i.e., when they maximize their own profit regardless of the incentive gained by the community.

For both simulated setups, the optimization horizon is set to 24 hours, the efficiency of the BESS and EV batteries are set to $\eta^{cha}_u = \eta^{dis}_u = \eta^{cha}_v = \eta^{dis}_v = 0.9$. The prices of energy exported to the grid are taken from *Ritiro Dedicato* historic prices provided by Italian company GSE [14], while the prices of energy imported from the grid are taken from *Servizio di Maggior Tutela* provided by the Italian authority ARERA [15]. Their value changes during the day, according to three time periods as reported in Table I. Such time periods are defined as:

F1: 8:00-19:00 working days;
F2: 7:00-8:00 and 19:00-23:00 working days, 7:00-23:00 Saturday;
F3: 23:00-7:00 working days, entire day of Sunday.

The cost for using the storage is set to $\pi^{sto}_{u,t} = 0.01$ €/kWh, while the self-consumption incentive is $\pi^{inc}_t = 0.12$ €/kWh. Finally, vehicles are assumed to be equipped with identical BESSs, with capacity $S^{max}_v = 50$ kWh ($S^{min}_v = 0$ kWh) and maximum charging power $P^{cha}_v = 22$ kW.

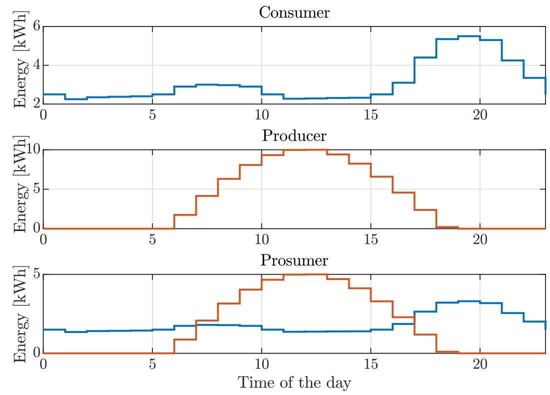

Fig. 1. Load (blue) and generation (orange) profile of the consumer, producer and prosumer of the community.

A. Illustrative example

A toy example describing a working day of operation (sampling time $\Delta_T = 1$ hour) is introduced, in order to show how the community behaves according to given profiles of load, generation and price. The community is composed of four entities: one consumer, one photovoltaic (PV) producer, one prosumer equipped with a storage, and one charging station serving two vehicles. Profiles showing generation and load of the first three entities are depicted in Fig. 1. The capacity of the storage is $S^{max}_u = 30$ kWh ($S^{min}_u = 0$ kWh), while the maximum charging/discharging power rate is $P^{cha}_u = P^{dis}_u = 10$ kW. Concerning the EV requests, two of them are assigned to the first vehicle, and one is assigned to the second one. The request schedule and the corresponding data are summarized in Table II. Results concerning the community profit for both procedures and setups are reported in Table III. In the setup of this illustrative example,

TABLE I
Energy prices

	F1	F2	F3
Import [€/kWh]	0.4855	0.4558	0.4558
Export [€/kWh]	0.2422	0.2286	0.1915

TABLE II
EV requests and assigned vehicles

Request [#]	t^l	t^r	E [kWh]	Vehicle Assigned [#]
1	5	10	15	1
2	6	11	15	2
3	14	17	9	1

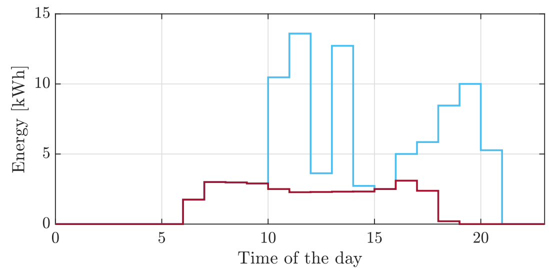

Fig. 2. Self-consumption profile using the coordinated (cyan) and selfish (red) strategy.

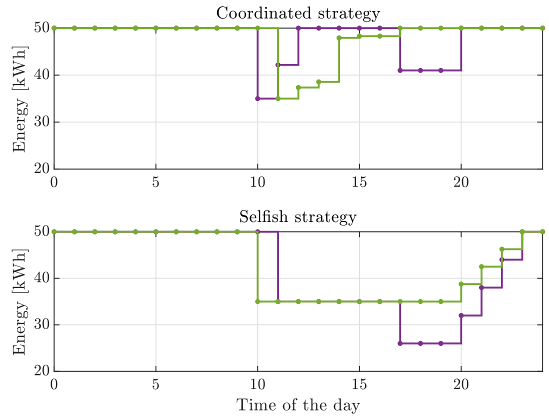

Fig. 3. Energy stored in EV 1 (purple) and EV 2 (green) using the coordinated and selfish strategy.

the community profit shows an increase of nearly 20% when the coordinated strategy is compared with the selfish strategy. When acting in a coordinated fashion, the entities boost the community self-consumption thus obtaining a higher incentive. The self-consumption profiles resulting from both strategies are depicted in Fig. 2. It is apparent that the coordinated strategy schedules the operation of EV batteries and BESS so as to exploit as much as possible the renewable generation available during the central hours of the day (see Figs. 3 and 4). In particular, the selfish strategy postpones the EV charging at the end of the day when the energy price is lower. On the other hand, the coordinated strategy favors vehicle charging when renewable generation is higher. Concerning the BESS, the selfish solution does not use it, whereas the coordinated approach discharges the storage in time periods of high load demand, thus increasing the REC self-consumption.

TABLE III
COMMUNITY PROFIT FOR THE CONSIDERED SETUPS

	Illustrative example	Extensive simulations
Coordinated strategy	-34.24€	-1080.54€
Selfish strategy	-41.83€	-1273.13€

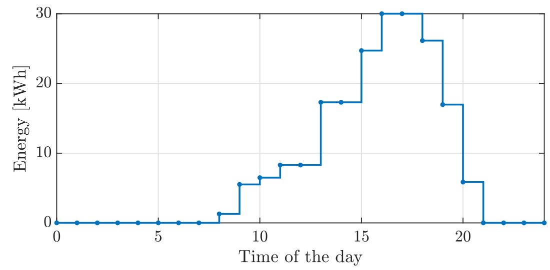

Fig. 4. Energy stored in the BESS using the coordinated strategy.

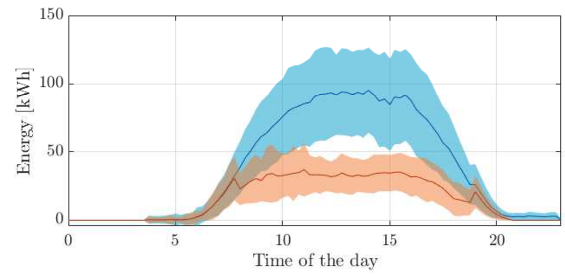

Fig. 5. Mean (solid line) and standard deviation (shaded area) of the daily self-consumption profile using the coordinated (blue) and selfish (orange) strategy.

B. Extensive simulations

In this setup, a 100-day simulation involving 104 entities is carried out. The sampling time for this simulation is set to $\Delta_T = 15$ minutes. The entities are chosen as follows: 50 consumers, 20 prosumers, 30 prosumers equipped with storage, 1 charging station managing 50 EVs, and 3 PV producers. Load profiles are taken form a real data set of 100 consumers connected to the same distribution network, spanning from April 7, 2008, to July 16, 2008. The PV generation profile of the community is taken from a real photovoltaic plant, with data recorded from April 7, 2023, to July 16, 2023. For each prosumer, the PV profile is scaled to be consistent with its corresponding consumption pattern. Additionally, each PV producer is assumed to be equipped with a 200 kWp plant.

For each day of the simulation, up to 150 requests are randomly generated. The leaving time for these requests ranges from 00:00 to 18:00, with durations falling within the interval [1, 4] hours. The energy required by these requests is uniformly chosen in the interval [10, 40] kWh. Similarly to the previous example, vehicle charging and storage operation are coordinated in order to increase significantly the self-consumption when the PV production is higher. Consequently, as reported in Table III, the coordinated strategy boosts the overall profit of the community by almost 15%.

In Fig. 5, the mean and the standard deviation (shaded area) of the daily self-consumption profile for both strategies are depicted. As observed, the self-consumption profile for the selfish solution shows two local maxima, corresponding to the time instants when energy prices increase

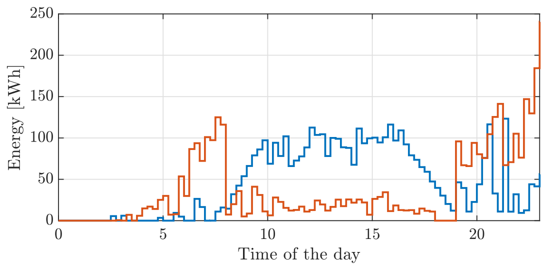

Fig. 6. Charging station energy demand for coordinated (blue) and selfish (orange) strategy.

and when they return to low levels. This behavior is mainly driven by the charging station, which attempts to coordinate EV charging when energy prices are lower. A similar phenomena can also be noted in Fig. 6 that shows the energy demand of the charging station for a given day. On the contrary, when the community entities are coordinated, the opposite behavior can be observed, and vehicles are charged during the central hours of the day in order to provide a higher self-consumption.

Finally, it is worthwhile to stress that the complementary constraints $e^{gri}_{u,t}\, i^{gri}_{u,t} = 0$ are always satisfied in the solutions of the optimization problems.

C. Discussion

In terms of performance, the proposed approach is capable of reducing the community cost of about 15%, compared to an uncoordinated strategy that optimizes the behavior of each individual entity. Concerning self-consumption, the optimal strategy coordinates the operation of the charging station and the storage units in order to match energy consumption with renewable generation. Notably, on average the self-consumption is more than doubled during the central hours of the day, providing significant benefits from incentive and sustainability standpoint.

The obtained results are in line with European energy policies directives [1], since the proposed approach enables environmental, economic and social benefits to the community members. In fact, by suitably coordinating vehicle charging and storage operations, a substantial cost reduction is achieved for the entire community system, while environmental benefits are attained through the increased renewable self-consumption.

IV. Conclusions

In this paper, an optimal energy management system for incentive-based RECs in the presence of EVs is presented. A coordinated strategy for EV charging schedule and storage operation is derived as the solution of an optimization problem. Results show that substantial cost reduction is achieved by significantly increasing the virtual self-consumption within the community. The proposed approach requires the solution of a linear program, thus providing an efficient technique which is viable even for large communities and high EV penetration. Future works will be focused on investigating uncertainties affecting load, renewable generation and EV requests. Moreover, decentralized frameworks will be analyzed in order to coordinate REC entities in a distributed fashion, without the need of a community manager.

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