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Optimal operation of renewable energy communities under demand response programs

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ABSTRACT

Within the context of renewable energy communities, this paper focuses on optimal operation of producers equipped with energy storage systems in the presence of demand response. A novel strategy for optimal scheduling of the storage systems of the community members under price-volume demand response programs, is devised. The underlying optimization problem is designed as a low-complexity mixed-integer linear program that scales well with the community size. An algorithm for redistributing the demand response rewards corresponding to the optimal solution is also developed in order to guarantee fairness among participants. The proposed approach is evaluated using two different objective functions through extensive numerical simulations. In all cases, economic benefits are demonstrated for producers that participate in a community rather than operating independently.

1. Introduction

The need to address the environmental impact of electric energy systems and to advance the global transition toward net-zero CO_2 emissions, as set forth in initiatives such as the European Green Deal [1], has led to extensive investigation of novel paradigms and strategies. This requirement stems from the challenge of mitigating climate change and ensuring the sustainability and reliability of the energy infrastructure. In this respect, renewable energy communities (RECs) and demand response (DR) programs stand out as particularly promising tools, due to their capacity to address electricity grid and environmental constraints while also accounting for socio-economic benefits.

A REC consists of a collective of entities that engage in energy exchange through the power grid [2,3]. The primary objective of a REC is to deliver social, economic, and environmental benefits to its members through the strategic management of distributed energy resources, including load profiles, renewable generation assets (such as photovoltaic panels and wind turbines), and energy storage systems [4]. While national regulations often govern REC organization [5], individual communities retain some autonomy as far as the operation strategy for their activities is concerned. This autonomy enables RECs to optimize the collective welfare derived from active participation, balancing the technical demands of energy coordination with equitable distribution of the resultant benefits among members.

1.1. Related studies

One of the main objectives of a REC operation strategy is to optimize the overall welfare coming from active participation of the entities. In this respect, suitable rules must be implemented for the redistribution of benefits among participants, ensuring that no member may find it advantageous to exit the community [6]. Moreover, the redistribution policy should ensure fairness among participants [7].

Demand response programs represent another avenue for reducing environmental impact [8–12]. In this framework, participants voluntarily adjust their load profiles in response to specific requests by an aggregator (e.g., the Distribution System Operator (DSO)), thereby providing ancillary services to the grid, such as peak power reduction and enhanced network stability [13]. In exchange, a monetary reward is granted to participants that fulfill a given DR request. In addition to the flexibility provided by load profile shaping, the optimal operation of electrical energy storage (EES) systems can contribute to achieving DR goals [14,15]. In this respect, RECs have been found to represent an important source of DR flexibility, especially when equipped with EES facilities [16]. Optimized scheduling of a smart community with shared storage in the presence of DR is addressed in [17]. A detailed review of DR programs and their potential application to RECs is available in the literature [18].

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Nomenclature

Symbol	Explanation	Unit
Math notation		
$\mathcal{T} = \{0, \dots, T-1\}$	Set of time periods t in a given time horizon	–
τ_s	Duration of a time period (sampling time)	[h]
$\mathcal{I}(\underline{t}, \bar{t}) = [\underline{t}, \bar{t}) \subseteq \mathcal{T}$	Generic time interval	–
Model variables		
$\mathcal{U}$	Set of producer entities with storage, $\mathcal{U} = \{1, \dots, U\}$	–
$\overline{S}_u$	Maximum BESS capacity of entity u	[kWh]
$\overline{E}_u^d$	Maximum BESS discharging energy of entity u per time slot	[kWh]
$\overline{E}_u^c$	Maximum BESS charging energy of entity u per time slot	[kWh]
η_u^d	Discharging efficiency of BESS of entity u	–
η_u^c	Charging efficiency of BESS of entity u	–
S_u^0	Energy level of BESS of entity u at time $t = 0$	[kWh]
S_u^T	Energy level of BESS of entity u at time $t = T$	[kWh]
$\pi_u^g(t)$	Unitary price of energy sold to the grid by entity u	[€/kWh]
π_u^s	Unitary cost for operating the BESS of entity u	[€/kWh]
$E_u(t)$	Energy production of entity u	[kWh]
$\hat{E}_u(t)$	Forecast of $E_u(t)$	[kWh]
$E_u^g(t)$	Energy sold to the grid by entity u	[kWh]
$E_u^d(t)$	BESS discharging energy of entity u	[kWh]
$E_u^c(t)$	BESS charging energy of entity u	[kWh]
$S_u(t)$	Energy level of BESS of entity u	[kWh]
$E^l(t)$	Overall REC loads	[kWh]
$E^n(t)$	Net energy injected into the grid by the REC	[kWh]
$E^p(t)$	Overall energy generation by non-schedulable producers	[kWh]
$J_{u,0}$	Net profit of entity u when operating standalone	[€]
J_u	Net profit of entity u when operating within the REC	[€]
$\mathcal{R}_j$	DR request	–
$\mathcal{I}(\underline{t}_j, \bar{t}_j)$	Time horizon of DR request $\mathcal{R}_j$	–
$\underline{E}_j^{DR}, \overline{E}_j^{DR}$	Lower and upper energy bounds for DR request $\mathcal{R}_j$	[kWh]
$\overline{\gamma}_j$	Maximum DR reward for DR request $\mathcal{R}_j$	[€]
γ_j	DR reward for DR request $\mathcal{R}_j$	[€]
E_j^{DR}	Net energy injected into the grid in $\mathcal{I}(\underline{t}_j, \bar{t}_j)$	[kWh]
$\mathcal{R}$	DR program, $\mathcal{R} = \{\mathcal{R}_1, \dots, \mathcal{R}_R\}$	–
γ	Total reward for DR program $\mathcal{R}$	[€]
α	Fraction of γ_j retained by the REC manager	–
Ψ_u	Revenue of entity u for selling energy to the grid	[€]
ξ_u	DR reward assigned to entity u	[€]
$z_{r,1}, z_{r,2}, z_{r,3}$	Binary variables	[–]

This paper deals with the integration of incentive-based DR [19,20] in the design of REC operation policies. In particular, we focus on the so-called price-volume model. In this paradigm, customers receive monetary incentives for maintaining consumption below a specified threshold during fixed time intervals. Price-volume DR has been successfully applied in various contexts, including load forecasting [21,22], smart buildings [23–25], electric vehicle charging station management [26–28], and market optimization [29]. Our study diverges from existing research which mainly focuses on load profile shaping, both in the general smart grid [30–33] and in the specific REC context [34–36], by investigating how DR requests can be effectively met through optimized operation of individual EES systems associated with renewable generation sources (e.g., photovoltaic (PV) panels or wind turbines) in a REC. Specifically, we assume that the DSO communicates a price-volume DR program to the REC at the beginning of each day and grants an incentive if the overall community load/generation lies within prescribed thresholds in given time intervals. These thresholds align with periods where net load reduction supports grid stability. To the best of our knowledge, this problem remains unexplored in the literature.

1.2. Novelty and contribution

This work deals with the design of an optimal scheduling policy that enables renewable energy producers equipped with battery energy storage systems (BESS) to participate in a REC and get involved in DR programs. The innovations of this paper are outlined in the following points.

- A novel mathematical formulation is introduced to address the problem of optimal management of storage systems connected to renewable generation facilities within a REC in the presence of price-volume DR requests. A major feature of such a formulation is that it always guarantees additional economic benefits to producers participating in the REC with respect to acting autonomously. The optimization problem stemming from the proposed approach turns out to be a low-complexity mixed-integer linear program (MILP) involving few binary variables, thus making the approach computationally tractable even for large REC memberships.
- Two different objective functions are introduced for the aforementioned problem. One is devoted to the maximization of the total community revenue from DR, while the other aims to maximize the total profit of REC producers. Comparisons showing the benefits and drawbacks of the two functions are provided.
- An innovative algorithm aimed at partitioning the overall community DR reward among REC members is designed. Such an assignment is based on the distribution of the reward among community entities according to a fairness principle.

Extensive numerical simulations are provided to evaluate the effectiveness of the proposed approach, as well as to emphasize the pros and cons of the overall procedure and of the considered objective functions.

1.3. Paper structure

The paper is organized as follows: in Section 2, the considered problem is formulated and models of REC entities and DR requests are reported. In Section 3, the optimization problem that yields the storage system operation policy is designed, and an algorithm for providing a fair redistribution of the community DR reward is proposed. Numerical examples are presented in Section 4 and discussed in Section 5. Finally, conclusions are drawn in Section 6.

2. Problem formulation and modeling

The REC considered in this paper consists of a set of entities (participants) $\mathcal{U}$, each equipped with a renewable generator, e.g., a PV plant, and a battery energy storage system, whose operation is scheduled by the REC manager via a centralized energy controller. The REC is also assumed to include additional entities composed by pure generators not connected to a BESS, as well as entities represented by loads. Such players contribute to the REC energy balance as a whole, but are not subject to scheduling.

2.1. REC entity model

Operation decisions are assumed to be taken at discrete time instants t within a given time horizon $\mathcal{T} = \{0, \dots, T-1\}$, e.g., one day. For each $t \in \mathcal{T}$, let $E_u(t)$ represent the amount of energy generated by entity $u \in \mathcal{U}$ in the corresponding time slot, i.e., in the time frame beginning at t and ending at $t+1$. Moreover, let $E_u^c(t)$ and $E_u^d(t)$ denote the controlled variables representing the energy injected into and drawn from the BESS, respectively, during time slot t, and let $S_u(t)$ be the BESS energy level at the beginning of the time slot, whose dynamics is modeled by the difference equation

$$S_u(t+1) = S_u(t) + \eta_u^c E_u^c(t) - \frac{1}{\eta_u^d} E_u^d(t), \tag{1}$$

where $0 < \eta_u^c < 1$ $[0 < \eta_u^d < 1]$ represents the charging [discharging] efficiency. The controlled variables $E_u^c(t)$ and $E_u^d(t)$ are assumed to be bounded, i.e.,

$$0 \le E_u^c(t) \le \overline{E}_u^c, \quad 0 \le E_u^d(t) \le \overline{E}_u^d, \tag{2}$$

while $S_u(t)$ is bounded by the storage capacity, i.e.,

$$0 \le S_u(t) \le \bar{S}_u. \tag{3}$$

Let $E_u^g(t)$ be the amount of energy injected into the grid in time slot t. The energy balance of participant u relative to such time slot is therefore expressed by

$$E_u^g(t) = E_u(t) - E_u^c(t) + E_u^d(t). \tag{4}$$

The energy amount $E_u^g(t)$ is sold according to a known pricing signal $\pi_u^g(t)$ assumed known in advance, while the BESS is subject to a unitary operation cost π_u^s. Then, the net profit obtained by entity u from energy sale over the time horizon $\mathcal{T}$ is given by

$$J_{u,0} = \sum_{t \in \mathcal{T}} \Big[\pi_u^g(t) E_u^g(t) - \pi_u^s \big(\eta_u^c E_u^c(t) + \frac{1}{\eta_u^d} E_u^d(t) \big) \Big]. \tag{5}$$

Finally, the total energy provided to the REC by non-schedulable producers is denoted by $E^p(t)$, while the overall load is indicated with $E^l(t)$, so that the net energy injected into the grid by the REC in time slot t reads

$$E^n(t) = \sum_{u \in \mathcal{U}} E_u^g(t) \; + E^p(t) - E^l(t). \tag{6}$$

2.2. Demand response model

The following demand response model based on price-volume signals is considered in this paper. A DR program $\mathcal{R}$ is modeled as a sequence of DR requests sent out by the DSO to the REC manager within the time frame $\mathcal{T}$, each one consisting of a time horizon and an associated monetary reward function. A suitable reward is granted to the REC if the net energy injected into the grid by the REC falls within suitable bounds. More specifically, a DR request $\mathcal{R}_j$ is defined by the following tuple:

$$\mathcal{R}_j = \left\{ \mathcal{I}(\underline{t}_j, \bar{t}_j),\ \underline{E}_j^{DR},\ \overline{E}_j^{DR},\ \overline{\gamma}_j \right\}, \tag{7}$$

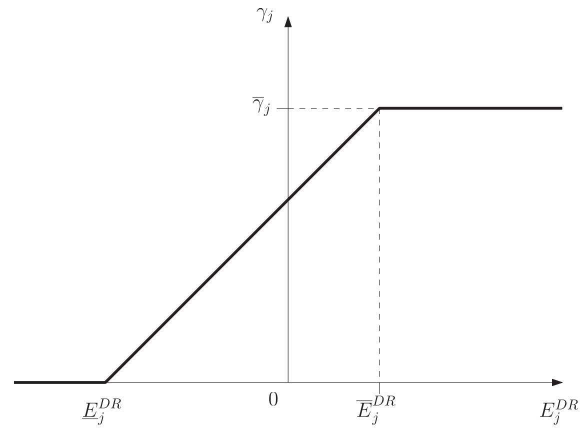

Fig. 1. Overall reward related to the j−th DR request as a function of the net energy injected in the grid.

where $\mathcal{I}(\underline{t}_j, \bar{t}_j) \subseteq \mathcal{T}$ is the time horizon and $\underline{E}_j^{DR}, \overline{E}_j^{DR}$, and $\overline{\gamma}_j$ are positive bounds. Let

$$E_j^{DR} = \sum_{t \in \mathcal{I}(\underline{t}_j, \bar{t}_j)} E^n(t) \tag{8}$$

be the net energy injected into the grid by the REC within the time frame $\mathcal{I}(\underline{t}_j, \bar{t}_j)$. Then, the reward γ_j corresponding to $\mathcal{R}_j$ granted to the REC is given by (see Fig. 1)

$$\gamma_j = \begin{cases} \overline{\gamma}_j & \text{if } E_j^{DR} \ge \overline{E}_j^{DR} \\ \frac{(E_j^{DR} - \underline{E}_j^{DR})}{(\overline{E}_j^{DR} - \underline{E}_j^{DR})} \overline{\gamma}_j & \text{if } \underline{E}_j^{DR} \le E_j^{DR} \le \overline{E}_j^{DR} \\ 0 & \text{if } E_j^{DR} \le \underline{E}_j^{DR}. \end{cases} \tag{9}$$

The overall reward associated to a given DR program $\mathcal{R}$ is given by

$$\gamma = \sum_{j : \mathcal{R}_j \in \mathcal{R}} \gamma_j.$$

It is assumed that the REC manager redistributes a portion

$$\xi = \alpha \gamma \quad (0 < \alpha < 1)$$

of the overall reward γ among the entities in $\mathcal{U}$ according to a fairness policy introduced later on, while retaining the remaining fraction to cover the profit of the REC manager itself and the reward granted to other REC participants (i.e., loads and generators without storage).

3. Optimal REC management under DR program

In this section we present the main contribution of this paper, which consists in the design of a three-step optimization procedure aimed at optimally operating the BESS resources of the community in the presence of DR programs. The key feature of the proposed method is to guarantee that for each $u \in \mathcal{U}$, the total profit obtained by joining the REC is always greater or equal to the maximum achievable profit from energy sales obtained by optimally managing the BESS resources in an autonomous fashion, which is derived as a baseline in the first step. In the second step, an optimal scheduling of the energy storage systems of producers is computed so that a suitable performance index is maximized, accounting for the constraints arising from the models sketched in the previous section. In the last step, a policy for the distribution of the DR rewards among the participants is devised based on a fairness principle.

Given a scheduling time horizon $\mathcal{T}$, the proposed three-step design procedure is broken down as follows.

Step 1. The optimal perspective profit $J^*_{u,0}$ that each single entity $u \in \mathcal{U}$ can achieve over $\mathcal{T}$ without joining the REC, i.e., without participating in the DR program, is calculated. The overall profit J^*_0 of all $u \in \mathcal{U}$ is computed and exploited in the second step as a lower bound constraint on the overall expected profit when participating in the REC.

Step 2. The optimal scheduling of the control variables of the BESSs of the whole REC under the DR program is computed in order to maximize a suitable overall REC performance index H while guaranteeing an overall profit of at least J^*_0. Possible choices for H are discussed at the end of this section.

Step 3. The redistribution of the DR reward obtained using the control policy in Step 2 is computed, ensuring both fairness among participants and a total (i.e., energy sales plus DR rewards) revenue $J^*_u \geq J^*_{u,0}$ for each $u \in \mathcal{U}$.

Let us define

$$\Psi_u = \sum_{t\in\mathcal{T}} \Big[\pi^g_u(t) E^g_u(t) - \pi^s_u \big(\eta^c_u E^c_u(t) + \frac{1}{\eta^d_u} E^d_u(t) \big) \Big], \tag{10}$$

which represents the net operation profit of entity u over the time horizon $\mathcal{T}$ arising from energy sales. Moreover, let $\hat{E}_u(t)$, $t \in \mathcal{T}$ denote a forecast of the renewable energy generation of u. Step 1 of the above procedure can be accomplished by solving for each $u \in \mathcal{U}$ an optimization problem involving the set of decision variables

$$\Theta_u = \big\{ \{ E^g_u(t),\ E^c_u(t),\ E^d_u(t),\ S_u(t),\ \forall t \in \mathcal{T} \},\ S_u(T) \big\} \tag{11}$$

and formulated as follows.

Problem 1.

$$J^*_{u,0} = \max_{\Theta_u} \Psi_u$$

subjected to:

$$0 \leq E^c_u(t) \leq \overline{E}^c_u, \quad 0 \leq E^d_u(t) \leq \overline{E}^d_u \tag{12}$$

$$S_u(t+1) = S_u(t) + \eta^c_u E^c_u(t) - \frac{1}{\eta^d_u} E^d_u(t) \tag{13}$$

$$0 \leq S_u(t) \leq \overline{S}_u \qquad \forall t \in \mathcal{T} \tag{14}$$

$$E^g_u(t) + E^c_u(t) = \hat{E}_u(t) + E^d_u(t) \tag{15}$$

$$E^c_u(t) E^d_u(t) = 0 \tag{16}$$

$$E^c_u(t) \leq \hat{E}_u(t) \tag{17}$$

$$S_u(0) = S^0_u, \quad S_u(T) = S^T_u \tag{18}$$

In Problem 1, constraints (12)–(15) derive from the models in Section 2.1, where the generation forecast time series $\hat{E}_u(t)$ is used in place of the actual generation $E_u(t)$. Moreover, (16) and (17) are used to avoid simultaneous BESS charging/discharging and BESS charging from the grid, respectively. Finally, constraints (18) ensure that the initial energy level of the storage is reset to a prescribed value at the end of the operation horizon.

Remark 1. It is not difficult to show that the complementarity constraint (16) in Problem 1 is always satisfied at the optimum and therefore it can be omitted. In fact, among all feasible solutions for which the term $\eta^c_u E^c_u(t) - \frac{1}{\eta^d_u} E^d_u(t)$ is constant, the ones satisfying either $E^c_u(t) = 0$ or $E^d_u(t) = 0$ yield a higher objective value. By neglecting constraint (16), Problem 1 turns out to be a linear program.

In order to devise the optimal REC scheduling strategy in Step 2, it is first convenient to reformulate the reward policy (9) associated to each DR request $\mathcal{R}_j$ as a set of linear inequalities involving binary variables. Indeed, it is easily seen that E^{DR}_j and γ_j satisfy (9) if and only if there exist $z_{j,1}, z_{j,2}, z_{j,3}$ such that

$$z_{j,1}, z_{j,2}, z_{j,3} \in \{0,1\} \tag{19}$$

$$z_{j,1} + z_{j,2} + z_{j,3} = 1 \tag{20}$$

$$-M z_{j,1} + \underline{E}^{DR}_j z_{j,2} + \overline{E}^{DR}_j z_{j,3} \leq E^{DR}_j \leq \underline{E}^{DR}_j z_{j,1} + \overline{E}^{DR}_j z_{j,2} + M z_{j,3} \tag{21}$$

$$-M(1 - z_{j,3}) \leq \gamma_j - \overline{\gamma}^{DR}_j \leq M(1 - z_{j,3}) \tag{22}$$

$$-M(1 - z_{j,2}) \leq \gamma_j - \frac{(E^{DR}_j - \underline{E}^{DR}_j)}{(\overline{E}^{DR}_j - \underline{E}^{DR}_j)} \overline{\gamma}^{DR}_j \leq M(1 - z_{j,2}) \tag{23}$$

$$-M(1 - z_{j,1}) \leq \gamma_j \leq M(1 - z_{j,1}) \tag{24}$$

where $M \gg 0$ denotes a constant big enough to avoid inconsistencies in the formulation.

The proposed optimal storage scheduling strategy in Step 2 is computed via the solution of the following optimization problem, where

$$J^*_0 = \sum_{u\in\mathcal{U}} J^*_{u,0}$$

and the set of decision variables is defined as

$$\Theta = \big\{ \Theta_u, \gamma_j, z_{j,1}, z_{j,2}, z_{j,3}, \forall u \in \mathcal{U},\ \forall j : \mathcal{R}_j \in \mathcal{R} \big\}. \tag{25}$$

Problem 2.

$$H^* = \max_{\Theta}\ H \tag{26}$$

subjected to:

$$(10), (12)\text{–}(18),\ \forall u \in \mathcal{U},\ \forall t \in \mathcal{T} \tag{27}$$

$$(6), (8), (19)\text{–}(24),\ \forall j : \mathcal{R}_j \in \mathcal{R} \tag{28}$$

$$\sum_{u\in\mathcal{U}} \Psi_u + \alpha \sum_{j:\mathcal{R}_j\in\mathcal{R}} \gamma_j - J^*_0 \geq 0 \tag{29}$$

Remark 2. To avoid complicating the notation, constraint (6) in Problem 2 is assumed to be evaluated for $E^p(t)$ and $E^l(t)$ equal to suitable forecasts of the respective variables.

Once Problem 2 is solved, the optimal Θ^*_u, $u \in \mathcal{U}$ yields the optimal scheduling strategy of the BESS resources. Moreover, let γ^*_j and Ψ^*_u be the optimal values of γ_j and Ψ_u, respectively. Notice that Ψ^*_u represents the operation profit of entity u under the optimal policy Θ^*_u, not considering any extra reward from DR. Finally, the optimal total DR reward for all entities in $\mathcal{U}$ is given by

$$\xi^* = \alpha \sum_{j:\mathcal{R}_j\in\mathcal{R}} \gamma^*_j. \tag{30}$$

Such a reward is to be shared among entities in $\mathcal{U}$ according to the policy described in the next subsection.

Remark 3. From a computational viewpoint, Problem 2 turns out to be a mixed-integer linear program involving a number of binary variables equal to $3R$ being R the cardinality of $\mathcal{R}$. Since the daily number of DR requests amounts to a few units at most, the total number of binary variables is low regardless of the community size. Notice that the observation concerning the possibility of neglecting the nonlinear constraint (16) still stands for Problem 2 if the objective function H is reasonably defined, e.g., as a positively weighted sum of the profits Ψ_u and of the DR rewards γ_j, due to the monotonicity of γ_j with respect to E^{DR}_j. This will indeed be the case with the indices proposed later on.

3.1. DR reward redistribution

Let ξ^*_u, $u \in \mathcal{U}$ denote a partition of ξ^* among the entities of $\mathcal{U}$, i.e.,

$$\sum_{u\in\mathcal{U}} \xi^*_u = \xi^*, \quad \xi^*_u \geq 0. \tag{31}$$

The total profit of entity $u \in \mathcal{U}$ in the presence of DR is then given by

$$J^*_u = \Psi^*_u + \xi^*_u.$$

As previously discussed, the partitioning is deemed convenient if for all $u \in \mathcal{U}$, the total profit equals at least the baseline $J^*_{u,0}$, i.e.,

$$J^*_u \geq J^*_{u,0} \quad \forall u \in \mathcal{U}. \tag{32}$$

Hence, we look for a partition ξ^*_u, $u \in \mathcal{U}$ satisfying (31), (32). Many possible schemes can be devised to this purpose. In the following, we propose a reward assignment based on a fairness principle, which guarantees to all entities a reward proportional to their baseline profit. To this purpose, we introduce the ratio

$$\rho = \frac{\Psi^* + \xi^* - J^*_0}{J^*_0} \tag{33}$$

being

$$\Psi^* = \sum_{u \in \mathcal{U}} \Psi^*_u.$$

By virtue of constraint (29) in Problem 2, it turns out that $\rho \geq 0$. Let us define ξ^*_u as

$$\xi^*_u = (1+\rho)J^*_{u,0} - \Psi^*_u. \tag{34}$$

This corresponds to a total entity profit

$$J^*_u = (1+\rho)J^*_{u,0}.$$

Hence, the partition (34) trivially satisfies (32), while (31) simply follows by taking the sum of both sides of (34) over all $u \in \mathcal{U}$ and using (33).

Clearly, the additional profit gained by u by joining the REC is given by

$$\delta_u = \rho J^*_{u,0}.$$

Note that fairness among entities is guaranteed by the proposed sharing policy since the extra profit obtained by each producer δ_u is proportional to the profit achieved if operating autonomously. In other words, ρ denotes the ratio between the additional profit and the baseline, for each entity.

It is worth remarking that reward distribution policies different from the one proposed here can be easily devised. In fact, the computations in steps 1 and 2 are independent of the particular distribution strategy implemented in step 3.

3.2. Performance indices

Depending on the main aims of the community (e.g., maximizing the REC manager profit, maximize the overall revenue of entities, etc.), several objective functions H can be defined for Problem 2. The following two choices are proposed and compared in this paper:

- *REC manager interest:* the objective function is taken equal to the revenue of the REC manager, i.e.,

$$H = H^M = (1-\alpha) \sum_{j:\mathcal{R}_j \in \mathcal{R}} \gamma_j. \tag{35}$$

  Note that maximizing H^M is equivalent to maximizing the overall DR reward gained by the community.
- *Overall entities' interest*: the considered objective function is the total profit of the entities $u \in \mathcal{U}$, i.e.,

$$H = H^E = \sum_{u \in \mathcal{U}} \Psi_u + \alpha \sum_{j:\mathcal{R}_j \in \mathcal{R}} \gamma_j. \tag{36}$$

Different choices of the performance index H are indeed possible, as well as different definitions of the reward redistribution policy. Such extensions will be the topic of further research.

4. Test cases

This section offers two examples to validate the proposed approach. The first one is a simple illustrative example aimed at showing the main features of the procedure, while the second one has the purpose to evaluate the performance and the computational feasibility of the proposed technique in a larger scale practical setting. In all simulations, the optimization horizon $\mathcal{T}$ is assumed to span 24 hours with a sampling time of $\tau_s = 15$ minutes. In both examples, the parameters of the energy storage systems as well as the energy generation profiles of the various entities have been obtained by a suitable scaling of the real data used in [37]. For all entities u, the considered initial and final BESS energy levels are $S^0_u = S^T_u = 0$, the charging and discharging efficiencies are set to $\eta^c_u = \eta^d_u = 0.95$, and the unit price of the energy sold to the grid $\pi^g_u(t)$ is set as the time series depicted in green in Fig. 2, while the unitary cost for operating the storage system is $\pi^s_u = 0.01$ €/kWh. Simulations are performed assuming the availability of suitable forecasts of the generation profiles of each PV producer. The generation data cover the period from April 1, 2019 to April 30, 2019, for a total of 30 days. Simulations and optimization of Problems 1 and 2 have been implemented in Python and solved using the CPLEX solver [38] on an Intel i7-11700@3.60 GHz, 16 GB of RAM. Results from the simulations are discussed in Section 5.

Example 1. In this illustrative example, a community composed of two PV producers equipped with a BESS is considered. The nominal peak power of the PV plant of the first entity is set to $\overline{P}_1 = 700$ kW, with a battery capacity $\overline{S}_1 = 500$ kWh. In contrast, the second entity can supply generation with $\overline{P}_2 = 300$ kW peak power, with a battery capacity $\overline{S}_2 = 250$ kWh. We assume two DR requests for each day. The parameters associated with each request are provided in Table 1. Such DR requests are assumed to remain the same in all the considered days.

In Table 2, the following daily amounts are reported for 5 simulation days: the optimal total daily profit of entities when operating outside the REC (J^*_0), the total daily extra profit of the entities when joining the REC ($\delta_1 + \delta_2$), and the total daily DR reward received at REC level ($\gamma^*_1 + \gamma^*_2$). Results for both objective functions H^E and H^M introduced in Section 3.2 are reported. The individual profit for each entity under Problem 1 ($J^*_{u,0}$) and Problem 2 (J^*_u) for both objective functions, as well as the corresponding ρ are reported in Table 3. The time evolution of relevant energy signals concerning Entity 1 (along with that of energy selling price) in a representative day (day 24) are reported in Fig. 2, assuming the entity operates individually without joining the REC (Problem 1). The case of the same entity participating in the REC according to the proposed scheduling under the objective function H^E is depicted in Fig. 3. The daily extra profits gained by both entities under the objective functions H^E and H^M, are illustrated in Fig. 4. Fig. 5 shows the daily reward for the two DR requests $\mathcal{R}_1$ and $\mathcal{R}_2$, under the two objective functions H^E and H^M.

Example 2. In this example, a community composed of 30 PV producers equipped with energy storage systems is considered. The peak power $\overline{P}_u$ of the PV plant of each entity and the corresponding battery capacity $\overline{S}_u$ are shown in Table 5.

Two DR requests are considered for each day, with random start and duration, so that $\underline{t}_j$ and $\overline{t}_j$ can differ each day ($\underline{t}_2 > \overline{t}_1$). The lower and upper energy bounds for DR requests are fixed, and they equal to $\underline{E}^{DR}_1 = \underline{E}^{DR}_2 = -10000$ kWh, $\overline{E}^{DR}_1 = 10000$ kWh and $\overline{E}^{DR}_2 = 50000$ kWh, while both $\overline{\gamma}_1$ and $\overline{\gamma}_2$ are fixed to 3000€. For a representative day (day 3), the total load of the community and the total generation by producers not equipped with a BESS are reported in Fig. 6, while the net energy injected into the grid is depicted in Fig. 7. Table 6 summarizes the profit of each unit both when working individually and when joining the community, for three days of simulation. Finally, the overall extra profit and DR reward of all entities are reported in Table 7.

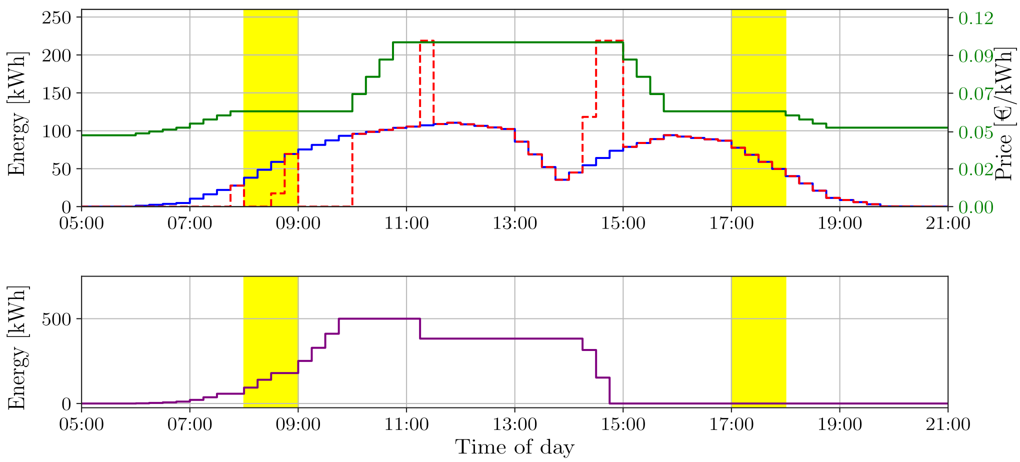

Fig. 2. Results for Entity 1 on day 24 under Problem 1. Energy production forecast $\hat{E}_u(t)$ (blue), sold energy $E_u^g(t)$ (dashed red), energy selling price $\pi_u^g(t)$ (green), storage energy level $S_u(t)$ (purple), and time periods of DR requests (yellow). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

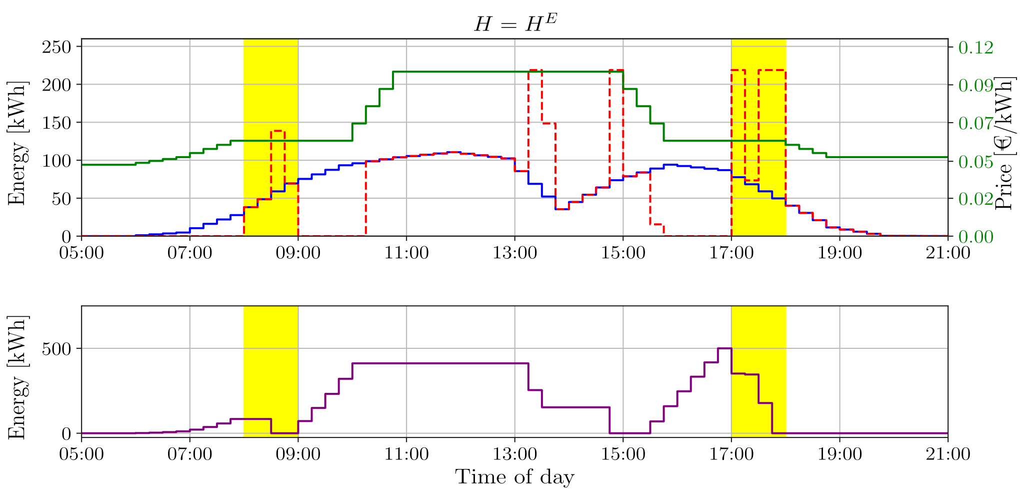

Fig. 3. Example 1. Results for Entity 1 on day 24 under Problem 2 with $H = H^E$. Energy production forecast $\hat{E}_u(t)$ (blue), sold energy $E_u^g(t)$ (dashed red), energy selling price $\pi_u^g(t)$ (green), storage energy level $S_u(t)$ (purple), and time periods of DR requests (yellow). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

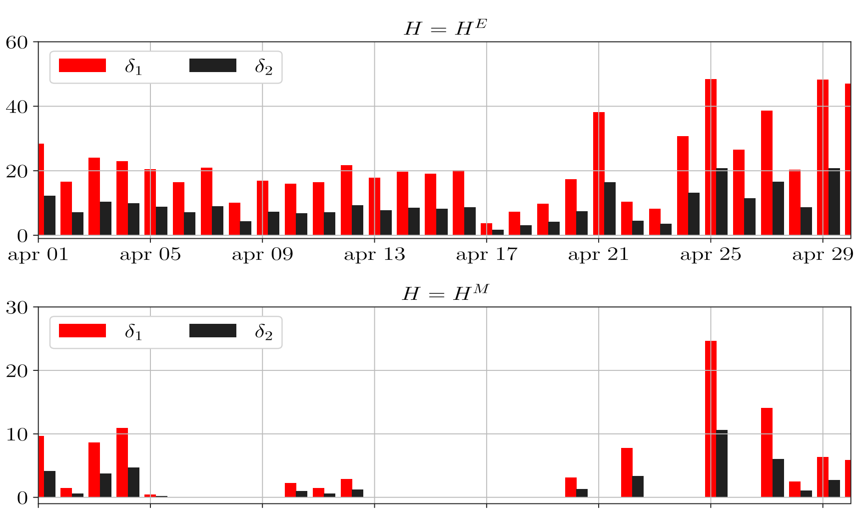

Fig. 4. Example 1. Daily additional profits δ_1 and δ_2 under the objective functions H^E (top) and H^M (bottom).

Table 1
Example 1. Set of DR requests for all days.

Request ID	$\underline{t}_j$	$\bar{t}_j$	$\underline{E}_j^{DR}$[kWh]	$\overline{E}_j^{DR}$[kWh]	$\overline{\gamma}_j[e]$	α
$\mathcal{R}_1$	08:00	09:00	0	800	65	0.85
$\mathcal{R}_2$	17:00	18:00	0	1400	65	0.85

Table 2
Example 1. Total daily amounts related to two different objective functions H, in 5 simulated days.

		$H = H^E$		$H = H^M$	
Date	J_0^*[€]	$\delta_1 + \delta_2$[€]	$\gamma_1^* + \gamma_2^*$[€]	$\delta_1 + \delta_2$[€]	$\gamma_1^* + \gamma_2^*$[€]
04–01	438.33	40.59	74.56	13.84	82.15
04–02	355.10	23.63	47.48	2.08	62.49
04–03	403.71	34.39	67.28	12.35	77.46
04–04	406.58	32.68	64.60	15.65	75.59
04–05	375.59	29.11	61.20	0.58	72.08

Table 3
Example 1. Profit of each entity working outside the REC and profit and fairness index for different objective functions H, in 5 simulated days.

			$H = H^E$			$H = H^M$		
Date	$J_{1,0}^*$[€]	$J_{2,0}^*$[€]	J_1^*[€]	J_2^*[€]	ρ	J_1^*[€]	J_2^*[€]	ρ
04–01	306.48	131.85	334.86	144.06	0.092	316.15	136.01	0.0316
04–02	248.55	106.55	265.09	113.64	0.066	250.01	107.18	0.0050
04–03	282.25	121.46	306.29	131.81	0.085	290.88	125.18	0.0031
04–04	284.28	122.30	307.13	132.13	0.080	295.233	127.01	0.0385
04–05	262.87	112.72	283.24	121.46	0.077	263.27	112.9	0.0015

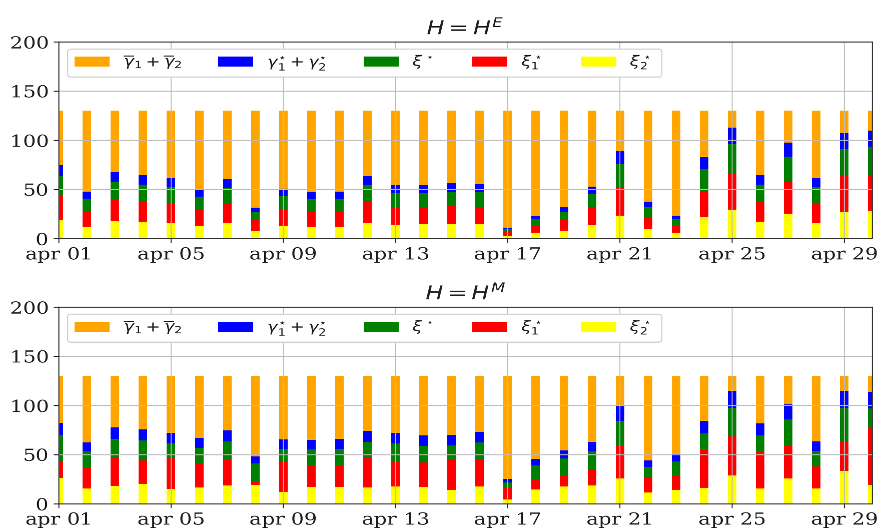

Fig. 5. Example 1. Daily DR reward profiles for requests 1 and 2, under the objective functions H^E (top) and H^M (bottom). Maximum achievable DR reward $\overline{\gamma}_1 + \overline{\gamma}_2$ (orange), actual DR reward at community level $\gamma_1^* + \gamma_2^*$ (blue), DR reward of Entity 1 ξ_1^* (red) and 2 ξ_2^* (yellow), and total reward of entities $\xi^* = \xi_1^* + \xi_2^*$ (green). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Example 1. Extra profits and achieved DR rewards under H^E and H^M, for different values of the maximum DR reward.

		$\overline{\gamma}_j = 40$[€]				$\overline{\gamma}_j = 100$[€]			
		$H = H^E$		$H = H^M$		$H = H^E$		$H = H^M$	
Date	J_0^*[€]	$\delta_1 + \delta_2$[€]	$\gamma_1^* + \gamma_2^*$[€]	$\delta_1 + \delta_2$[€]	$\gamma_1^* + \gamma_2^*$[€]	$\delta_1 + \delta_2$[€]	$\gamma_1^* + \gamma_2^*$[€]	$\delta_1 + \delta_2$[€]	$\gamma_1^* + \gamma_2^*$[€]
04–01	438.33	19.13	30.2	0.0	50.55	77.77	126.38	57.16	126.38
04–02	355.10	10.08	18.1	0.0	38.45	51.41	96.13	37.37	96.13
04–03	403.71	15.01	27.31	0.0	47.67	69.29	119.17	44.21	119.17
04–04	406.58	14.13	26.16	3.59	46.52	66.68	116.29	62.90	116.29
04–05	375.59	11.68	24.00	0.55	44.36	61.50	110.89	56.74	110.89

5. Discussion

In this section, the results of the simulations provided in the above examples are commented in detail. First, let us focus on Example 1. From Table 2, one can notice that the total extra profit of entities ($\delta_1 + \delta_2$) is consistently higher under the objective function H^E compared to H^M, across all days. On the contrary, the community daily DR reward ($\gamma_1^* + \gamma_2^*$), and hence the revenue of the REC manager, is higher when the objective function H^M is employed. Such results are consistent with the goals of the two objective functions, as reported in Section 3.2. As shown in Table 3, the proposed DR reward redistribution approach ensures that all entities receive a reward proportional to the individual

Table 5
Example 2. Values of entity parameters.

Entity	1	2	3	4	5	6	7	8	9	10
$\overline{P}_u$	548	412	652	592	364	320	468	588	540	556
$\overline{S}_u$	603	277	744	377	291	169	344	711	298	717
Entity	11	12	13	14	15	16	17	18	19	20
$\overline{P}_u$	516	600	412	400	356	360	472	416	476	464
$\overline{S}_u$	403	563	334	342	370	377	324	245	270	253
Entity	21	22	23	24	25	26	27	28	29	30
$\overline{P}_u$	524	696	584	440	328	528	320	364	648	388
$\overline{S}_u$	474	846	624	344	213	527	181	435	499	402

Table 6
Example 2. Profit of all entities acting individually ($J_{i,0}^*$) and joining the community (J_i^*), $i = 1, \ldots, 30$ under H^E, in 3 simulation days.

Date	$J_{1,0}^*$	$J_{2,0}^*$	$J_{3,0}^*$	$J_{4,0}^*$	$J_{5,0}^*$	$J_{6,0}^*$	J_1^*	J_2^*	J_3^*	J_4^*	J_5^*	J_6^*
04–01	242.18	180.15	288.2	258.55	159.79	139.27	351.66	261.59	418.48	375.43	232.02	202.24
04–02	194.64	146.24	231.58	210.07	129.28	113.1	281.56	211.55	334.99	303.88	187.02	163.62
04–03	222.17	165.89	264.33	238.06	147.19	128.2	298.25	222.69	354.85	319.57	197.59	172.1
Date	$J_{7,0}^*$	$J_{8,0}^*$	$J_{9,0}^*$	$J_{10,0}^*$	$J_{11,0}^*$	$J_{12,0}^*$	J_7^*	J_8^*	J_9^*	J_{10}^*	J_{11}^*	J_{12}^*
04–01	205.04	259.91	235.2	245.76	226.41	264.58	297.73	377.40	341.52	356.86	328.76	384.19
04–02	166.2	208.84	191.04	197.48	183.27	213.10	240.43	302.11	276.35	285.67	265.11	308.27
04–03	188.84	238.39	216.5	225.41	208.55	243.2	253.50	320.02	290.64	302.60	279.96	326.48
Date	$J_{13,0}^*$	$J_{14,0}^*$	$J_{15,0}^*$	$J_{16,0}^*$	$J_{17,0}^*$	$J_{18,0}^*$	J_{13}^*	J_{14}^*	J_{15}^*	J_{16}^*	J_{17}^*	J_{18}^*
04–01	180.94	175.92	157.26	159.04	206.48	181.41	262.74	255.44	228.36	230.94	299.83	263.42
04–02	146.33	142.07	126.44	127.86	167.56	147.39	211.68	205.51	182.91	184.96	242.39	213.21
04–03	166.68	162.04	144.33	145.95	190.14	167.01	223.75	217.52	193.75	195.93	255.25	224.20
Date	$J_{19,0}^*$	$J_{20,0}^*$	$J_{21,0}^*$	$J_{22,0}^*$	$J_{23,0}^*$	$J_{24,0}^*$	J_{19}^*	J_{20}^*	J_{21}^*	J_{22}^*	J_{23}^*	J_{24}^*
04–01	207.44	202.06	230.81	307.65	258.03	193.06	301.21	293.40	335.16	446.72	374.68	280.35
04–02	168.51	164.12	186.11	247.2	207.42	156.27	243.76	237.40	269.22	357.60	300.05	226.07
04–03	190.96	186.0	212.34	282.17	236.76	177.84	256.35	249.69	285.06	378.79	317.84	238.73
Date	$J_{25,0}^*$	$J_{26,0}^*$	$J_{27,0}^*$	$J_{28,0}^*$	$J_{29,0}^*$	$J_{30,0}^*$	J_{25}^*	J_{26}^*	J_{27}^*	J_{28}^*	J_{29}^*	J_{30}^*
04–01	143.31	233.18	139.44	160.9	284.22	171.39	208.10	338.60	202.48	233.63	412.71	248.87
04–02	116.4	187.53	113.28	129.28	230.16	137.80	168.39	271.28	163.86	187.02	332.93	199.35
04–03	131.96	214.06	128.37	147.57	261.79	157.30	177.15	287.36	172.32	198.10	351.43	211.17

Table 7
Example 2. Total daily amounts related to two different objective functions H, in 5 simulated days.

		$H = H^E$		$H = H^M$	
Date	J_0^*	$\sum_{u\in\mathcal{U}} \delta_u$	$\sum_{j:R_j\in R} \gamma_j^*$	$\sum_{u\in\mathcal{U}} \delta_u$	$\sum_{j:R_j\in R} \gamma_j^*$
04–01	6297.61	2846.95	3996.31	2550.03	3996.31
04–02	5086.64	2271.51	2469.96	1937.66	2853.52
04–03	5790.00	1982.63	2573.94	1767.63	2601.74
04–04	5829.33	1884.17	2415.16	1559.73	2525.93
04–05	5378.23	3006.71	3118.36	2667.43	3488.99

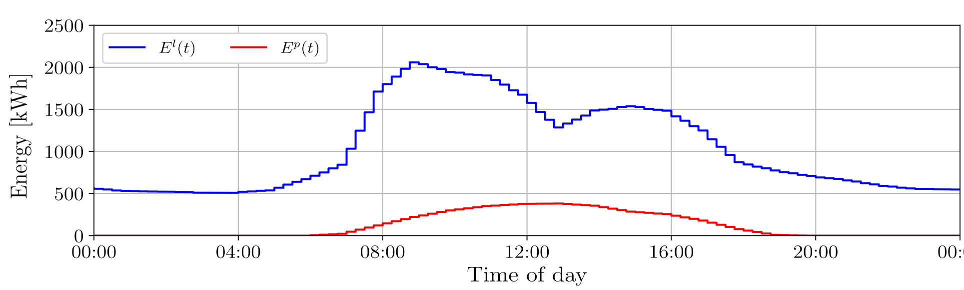

Fig. 6. Example 2 Overall REC loads (blue), overall energy generation by non-schedulable producers (red) on day 3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

profits obtained when operating independently. However, the factor ρ is considerably smaller when considering the objective function H^M, which implies a reduction of the extra profit for all entities.

Fig. 2 , which refers to standalone operation, reveals that during the early hours of the day, when the selling price is low, the entity prioritizes storing its energy production, while discharging starts occurring around 10:00 to take advantage higher selling prices. By 14:00, the BESS is fully discharged to avoid selling the stored energy at lower prices. On the other hand, when joining the REC, both entities stop charging and start exporting their energy production once the first DR request horizon begins (see Fig. 3). During this period, Entity 1 exports 294 kWh, while Entity 2 exports 126 kWh. After the first DR request ends, entities resume charging due to low energy price and later export to the grid during the period with highest energy price. Between 15:15 and 17:00 charging is restarted again, thus allowing for subsequent discharge. This strategy enables Entities 1 and 2 to provide 729 kWh and 318 kWh, respectively, during the second DR request. From Fig. 4 it is apparent that both δ_1 and δ_2 are higher

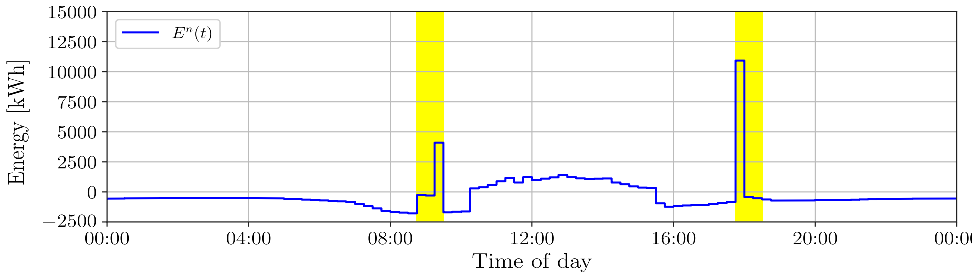

Fig. 7. Example 2 Net energy injected into the grid by the REC under H^E (blue), and period of DR requests (yellow) on day 3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

when the objective function is set to H^E compared to H^M. This result is expected, as H^E is designed to maximize the total revenue of the entities, whereas H^M focuses on maximizing the revenue of the REC manager, which naturally leads to lower extra profits for the entities. Fig. 4 also shows that a fair redistribution of rewards occurs among the entities, that is, the additional profit from REC participation is proportional to their respective individual revenue when operating independently, i.e., outside the REC. This ensures that the additional profits δ_1 and δ_2 are allocated equitably, reflecting the contribution provided by each entity to the REC. Notice that, when the objective function H^M is used, $\delta_1 = \delta_2 = 0$ on some days, that is, the profit of the entities joining the REC equals the profit they would gain if acting individually.

Regarding the DR rewards assigned to the entities, Fig. 5 shows that when optimizing H^M, the total community reward is no less than that obtained by using H^E, as expected. However, even if optimizing H^M, the REC is in general unable to provide the upper DR request energy bounds (i.e., $\gamma_1^* + \gamma_2^* < \overline{\gamma}_1 + \overline{\gamma}_2$). Clearly, the sum of the rewards assigned to the two entities is less than the total reward received by the community, since a fraction of it is retained by the REC manager according to (30).

The sensitivity of the proposed method with respect to the DR reward bound $\overline{\gamma}_j$ is explored in Table 4. When the DR reward bound $\overline{\gamma}_j$ is increased from 40 to 100€, the achieved DR rewards $\gamma_1^* + \gamma_2^*$ under both objectives H^E and H^M are the same. This basically means that the DR reward is large enough to make fulfillment of DR requests always advantageous regardless of all costs and energy losses arising when operating storage. So, any further increase in $\overline{\gamma}_j$ will provide the same BESS control commands and consequently the same amount of energy injected into the grid.

Concerning Example 2, in Fig. 7 it can be observed that entities discharge their storage systems during the DR periods to increase the energy injected into the grid. This contributes to achieving the REC monetary reward, which is then shared among entities, thus allowing them to substantially increase their profit compared to the baseline, see Tables 6 and 7. Regarding the two considered objective functions H^E and H^M, they yield behaviors similar to those in Example 1, i.e., favoring the entity profit and the total DR reward, respectively.

Example 2 allows one to evaluate the computational burden of the proposed procedure. Indeed, it turns out that the algorithm is computationally tractable even in the presence of a large number of entities. In fact, the average time needed to solve 30 instances of Problem 1 and one instance of Problem 2 for the time frame of one day is about 0.15 s on average, thus allowing this technique to be practically adopted in real-world scenarios. The low computational effort of the whole procedure is due to two reasons: first, Problem 1 which needs to be solved for each entity is a linear program, and so it can be efficiently solved by standard tools; second, although Problem 2 is a MILP, the low number of involved integer variables allows it to be quickly solved at the optimum.

Summarizing, the obtained results highlight the possibility of exploiting the potential of DR to increase the benefits associated to REC participation. In this specific context, DR turns out to be a viable alternative/complement to commonly employed incentive-based paradigms such as those presented in [37]. On the downside, the proposed optimization framework is expected to be sensitive to uncertainty in load and generation forecasts. In this respect, stochastic formulations explicitly accounting for such uncertainty can help improve robustness of storage operation policies and are the subject of current investigation. Finally, although the proposed formulation is reasonably general, a further effort is necessary in order to tailor the performance objective and the problem constraints to specific local regulations and to the presence of different types of players within the REC such as, e.g., prosumers.

6. Conclusion and future research

In this paper, the potential of coordinating storage operations inside a REC in the presence of DR programs has been investigated. Under the assumption that the REC is involved in price-volume DR programs, a novel 3-step procedure has been proposed to optimize individual storage operation with respect to objective functions that represent overall community benefit. The proposed approach guarantees both an increased profit for REC producers compared to optimally acting outside the community, and the redistribution of DR rewards among participants according to a fairness principle. The optimization procedure involves the solution of an LP for each schedulable entity and of one MILP with only few integer variables irrespective of the community size, thus making the approach viable for large-scale problem instances. Extensive numerical simulations have been provided showing the effectiveness of the proposed method and comparing the results under two different objective functions.

The results obtained in this work explored the potential of DR in the management of RECs and showed that DR programs can be efficiently handled in an optimal fashion within this context, both as an alternative and as a complement to commonly used incentive-based models.

Future work will focus on the extension of the proposed procedure to different performance indices and reward redistribution policies accounting for specific local regulations. A further development will address the presence of REC prosumers and stochastic behavior of participating entities, as well as uncertainty affecting load and generation profiles.

CRediT authorship contribution statement

Gianni Bianchini: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Marco Casini:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Conceptualization. **Milad Gholami:** Writing – original draft, Validation, Software, Investigation, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Marco Casini reports financial support was provided by European Union. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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