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Control Frameworks for Transactive Energy Storage Services in Energy Communities

Preprint, compiled October 31, 2022

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Abstract

Recently, the decreasing cost of storage technologies and the emergence of economy-driven mechanisms for energy exchange are contributing to the spread of energy communities. In this context, this paper aims at defining innovative transactive control frameworks for energy communities equipped with independent service-oriented energy storage systems. The addressed control problem consists in optimally scheduling the energy activities of a group of prosumers, characterized by their own demand and renewable generation, and a group of energy storage service providers, able to store the prosumers' energy surplus and, subsequently, release it upon a fee payment. We propose two novel resolution algorithms based on a game theoretical control formulation, a coordinated and an uncoordinated one, which can be alternatively used depending on the underlying communication architecture of the grid. The two proposed approaches are validated through numerical simulations on realistic scenarios. Results show that the use of a particular framework does not alter fairness, at least at the community level, i.e., no participant in the groups of prosumers or providers can strongly benefit from changing its strategy while compromising others' welfare. Lastly, the approaches are compared with a centralized control method showing better computational results.

Publication doi: https://doi.org/10.1016/j.conengprac.2022.105364

1 Introduction

A powerful solution contributing to the green transformation of modern power systems is represented by the so-called *energy community* [1]. The term denotes a community of users (private, public, or mixed) located in a specific reference area, where all stakeholders – such as end-users (e.g., citizens, companies, etc.), market players (e.g., utilities, service providers), practitioners, planners and policy-makers – actively cooperate to develop a 'smart' energy system. More specifically, these communities promote the optimal exploitation of renewable sources and the widespread use of distributed storage while enabling the application of measures oriented to cost-effectiveness, sustainability, and reliability [1, 2, 3]. In the last years, the community action on the use of renewable energy has increased remarkably, pushed by several energy-efficiency initiatives as well as financial incentives [4, 5].

Fostered by the decreasing cost of storage technologies and emerging mechanisms of energy exchange and sharing, a viable solution to attain self-consumption of on-site production is represented by the use of *energy storage systems* (ESSs) that are valuable resources of the community at the local level [6]. The use of ESSs allows users to create energy arbitrage by discharging during price peaks and charging during off-peak periods if a variable energy price is considered [7, 8]. In addition, ESSs contribute to the overall resilience of the energy community when facing systematic failures or natural disasters [9]. Moreover, ESSs guarantee stability and power quality when uncertain renewable energy sources, such as wind power and photovoltaic, highly influence the energy community [10, 11]. Nevertheless, the full penetration of ESSs presents various challenges. Due to economic and logistic reasons, the deployment of on individual ESS for each prosumer is not always a viable option. Conversely, sharing ESSs among prosumers or relying on energy storage services innovatively offered by providers is a widespread solution in energy communities [12, 13].

Among the most popular methods, the *transactive control* techniques are especially suitable to address the issues related to the energy storage sharing in a sustainable and reliable fashion [14]. Indeed, transactive energy management methods incorporate powerful economy driven control mechanisms for effectively coordinating and trading energy flows among the actors of microgrids and energy communities [15]. Differently from peer-to-peer (P2P) energy trading, that suffers from sustainability issues (if a prosumer sells energy to another one, the former gains an economical bonus, but it is not guaranteed that the latter will be able to provide energy to the former when needed: in such a case, the prosumer lacking energy will be forced to resort to the retailer [16]), the deployment of energy storage services continuously guarantee that the amount of stored energy is available for future use, injecting back energy sourced from renewable means.

In this context, this paper aims at defining innovative transactive control frameworks to optimally manage and share energy within a community with multiple and independent service-oriented energy storage systems. In particular, the considered energy community comprises prosumers, characterized by their own demand and renewable generation, and energy storage service providers, able to store the prosumers energy surplus and subsequently release it upon a fee payment. The addressed control problem consists in optimally scheduling the energy activities of prosumers and providers, relying on an economy-driven mechanism, in order to make the prosumers' energy supply more efficient,

How to cite: Nicola Mignoni, Paolo Scarabaggio, Raffaele Carli, Mariagrazia Dotoli, "Control frameworks for transactive energy storage services in energy communities", Control Engineering Practice, Volume 130, 2023, 105364, ISSN 0967-0661

while creating a sustainable and profitable business model for storage providers. In order to guarantee a solution to the problem, an energy retailer, characterized by conventional power generation, allows prosumers to buy/sell energy from/to the main grid. The novel proposed resolution algorithms are based on a game theoretical control formulation of the transactive energy storage management problem. In particular, a coordinated and an uncoordinated control scheme are defined, to be alternatively used depending on the underlying communication architecture of the grid. The two proposed approaches are validated through numerical simulations on realistic scenarios. Lastly, the approaches are compared with a centralized control method showing better computational results.

1.1 Related Works

The traditional approach in utilizing energy resources relies on the individual distributed framework, in which an individually-owned resource is installed for each user separately [17]. Due to the logistic and cost inefficiency of such a framework, and the spread of energy community initiatives, recent studies suggest the sharing strategy for the utilization of key components such as ESSs to fully exploit their potentials [18]. However, no unifying framework has been proposed in the face of several access schemes based on the paradigms of physical/financial rights and of resource capacity/energy sharing [19]. A comprehensive review of the design and application of shared ESSs is provided in [20]. In such a paper, authors provide an architectural classification of shared ESSs, categorized into *private*, *interconnected*, *common*, and *independent* ESS solutions. Private and interconnected ESSs, which contemplate the presence of one ESS per user, are a highly inefficient solution, due to high infrastructural and maintenance costs as well as to the necessity of a dedicated physical space [20]. For these reasons, researchers are focusing on both the alternatives of common and independent ESSs. The former type of ESS consists of an ESS block that can be simultaneously accessed by multiple users. Control strategies for this architecture include formulations as resource allocation problem [21] and aggregator-based management [22]. Conversely, in the independent ESS architecture, storage devices are independently managed by profit-driven operators. Thus, the necessity of designing an adequate market mechanism for handling the interactions between ESS operators and users is necessary. For instance, authors in [23] propose a market framework considering the ESS operator as a stand-alone agent that evaluates the optimal storage trading strategy. In [24], a Stackelberg game-based energy trading strategy is developed for minimizing the energy cost in a neighborhood area with an independent shared ESS.

Many of the common and independent ESS applications fall in the realm of the *sharing economy* (SE) business model (also known as *access economy*), which has been growing in popularity in the last decade. Companies such as Airbnb and Uber are just two of the numerous examples of this economic paradigm. In [25] the opportunities arising from adopting SE models in energy communities have been explored. In particular, the authors consider a collection of firms that invest in ESS to arbitrage against variable energy prices and share the surplus of their stored energy. Authors in [26] show that applications of SE paradigms in ESS are an economically attractive solution for both ESS operators as well as ESS investors. In [27] the potential of shared ESS for a neighborhood area is demonstrated, in which residents are able to dynamically optimize the energy load the energy storage level to minimize their electricity costs. Regarding control schemes of SE applications of ESS, authors in [28] explore different market design options based on cooperative and non-cooperative game-theoretic models, showing that the SE reduces the cost volatility for most users while keeping the community operational costs unchanged. Among the different SE-based implementations of shared ESS, two promising concepts are the *Virtual ESS* (VESS) [29, 30] and the *Cloud ESS* (CESS) [31, 32]. The VESS is inspired by the *Virtual Power Plant* (VPP) concept. VPPs work as aggregators of coordinated distributed energy sources, in order to optimize the energy supply. Similarly, the VESS concept is based on integrating different distributed ESSs, in order to create a virtual single storage system, able to serve users in the network. In [33], an agent-based ESS management system is proposed for allowing the integration of storage devices into a VESS. Authors in [34] investigate the value of merchant-owned ESS in the day-ahead electricity market, developing an offering strategy for operating and optimizing the virtual storage plant constructed by merging the merchant-owned ESS units. In [35], a two-stage optimization model for VESS sharing is studied, where, in the first phase, the investment and pricing for the storage capacity are determined by the aggregator, while the purchase of virtual capacity is performed by the users during the second phase. As for the CESS, the originating idea is borrowed from *cloud computing* in computer science, where distributed machines are coordinated to provide data storage and computational power efficiently and readily. CESS adopts the same concept for ESS, differing from VESS in terms of size, since CESS applications are meant to reach grid-scale energy markets. In [31], the authors propose the concept of CESS which is constructed by centralizing ESS resources. The same authors also demonstrate the benefits of CESS by investigating the investment and operating decisions of both the CESS coordinator and the consumers [36]. Regarding the control mechanisms for CESS, peer-to-peer energy sharing and coordination mechanisms are designed in [32] in order to make the penetration of renewable energy sources more effective.

1.2 Paper Contribution

From the above literature review, it follows that the majority of studies on multiple ESS sharing focuses on the economy-driven control mechanisms that enable the interaction between the users and ESS operators. Despite the rich state of the art on the energy storage services and management, very few research studies pay attention to crucial operational aspects of the adopted transactive mechanism. In fact, in order to allow the large-scale deployment of VESSs or CESSs, challenges such as practical effectiveness, computational efficiency, scalability, and privacy are obviously of primary importance.

Differently from the reviewed works, the contributions of this paper can be summarized as follows.

- We define a transactive energy management model, characterized by limited information sharing and a scalable communication architecture, which includes two groups of participants, namely, the energy storage service providers and the energy community prosumers (intended as customers of the energy storage service). Thanks to its scalability, the proposed approach can be implemented more efficiently than contributions [23, 24], where only a single ESS can be handled. Moreover, differently from [32], where the ESS is considered as ideal, in our work we employ a realistic model, which accounts for energy losses.
- Differently from most approaches, such as [31, 27], that consider only a central coordinator managing all the different aspects of the energy community, we also propose a non-coordinated and fully distributed control architecture. However, we do not employ cooperative frameworks, such as [32], that cannot fully capture the real market interactions, or non-cooperative ones that are computationally demanding [28]. In fact, we develop uncoordinated and coordinated distributed control frameworks, which reach an overall economic performance close to the optimal centralized global formulation, whose implementation is in turn impractical for service-based solutions and is unfeasible from a computational point of view.
- Moreover, we avoid straightforward investments analysis act to to guarantee economic feasibility such as in [25, 26], but we fully analyze the proposed approach from an operational point of view, ensuring the feasibility of the underlying business model arising from the prosumer-provider interactions, by simulating the latter on real-case scenarios.
- Lastly, we compare the results of the optimal centralized global formulation, like in [35], with the ones of our frameworks. We show a considerable saving in the computational effort by our approaches, with minimal loss on the economic performance.

2 The Energy Community Model

Let us introduce some basic notation used throughout the rest of the paper. $\mathbb{R}$ and $\mathbb{R}^+$ denote the set of real and positive real numbers, respectively. $\mathbb{N}$ denotes the set of natural numbers. $A^\top$ denotes the transpose of matrix A. $\|\boldsymbol{a}\|$ is the 2-norm of vector $\boldsymbol{a}$. Moreover, for a set $\mathcal{N} := \{1, ..., i, ..., N\} \subset \mathbb{N}$ we have that $\boldsymbol{x} := (\boldsymbol{x}_i)_{i\in\mathcal{N}}$ is equal to $\boldsymbol{x} := (\text{vec}(\boldsymbol{x}_1)^\top, ..., \text{vec}(\boldsymbol{x}_n)^\top, ..., \text{vec}(\boldsymbol{x}_N)^\top)^\top$ where vec$(\cdot)$ is the vectorization operator.

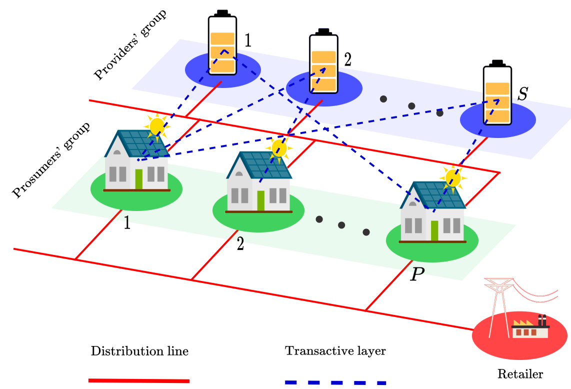


Figure 1: Energy community model: overview of distribution lines and transactive layer. Dashed lines represent the economic transactions allowed between the involved actors. For instance, in the figure, prosumer 1 negotiates with providers 1, 2, and S (i.e., $\mathcal{A}_{11} = 1$, $\mathcal{A}_{12} = 1$, $\mathcal{A}_{1S} = 1$); prosumer 2 negotiates with providers 2 and S (i.e., $\mathcal{A}_{22} = 1$, $\mathcal{A}_{1S} = 1$); prosumer P negotiates with providers 1 and S (i.e., $\mathcal{A}_{P1} = 1$, $\mathcal{A}_{PS} = 1$).

In this section we describe the proposed energy community model, shown in Fig. 1, which includes several independent actors. In particular, we formally define the set of energy community actors (or agents) $\mathcal{C} := \{1, ..., C\} \subset \mathbb{B}$ as the union of the group of *prosumers* $\mathcal{P} := \{1, ..., P\} \subset \mathbb{N}$ and the group of *energy storage providers* –briefly called *providers*– $\mathcal{S} := \{1, ..., S\} \subset \mathbb{N}$. Note that $\mathcal{C} = \mathcal{S} \cup \mathcal{P}$ while $\mathcal{S} \cap \mathcal{P} = \varnothing$ (consequently, $C = P + S$). Let us now define the topology related to the allowed economic transactions between active agents. In particular, we define the matrix $\mathcal{A}$ as a symmetric $P \times S$ binary matrix such that for each prosumer $i \in \mathcal{P}$ and provider $j \in \mathcal{S}$ the element $\mathcal{A}_{ij}$ is one if the two agents have an agreement for exchanging energy or is zero otherwise. Moreover, we indicate the set of the provider neighbors associated to the prosumer $i \in \mathcal{P}$ as $\mathcal{N}_i = \{j \in \mathcal{S} \mid \mathcal{A}_{ij} = 1\}$ with cardinality $N_i = |\mathcal{N}_i|$, and the set of the prosumer neighbors associated to the provider j as $\mathcal{M}_j = \{i \in \mathcal{P} \mid \mathcal{A}_{ij} = 1\}$ with cardinality $M_j = |\mathcal{M}_j|$.

The control frameworks proposed in this paper are based on the well-known rolling horizon paradigm, therefore let us define a control horizon composed of T time intervals, with $\mathcal{T} := \{1, ..., T\} \in \mathbb{N}$ [37].

The proposed energy community model relies on the following standing assumptions that are typically employed in related papers, e.g. [38, 39]

- *Market structure*: the energy transactions between members of the same group cannot occur (e.g., a prosumer cannot exchange energy with another prosumer).
- *Energy retailer*: the energy community interacts with an external passive actor, required to guarantee the power balance in the community network. In particular, the *energy retailer* allows prosumers/sell energy from/to the main grid.

- *Perfect competition*: the profile of the energy storage pricing coefficient is equal for all providers.
- *Storage efficiencies*: the ESSs parameters, such as the leakage coefficient and the charging/discharging efficiencies, are constant for all providers.
- *Nonstochasticity*: the energy demand and the renewable energy production profiles are known for the entire time horizon and deterministic.

Having defined the structure of the energy community and the standing assumptions, we now describe in detail the model of the aforementioned independent actors.

2.1 Prosumers

These actors are characterized by variable load consumption and renewable energy production. They sell the surplus energy to or buy the deficit energy from the energy retailer in accordance with a time-variable pricing. As an alternative, they can store/withdraw energy in/from the ESSs owned by the storage providers, upon a renting fee.

For prosumer $i \in \mathcal{P}$, we indicate the energy demand and generation, at the generic time slot $t \in \mathcal{T}$, with D_{it} and G_{it}, respectively. The energy bought from the retailer at the time slot $t \in \mathcal{T}$ is $p^{\uparrow}_{it}$, while the energy sold to it is denoted by $p^{\downarrow}_{it}$. Moreover, the energy delivered to the storage provider $h \in \mathcal{N}_i$ at the time slot $t \in \mathcal{T}$ is $d^{\downarrow}_{iht}$, while the retrieved amount is $d^{\uparrow}_{iht}$. The portion of the charge level fraction dedicated to prosumer $i \in \mathcal{P}$ by provider $h \in \mathcal{N}_i$ is indicated with s_{iht}. We define vectors $\boldsymbol{p}^{\uparrow}_i = (p^{\uparrow}_{it})_{t\in\mathcal{T}}$, $\boldsymbol{p}^{\downarrow}_i = (p^{\downarrow}_{it})_{t\in\mathcal{T}}$, $\boldsymbol{d}^{\uparrow}_i = (\boldsymbol{d}^{\uparrow}_{it})_{t\in\mathcal{T}}$, $\boldsymbol{d}^{\downarrow}_i = (\boldsymbol{d}^{\downarrow}_{it})_{t\in\mathcal{T}}$, $\boldsymbol{s}_i = (s_{it})_{t\in\mathcal{T}}$ collecting all the aforementioned variables for the entire control horizon $\mathcal{T}$, where $\boldsymbol{d}^{\uparrow}_{it} = (d^{\uparrow}_{iht})_{h\in\mathcal{N}_i}$, $\boldsymbol{d}^{\downarrow}_{it} = (d^{\downarrow}_{iht})_{h\in\mathcal{N}_i}$, $\boldsymbol{s}_{it} = (s_{iht})_{h\in\mathcal{N}_i}$. Accordingly, we define the control vector $\boldsymbol{v}_{\mathcal{P},i} = (\boldsymbol{p}^{\uparrow}_i, \boldsymbol{p}^{\downarrow}_i, \boldsymbol{d}^{\uparrow}_i, \boldsymbol{d}^{\downarrow}_i, \boldsymbol{s}_i)$ to collect all the decision variables for prosumer $i \in \mathcal{P}$.

Each prosumer $i \in \mathcal{P}$ aims at determining the optimal value of the control vector that minimizes the energy cost incurred throughout the entire time horizon $\mathcal{T}$, which can be formally defined as in (*), where $C_t \in \mathbb{R}^+$ and $R_t \in \mathbb{R}^+$ are the retailer's energy selling price and buying cost, respectively. Moreover, $L_t \in \mathbb{R}^+$ is the storage fee coefficient, which is equal for all providers, while $\xi_i \in \mathbb{R}^+$ represents the energy transmission cost coefficient for prosumer $i \in \mathcal{P}$. Note that the cost function (*) comprises two terms: the first contribution is composed by linear terms representing the cost/revenue due to energy exchanged with the retailer and the storage fee, while the second includes quadratic terms modeling the transmission costs.

Each i-th prosumer, $i \in \mathcal{P}$, is forced to respect the following constraints, for all $t \in \mathcal{T}$:

$$D_{it} - G_{it} = \sum_{h\in\mathcal{N}_i} \left(d^{\uparrow}_{iht} - d^{\downarrow}_{iht}\right) + p^{\uparrow}_{it} - p^{\downarrow}_{it}, \tag{1a}$$

$$s_{iht} = \alpha s_{ih,t-1} + \eta^{\uparrow} d^{\downarrow}_{iht} - \eta^{\downarrow} d^{\uparrow}_{iht}, \quad \forall h \in \mathcal{N}_i \tag{1b}$$

$$s_{ih1} = s_{ihT}, \quad \forall h \in \mathcal{N}_i \tag{1c}$$

$$d^{\uparrow}_{igt},\ d^{\downarrow}_{igt} = 0, \quad \forall g \notin \mathcal{N}_i \tag{1d}$$

$$0 \leq\ d^{\downarrow}_{iht},\ d^{\uparrow}_{iht} \leq d^{\max}_i, \quad \forall h \in \mathcal{N}_i \tag{1e}$$

$$0 \leq\ p^{\downarrow}_{it},\ p^{\uparrow}_{it} \leq p^{\max}_i, \tag{1f}$$

$$s_{iht} \geq 0, \quad \forall h \in \mathcal{N}_i \tag{1g}$$

Constraints (1a) represent the energy balance equation over the whole control horizon. Constraints (1b) include the dynamical state equation for the charge level related to the ESS of each provider $h \in \mathcal{N}_i$, where α, $\eta^{\uparrow}$, and $\eta^{\downarrow}$ denote the leakage coefficient, and the charging and discharging efficiencies, respectively. Constraint (1c) ensures that the storage fraction held by prosumer $i \in \mathcal{P}$ in the ESS of provider $h \in \mathcal{N}_i$ is equal, at the end of time horizon, to the initial level. Constraints (1d) impose that the energy flow between prosumer i and any disconnected provider $g \notin \mathcal{N}_i$ is null. Equations (1e) and (1f) are technological constraints imposing the energy flows towards the ESS of each provider $h \in \mathcal{N}_i$ and towards the energy retailer to be non-negative and limited by the upper bounding values $d^{\max}_i$ and $p^{\max}_i$, respectively. Lastly, (1g) ensures the non-negativity of the i-th prosumer storage fraction. The resulting feasible set $\mathcal{K}_{\mathcal{P},i}$ for each prosumer $i \in \mathcal{P}$ is thus defined as:

$$\mathcal{K}_{\mathcal{P},i} = \left\{\boldsymbol{v}_{\mathcal{P},i} \in \mathbb{R}^{+}_{2T+3TN_i} \mid (1a) - (1g) \text{ hold}\right\}. \tag{2}$$

2.2 Energy storage providers

These actors are characterized by an energy storage capacity that can be used to store the prosumers' exceeding energy generation in return for a renting fee. In fact, energy storage is a key feature in energy communities, contributing to different services such as load shifting, frequency regulation, peak shaving, and energy arbitrage. Several energy storage technologies – such as the electrochemical (batteries and fuel cells), electromechanical (flywheels and pump hydro), electrostatic (ultra-capacitors), and electromagnetic (superconducting magnetic storage) type – are available. However, electrochemical batteries have recently been recognized as the game-changing technology in energy communities, due to their high applicability and low cost. Hence, in this work, we assume that each provider owns an electrochemical battery, whose model is detailed in the following.

$$J_{\mathcal{P},i}(\boldsymbol{v}_{\mathcal{P},i}) = \sum_{t\in\mathcal{T}} \Bigg[\underbrace{C_t p^{\uparrow}_{it} - R_t p^{\downarrow}_{it} + L_t \sum_{h\in\mathcal{N}_i} s_{iht}}_{\substack{\text{Energy exchange cost/revenue} \\ \text{and storage fee}}} + \underbrace{\frac{1}{2}\xi_i \left({p^{\uparrow}_{it}}^2 + {p^{\downarrow}_{it}}^2 + \sum_{h\in\mathcal{N}_i} \left({d^{\uparrow}_{iht}}^2 + {d^{\downarrow}_{iht}}^2 \right) \right)}_{\text{Energy transmission costs}} \Bigg] \tag{*}$$

For each provider $j \in \mathcal{S}$, we indicate the energy stored by and released to prosumer $k \in \mathcal{M}_j$ at the generic time slot $t \in \mathcal{T}$ with $q^{\uparrow}_{kjt}$ and $q^{\downarrow}_{kjt}$, respectively. The portion of the charge level reserved to prosumer $k \in \mathcal{M}_j$ by provider $j \in \mathcal{S}$ at time slot $t \in \mathcal{T}$ is indicated with b_{kjt}. We define vectors $\boldsymbol{q}^{\uparrow}_{j} = (\boldsymbol{q}^{\uparrow}_{jt})_{t\in\mathcal{T}}$, $\boldsymbol{q}^{\downarrow}_{j} = (\boldsymbol{q}^{\downarrow}_{jt})_{t\in\mathcal{T}}$, $\boldsymbol{b}_j = (\boldsymbol{b}_{jt})_{t\in\mathcal{T}}$ collecting all the aforementioned variables for the entire control horizon $\mathcal{T}$, where $\boldsymbol{q}^{\uparrow}_{jt} = (q^{\uparrow}_{kjt})_{k\in\mathcal{M}_j}$, $\boldsymbol{q}^{\downarrow}_{jt} = (q^{\downarrow}_{kjt})_{k\in\mathcal{M}_j}$ and $\boldsymbol{b}^{\downarrow}_{jt} = (b^{\downarrow}_{kjt})_{k\in\mathcal{M}_j}$. Accordingly, we define the control vector $\boldsymbol{v}_{\mathcal{S},j} = (\boldsymbol{q}^{\uparrow}_{j}, \boldsymbol{q}^{\downarrow}_{j}, \boldsymbol{b}_j)$ including all the decision variables for the j-th provider.

Each provider $j \in \mathcal{S}$ aims at determining the optimal value of the control vector that minimizes the energy storage service cost throughout the entire time horizon $\mathcal{T}$, which can be formally defined as:

$$J_{\mathcal{S},j}(\boldsymbol{v}_{\mathcal{S},j}) = \sum_{t\in\mathcal{T}} \sum_{k\in\mathcal{M}_j} \Bigg[\underbrace{\frac{1}{2}\zeta_j (q^{\uparrow}_{kjt} + q^{\downarrow}_{kjt})^2}_{\text{ESS degradation costs}} - \underbrace{L_t b_{kjt}}_{\text{Revenues}} \Bigg] \tag{3}$$

where $L_t \in \mathbb{R}^+$ is the storage revenue coefficient that is the same for all providers and $\zeta_j \in \mathbb{R}^+$ is the ESS technological degradation coefficient, modelled as in eq. (4) of [38]. The cost function (3) comprises two terms: the first contribution is a quadratic term accounting for the degradation cost of the ESS (to be minimized), whilst the second represent the revenue obtained from the provided storage service (to be maximized).

Each j-th provider, $j \in \mathcal{S}$, is forced to respect the following constraints, for all $t \in \mathcal{T}$:

$$b_{kjt} = \alpha b_{kj,t-1} + \eta^{\uparrow} q^{\uparrow}_{kjt} - \eta^{\downarrow} q^{\downarrow}_{kjt}, \qquad \forall k \in \mathcal{M}_j \tag{4a}$$
$$b_{kj1} = b_{kjT}, \qquad \forall k \in \mathcal{M}_j \tag{4b}$$
$$q^{\uparrow}_{gjt},\ q^{\downarrow}_{gjt} = 0, \qquad \forall g \notin \mathcal{M}_j \tag{4c}$$
$$0 \le\ q^{\uparrow}_{kjt},\ q^{\downarrow}_{kjt} \le q^{\max}_j, \qquad \forall k \in \mathcal{M}_j \tag{4d}$$
$$\sum_{k\in\mathcal{M}_j} b_{kjt} \le b^{\max}_j, \tag{4e}$$
$$b_{kjt} \ge 0, \qquad \forall k \in \mathcal{M}_j. \tag{4f}$$

Similarly to the prosumers case, constraints (4a) include the dynamical state equation for the portion of charge level reserved to each prosumer $k \in \mathcal{M}_j$. Constraint (4b) ensures that storage fraction held by provider $j \in \mathcal{S}$ for prosumer $k \in \mathcal{M}_j$ at the end of the time horizon is equal to the initial level. Constraints (4c) imposes that the energy flow between any provider $j \in \mathcal{S}$ and any disconnected prosumer $g \notin \mathcal{M}_j$ is null. Constraints (4d) impose that charging and discharging flows are non-negative and limited by the upper bound $q^{\max}_j$. Lastly, (4e) and (4f) impose that the cumulative charge level over all prosumers connected to provider $j \in \mathcal{S}$ is upper bounded by the maximum storage capacity $b^{\max}_j$ and that the charge level fraction reserved to each prosumer $k \in \mathcal{M}_j$ is non-negative. The constraints set $\mathcal{K}_{\mathcal{S},j}$ for each provider $j \in \mathcal{S}$ is thus defined as:

$$\mathcal{K}_{\mathcal{S},j} = \left\{ \boldsymbol{v}_{\mathcal{S},j} \in \mathbb{R}^+_{3TM_j} \mid (4a) - (4f)\ \text{hold} \right\}. \tag{5}$$

Note that, despite the similarity of the two equations, (1) and (4) do not express in general the same dynamics. In fact, they represent the storage dynamics that prosumers and providers are *willing* to follow, respectively, but not necessarily agree upon. However, in order to work properly, we define a suitable mechanism which ensures that (1) and (4) converge to a common dynamics, as it will be shown in the following.

3 The Transactive Energy Storage Management Problem

The transactive energy management problem involving prosumers and providers in the considered energy community can be formulated in several ways. As a first approach, all the agents in $\mathcal{C}$ (i.e., all prosumers in $\mathcal{P}$ and providers in $\mathcal{S}$), constitute the grand coalition pursuing a common goal in order to guarantee the global community welfare. From a game-theoretical point of view, agents behave in a cooperative fashion, concurring to the minimization of a collective cost function, $J_{\mathcal{C}}$, defined as the sum of the individual cost functions:

$$J_{\mathcal{C}}(\boldsymbol{v}_{\mathcal{C}}) = \sum_{n\in\mathcal{C}} J_{\mathcal{C},n}(\boldsymbol{v}_{\mathcal{C},n}) \tag{6}$$

where, for the sake of compactness, we define $\boldsymbol{v}_{\mathcal{C}} = (\boldsymbol{v}_{\mathcal{C},n})_{n\in\mathcal{C}}$ as the concatenation of all the decision variable vectors for all players. Note that $\boldsymbol{v}_{\mathcal{C},n} = \boldsymbol{v}_{\mathcal{P},n}$, $\forall n \in \mathcal{P}$ and $\boldsymbol{v}_{\mathcal{C},n} = \boldsymbol{v}_{\mathcal{S},n}$, $\forall n \in \mathcal{S}$, while $J_{\mathcal{C},n} = J_{\mathcal{P},n}$, $\forall n \in \mathcal{P}$ and $J_{\mathcal{C},n} = J_{\mathcal{S},n}$, $\forall n \in \mathcal{S}$. As for the constraints sets, we indicate $\mathcal{K}_{\mathcal{C},n} = \mathcal{K}_{\mathcal{P},n}$, $\forall n \in \mathcal{P}$ and $\mathcal{K}_{\mathcal{C},n} = \mathcal{K}_{\mathcal{S},n}$, $\forall n \in \mathcal{S}$.

It is possible to prove that optimizing (6) provides a Pareto solution to all players [40, 41]. Function $J_{\mathcal{C}}$ is composed only by exogenous cost sources with respect to the coalition $\mathcal{C}$. In other words, the storage fees payed by the prosumers over the time horizon correspond to the total revenues earned by the providers for the storage service.

In addition to the local feasible sets $\mathcal{K}_{\mathcal{C},n}$, the coherence of the energy flow has to be ensured in accordance with the following *coupling constraints*:

$$d^{\uparrow}_{ijt} = q^{\downarrow}_{ijt}, \quad \forall i \in \mathcal{P}, \forall j \in \mathcal{S} \tag{7a}$$
$$d^{\downarrow}_{ijt} = q^{\uparrow}_{ijt}, \quad \forall i \in \mathcal{P}, \forall j \in \mathcal{S}. \tag{7b}$$

Therefore, we can define the global constraints set as:

$$\mathcal{K}_{\mathcal{C}} = \left\{ \boldsymbol{v}_{\mathcal{C}} \in \left(\bigcup_{n\in\mathcal{C}} \mathcal{K}_{\mathcal{C},n} \right) \mid (7a) - (7b)\ \text{hold} \right\}. \tag{8}$$

Summing up, from the global perspective, the optimization problem is compactly written as:

$$\overline{\boldsymbol{v}}_{\mathcal{C}} = \arg\min_{\boldsymbol{v}_{\mathcal{C}}\in\mathcal{K}_{\mathcal{C}}} J_{\mathcal{C}}(\boldsymbol{v}_{\mathcal{C}}). \tag{9}$$

The above formulated problem can be solved in a centralized fashion by a central unit that operates on behalf of all actors, while scheduling and assigning resources accordingly. In particular, since (9) constitutes a quadratic programming problem, because of the quadratic terms in (*) and (3), the resolution of the global approach is straightforwardly achieved by using any convex optimization solver [42]. However, the global approach presents several drawbacks. First, such a formulation aims at minimizing the overall community cost, possibly penalizing some actors in the resulting control strategy. Furthermore, in the centralized architecture, privacy issues are not considered. In fact, the model is composed of heterogeneous agents for whom limiting the amount of shared information is highly recommended, if not requested. This is particularly relevant to providers, being independent companies for which data sharing could result in economic and security-related vulnerabilities. Finally, centralized solutions are prone to computational scalability concerns, when the number of agents becomes large, and low fault resiliency issues.

To overcome these drawbacks, let us introduce a reformulation of the transactive energy management problem, employing the non-cooperative game theory, assuming that each player addresses its own individual energy scheduling problem. In this way, each player $n \in \mathcal{C}$ aims at minimizing its own objective function $J_{\mathcal{C},n}(\boldsymbol{v}_{\mathcal{C},n})$ by modifying its decision variable vector $\boldsymbol{v}_{\mathcal{C},n}$, given the choices of all the other players $\boldsymbol{v}_{\mathcal{C},-n}$, where $\boldsymbol{v}_{C,-n} = (\boldsymbol{v}_{\mathcal{C},1}, \cdots, \boldsymbol{v}_{\mathcal{C},n-1}\ \boldsymbol{v}_{\mathcal{C},n+1}\ \cdots\ \boldsymbol{v}_{\mathcal{C},C})^\top$. Hence, we have that each player solves an independent optimization problem:

$$\overline{\boldsymbol{v}}_{C,n} = \underset{\boldsymbol{v}_{C,n} \in \mathcal{K}_{\mathcal{C}}(\boldsymbol{v}_{C,-n})}{\arg\min}\ J_{\mathcal{C},n}(\boldsymbol{v}_{C,n}), \quad \forall n \in \mathcal{C}. \tag{10}$$

This formulation can be considered as a Generalized Nash Equilibrium problem (GNEP), since the decisions of the players are coupled through not only the cost functions, but also a shared feasible set [43]. The solution of the GNEP is the so-called Generalized Nash Equilibrium (GNE) hereafter formally defined.

Definition 3.1. *A solution $\boldsymbol{v}^*_{\mathcal{C}} \in \mathcal{K}_{\mathcal{C}}$ is a GNE if $\forall n \in \mathcal{C}$*

$$J_{\mathcal{C},n}(\boldsymbol{v}^*_{C,n}) \leq J_{\mathcal{C},n}(\boldsymbol{v}_{C,n}), \quad \forall \boldsymbol{v}_{C,n} \in \mathcal{K}_{\mathcal{C}}(\boldsymbol{v}_{C,-n}). \tag{11}$$

In other words, at a GNE no player can benefit from independently changing its own strategy, given that all the remaining players don't deviate from their own. In general, the existence of a GNE is not guaranteed; neither the uniqueness nor the convergence to an equilibrium are ensured.

In particular, the solution of a GNEP is a nontrivial problem, mainly due to the variability of the feasible sets. Several approaches to solve this problem are based on its reformulation through a variational inequality (VI). In fact, it can be proven that every solution of the VI is a solution for its corresponding GNEP, but the vice versa is, in general, not true [44]. The solutions of the GNEP that are also valid for the VI are called "variational solutions" and are usually referred to as economically fair. In fact, these points have a fair behavior between all the possible GNEs due to the equivalence of the Lagrangian multipliers (acting as penalizing coefficients) for all players' stationarity and primal feasibility conditions [42]. Moreover, variational solutions are preferred in several applications, due to their uniqueness when further assumptions hold [45].

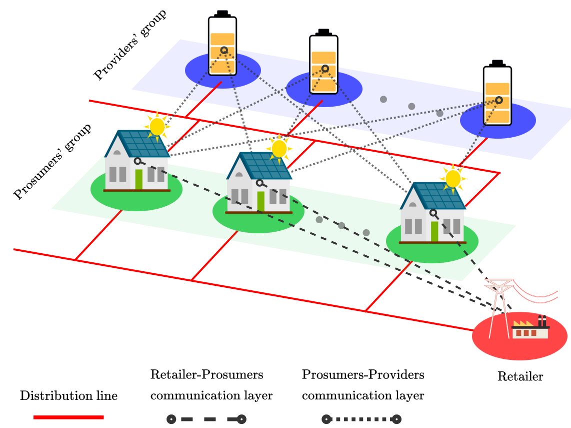


Figure 2: Energy community model: overview of the communication layer in case of the uncoordinated control framework: any prosumer can exchange information with any provider; each prosumer communicates with the retailer.

The following section is focused on describing effective methods aimed at reaching the variational solution for the above-defined individual formulation (10).

4 The Proposed Control Frameworks

In this section, we focus on solving the individual formulation transactive energy management problem, since it grasps the competitiveness of the real world energy market better than the global formulation. Several alternative algorithms have been proposed to solve the VI formulation of a GNEP [46].

In particular, two approaches are presented, namely the coordinated and the uncoordinated framework. In both cases, we leverage on a modified version of the classical Augmented Lagrangian Method (ALM) [47], where the quadratic penalty term of the Lagrangian $\mathcal{L}$ is substituted by a proximal regularizer, i.e.,

$$\mathcal{L}(\boldsymbol{v}_{\mathcal{C},n}, \boldsymbol{\pi}) = J_{\mathcal{C},n}(\boldsymbol{v}_{\mathcal{C},n}) + \boldsymbol{\pi} \cdot \boldsymbol{c}(\boldsymbol{v}_{\mathcal{C},n}) + \frac{\rho}{2} \left\| \boldsymbol{v}_{\mathcal{C},n} - \boldsymbol{v}^{(\tau-1)}_{\mathcal{C},n} \right\|^2 \tag{12}$$

with $\boldsymbol{c}(\boldsymbol{v}_{\mathcal{C},n})$ and $\boldsymbol{\pi}$ being, respectively, the vectors of the coupling constraints and related Lagrange multipliers vector. Note that in (12), and throughout the rest of the paper, τ denotes the iteration step. The regularization coefficient $\rho = \kappa a^C$ in (12) is based on parameters $\kappa, a \in \mathbb{R}^+$, determined empirically. The update rule for $\boldsymbol{\pi}$ is based on the well-known gradient formula:

$$\boldsymbol{\pi}^{(\tau)} = \boldsymbol{\pi}^{(\tau-1)} + \chi \left(\boldsymbol{v}^{(\tau-1)}_{\mathcal{C},n} - \boldsymbol{c}\left(\boldsymbol{v}^{(\tau-1)}_{\mathcal{C},n} \right) \right) \tag{13}$$

where $\chi \in \mathbb{R}^+$ is the convergence step-size. In the following, we characterize each term of (12) for, respectively, the uncoordinated and coordinated frameworks.

4.1 Uncoordinated Framework

In the uncoordinated framework, agents in $\mathcal{P}$ and $\mathcal{S}$ are able to directly interact with each other. The communication layer for this framework is shown in Fig. 2, where each

Algorithm 1: Uncoordinated ALM

1 $\tau \leftarrow 0$
2 **forall** $i \in \mathcal{P},\ j \in \mathcal{S},\ t \in \mathcal{T}$ **do**
3 $\quad \lambda_{ijt}^{(\tau)} \leftarrow 0,\ \ \mu_{ijt}^{(\tau)} \leftarrow 0$
4 $\quad d_{ijt}^{(\tau)} \leftarrow 0,\ \ q_{ijt}^{(\tau)} \leftarrow 0$
5 **while** *stopping criterion is not reached* **do**
6 $\quad \tau \leftarrow \tau + 1$
7 $\quad$ **do in parallel**
8 $\quad\quad$ Agents in $\mathcal{C}$ solve (17);
9 $\quad\quad$ Each prosumers $i \in \mathcal{P}$ communicates $d_{ijt}^{(\tau)}$ and $d_{ijt}^{(\tau)}$ to providers in $\mathcal{N}_i$;
10 $\quad\quad$ Each provider $j \in \mathcal{S}$ communicates $q_{ijt}^{(\tau)}$ and $q_{ijt}^{(\tau)}$ to prosumers in $\mathcal{M}_j$;
11 $\quad\quad$ Agents in $\mathcal{C}$ update the Lagrange multipliers by (14).

Algorithm 2: Coordinated ALM

1 $\tau \leftarrow 0$
2 **forall** $i \in \mathcal{P},\ j \in \mathcal{S},\ t \in \mathcal{T}$ **do**
3 $\quad \lambda_{t}^{(\tau)} \leftarrow 0,\ \ \mu_{t}^{(\tau)} \leftarrow 0$
4 $\quad d_{ijt}^{(\tau)} \leftarrow 0,\ \ q_{ijt}^{(\tau)} \leftarrow 0$
5 **while** *stopping criterion is not reached* **do**
6 $\quad \tau \leftarrow \tau + 1$
7 $\quad$ **do in parallel**
8 $\quad\quad$ Agents in $\mathcal{C}$ solve (22);
9 $\quad\quad$ Prosumers in $\mathcal{P}$ communicate flow variables $d_{ijt}^{(\tau)}$ and $d_{ijt}^{(\tau)}$ to the coordinator;
10 $\quad\quad$ Providers in $\mathcal{S}$ communicate flow variables $q_{ijt}^{(\tau)}$ and $q_{ijt}^{(\tau)}$ to the coordinator;
11 $\quad$ The coordinator aggregates the energy flow by (19), updates the Lagrange multipliers by (20), and sends the updated back to all agents.

prosumer communicates with the retailer and is allowed to communicate with all the providers. As regards the technological point of view, distributed ledger technologies have been proven to reliably support distributed communication and control in smart grids, in terms of cost-efficiency and privacy [48].

We now reformulate the Lagrangian formulation in (12) to solve the individual scheduling problem in (10) in the case of the uncoordinated architecture. To this aim, we define the Lagrange multipliers vectors $\lambda_{iht}^{(\tau)}$ and $\mu_{kjt}^{(\tau)}$ respectively associated to coupling constraints (7a)-(7b), whose update equations follow (13) for all $t \in \mathcal{T}$, i.e.,

$$\lambda_{iht}^{(\tau)} = \lambda_{iht}^{(\tau-1)} + \chi\left(d_{iht}^{\uparrow(\tau-1)} - q_{iht}^{\downarrow(\tau-1)}\right), \forall i \in \mathcal{P}, \forall h \in \mathcal{N}_i, \tag{14a}$$

$$\mu_{kjt}^{(\tau)} = \mu_{kjt}^{(\tau-1)} + \chi\left(d_{kjt}^{\downarrow(\tau-1)} - q_{kjt}^{\uparrow(\tau-1)}\right), \forall j \in \mathcal{S}, \forall k \in \mathcal{M}_j. \tag{14b}$$

Therefore, each prosumer and provider can calculate its penalty regularizers $\gamma_{\mathcal{P},i}^{(\tau)}$ and $\gamma_{\mathcal{S},j}^{(\tau)}$, defined, for all $i \in \mathcal{P}$ and $j \in \mathcal{S}$, as:

$$\gamma_{\mathcal{P},i}^{(\tau)} = \sum_{t\in\mathcal{T}} \sum_{h\in\mathcal{N}_i} \left(\lambda_{iht}^{(\tau)}\left(d_{iht}^{\uparrow} - q_{iht}^{\downarrow}\right) + \mu_{iht}^{(\tau)}\left(d_{iht}^{\downarrow} - q_{iht}^{\uparrow}\right)\right), \tag{15a}$$

$$\gamma_{\mathcal{S},j}^{(\tau)} = \sum_{t\in\mathcal{T}} \sum_{k\in\mathcal{M}_j} \left(\lambda_{kjt}^{(\tau)}\left(d_{kjt}^{\uparrow} - q_{kjt}^{\downarrow}\right) + \mu_{kjt}^{(\tau)}(d_{kjt}^{\downarrow} - q_{kjt}^{\uparrow})\right). \tag{15b}$$

In order to guarantee convergence, proximal regularization terms $\theta_{\mathcal{P},i}^{(\tau)}$ and $\theta_{\mathcal{S},j}^{(\tau)}$ are added to prosumers' and the providers' objective functions respectively, i.e.,

$$\theta_{\mathcal{P},i}^{(\tau)} = \frac{\rho}{2}\left(\left\|\boldsymbol{d}_i^{\downarrow} - \boldsymbol{d}_i^{\downarrow(\tau-1)}\right\|^2 + \left\|\boldsymbol{d}_i^{\uparrow} - \boldsymbol{d}_i^{\uparrow(\tau-1)}\right\|^2\right), \quad \forall i \in \mathcal{P} \tag{16a}$$

$$\theta_{\mathcal{S},j}^{(\tau)} = \frac{\rho}{2}\left(\left\|\boldsymbol{q}_j^{\downarrow} - \boldsymbol{q}_j^{\downarrow(\tau-1)}\right\|^2 + \left\|\boldsymbol{q}_j^{\uparrow} - \boldsymbol{q}_j^{\uparrow(\tau-1)}\right\|^2\right), \quad \forall j \in \mathcal{S}. \tag{16b}$$

For the sake of compactness, we define $\gamma_{\mathcal{C},n}^{(\tau)} = \gamma_{\mathcal{P},n}^{(\tau)}$, $\forall n \in \mathcal{P}$ and $\gamma_{\mathcal{C},n}^{(\tau)} = \gamma_{\mathcal{S},n}^{(\tau)}$, $\forall n \in \mathcal{S}$, while $\theta_{\mathcal{C},n}^{(\tau)} = \theta_{\mathcal{P},n}^{(\tau)}$, $\forall n \in \mathcal{P}$ and $\theta_{\mathcal{C},n}^{(\tau)} = \theta_{\mathcal{S},n}^{(\tau)}$, $\forall n \in \mathcal{S}$. Therefore, we can write the Lagrangian form of the optimization problem for the uncoordinated framework as:

$$\boldsymbol{v}_{C,n}^{(\tau+1)} = \underset{\boldsymbol{v}_{C,n}\in\mathcal{K}_{\mathcal{C}_n}}{\arg\min} \left(J_{\mathcal{C},n}(\boldsymbol{v}_{C,n}) + \gamma_{\mathcal{C},n}^{(\tau)} + \theta_{\mathcal{C},n}^{(\tau)}\right), \quad \forall n \in \mathcal{C}. \tag{17}$$

The corresponding uncoordinated algorithm is summarized in Algorithm 1, and is described in detail in the sequel. First, all agents initialize the penalty factors and flow variables (lines 2-4). The non-cooperative solution is reached in an uncoordinated manner through an iterative process until a termination criterion is not reached (lines 5-6). In detail, at each iteration τ, each agent independently solves its own optimization problem (line 9), and communicates the state of the energy flow variables to the corresponding neighbors (line 10). Lastly, the Lagrange multipliers are updated (line 11).

4.2 Coordinated Framework

In the coordinated framework, agents in $\mathcal{P}$ and $\mathcal{S}$ do not directly interact, since a coordinator is present to gather the energy flow variables determined by the prosumers and providers, compute the Lagrange multipliers on behalf of all the agents, and sending back to prosumers and providers

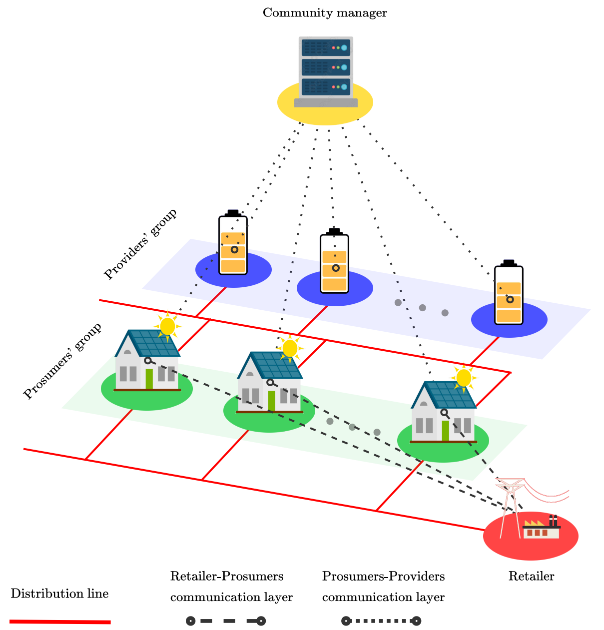


Figure 3: Energy community model: overview of the communication layer in the case of coordinated control framework: the coordinator allows any prosumer to exchange information with providers and each prosumer communicates with the retailer.

the updated Lagrange multipliers vectors. The coordinator is thus a non-profit actor that supports the selfish agents in the community in reaching an optimal solution to the transactive energy managament problem, while ensuring that the energy balance coupling constraints are satisfied. The communication layer for the coordinated framework is shown in Fig. 3, where each prosumer communicates with the retailer and all actors exchange information through the coordinator. This entity monitors and controls the energy activities in the community relying on an appropriate communication network (e.g., wireless radio connection, dial-up lines, Ethernet and IP protocol). Wireless data communications are more convenient in comparison to wired communications, since several advantages are available: cost effective installation, fast placement, and remote applicability increase the attractiveness of these approaches. Particularly, Internet of Things solutions, combined with edge computing, are increasingly gaining attention [49].

We now reformulate the Lagrangian formulation in (12) to solve the individual scheduling problem in (10) in the case of the coordinated architecture. In such a case, the Lagrange multipliers are equal for all agents, for each time slot t, since the coordinator is in charge of ensuring the balance of the *aggregate energy flow*, in accordance with the following *coupling constraints*:

$$D_t^{\uparrow} = Q_t^{\downarrow}, \quad \forall t \in \mathcal{T} \tag{18a}$$
$$D_t^{\downarrow} = Q_t^{\uparrow}, \quad \forall t \in \mathcal{T} \tag{18b}$$

where $D_t^{\uparrow}$, $D_t^{\downarrow}$, $Q_t^{\uparrow}$ and $Q_t^{\downarrow}$ are introduced to denote the flow variables aggregates:

$$D_t^{\uparrow} = \sum_{i\in\mathcal{P}} \sum_{h\in\mathcal{N}_i} d_{iht}^{\uparrow}, \quad D_t^{\downarrow} = \sum_{i\in\mathcal{P}} \sum_{h\in\mathcal{N}_i} d_{iht}^{\downarrow}, \tag{19a}$$
$$Q_t^{\uparrow} = \sum_{j\in\mathcal{S}} \sum_{k\in\mathcal{M}_j} q_{kjt}^{\uparrow}, \quad Q_t^{\downarrow} = \sum_{j\in\mathcal{S}} \sum_{k\in\mathcal{M}_j} q_{kjt}^{\downarrow}. \tag{19b}$$

In particular, the Lagrange multipliers $\lambda_t^{(\tau)}$ and $\mu_t^{(\tau)}$ associated to constraints (18) are computed as follows:

$$\lambda_t^{(\tau)} = \lambda_t^{(\tau-1)} + \chi(D_t^{\uparrow} - Q_t^{\downarrow}), \quad \forall t \in \mathcal{T} \tag{20a}$$
$$\mu_t^{(\tau)} = \mu_t^{(\tau-1)} + \chi(D_t^{\downarrow} - Q_t^{\uparrow}), \quad \forall t \in \mathcal{T} \tag{20b}$$

so that the penalty regularizers of the coordinated framework, $\varphi_{\mathcal{P},i}^{(\tau)}$ and $\varphi_{\mathcal{S},j}^{(\tau)}$, can be defined, for all $i \in \mathcal{P}$, $j \in \mathcal{S}$, as:

$$\varphi_{\mathcal{P},i}^{(\tau)} = \varphi_{\mathcal{S},j}^{(\tau)} = \sum_{t\in\mathcal{T}} \left(\lambda_t^{(\tau)}(D_t^{\uparrow} - Q_t^{\downarrow}) + \mu_t^{(\tau)}(D_t^{\downarrow} - Q_t^{\uparrow}) \right). \tag{21}$$

Similarly to the previous case, we define $\varphi_{\mathcal{C},n}^{(\tau)} = \varphi_{\mathcal{P},n}^{(\tau)}$, $\forall n \in \mathcal{P}$ and $\varphi_{\mathcal{C},n}^{(\tau)} = \varphi_{\mathcal{S},n}^{(\tau)}$, $\forall n \in \mathcal{S}$, while $\theta_{\mathcal{C},n}^{(\tau)} = \theta_{\mathcal{P},n}^{(\tau)}$, $\forall n \in \mathcal{P}$ and $\theta_{\mathcal{C},n}^{(\tau)} = \theta_{\mathcal{S},n}^{(\tau)}$, $\forall n \in \mathcal{S}$. Therefore, the Lagrangian form of the optimization problem for the coordinated framework is written as follows:

$$\boldsymbol{v}_{C,n}^{(\tau+1)} = \underset{\boldsymbol{v}_{C,n}\in\mathcal{K}_{\mathcal{C}_n}}{\arg\min}\ J_{\mathcal{C},n}(\boldsymbol{v}_{C,n}) + \varphi_{\mathcal{C},n}^{(\tau)} + \theta_{\mathcal{C},n}^{(\tau)}, \quad \forall n \in \mathcal{C}. \tag{22}$$

The coordinated algorithm, summarized in Algorithm 2, is hereafter described in detail. Similarly to the uncoordinated algorithm, we initialize the common Lagrange multipliers vectors and the energy flow variables (lines 2-4). The non-cooperative solution is reached in a coordinated fashion through an iterative process, until a termination criterion is reached (lines 5-6). At each iteration τ, every agent computes its optimal energy schedule (line 8) and communicates the updated strategy to the coordinator (lines 9-10). Then, the coordinator calculates the flow variables aggregates $D_t^{\uparrow}$, $D_t^{\downarrow}$, $Q_t^{\uparrow}$, and $Q_t^{\downarrow}$, updates the Lagrange multipliers (line 11), and sends the updated Lagrange multipliers back both to prosumers and providers (line 12).

5 Numerical Results

In this section, we assess the performance of the two proposed energy community control frameworks through numerical experiments on realistic scenarios. For the sake of providing a comparison with a reference method, the results obtained by the proposed uncoordinated and the coordinated distributed control framework are compared with those achieved by an optimal centralized framework.

All simulations are performed in MATLAB, using the Optimization Toolbox library, installed on a middle-end machine equipped with an Intel i5-7400, 3.00 GHz (4 cores) CPU, and 8 GB of RAM. Source code and dataset are fully available at [50].

Table 1: Parameters setup.

	Parameter	Value
Time horizon	T	24 (hours)
Group size	P	10
	S	8
Efficiencies	α	0.98
	$\eta^{\downarrow}$	1.03
	$\eta^{\uparrow}$	0.97
	σ	0.03
	$\overline{\zeta_j}$	0.005
	$\overline{\xi_j}$	0.0003
	ξ_j	$\sim N(\overline{\xi_i}, \sigma^2)$
	ζ_j	$\sim N(\overline{\zeta_i}, \sigma^2)$
Economical coefficients	ϵ	0.7
	β	0.5
Decision variables boundaries	$p^{\max}$	6 (kWh)
	$d^{\max}$	6 (kWh)
	$q^{\max}$	6 (kWh)
	$b^{\max}$	10 (kWh)
	b^{init}	0 (kWh)
	s^{init}	0 (kWh)
Convergence parameters	γ	0.098^{*}, $0.98^{\dagger}$
	a	$1.04^{*,\dagger}$
	χ	0.01^{*}, $0.7^{\dagger}$

* Coordinated
† Uncoordinated

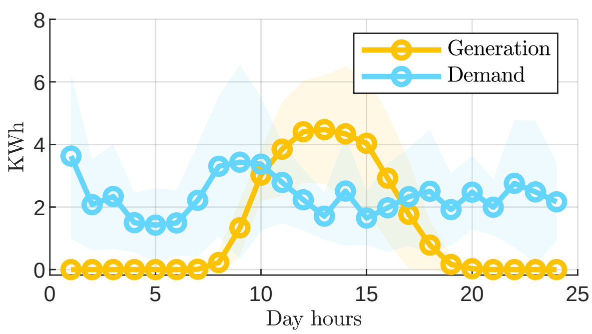


Figure 4: Prosumers' energy generation (yellow) and demand (cyan) curves. Lines corresponds to the values averaged over the involved agents, while the shaded areas are the bounds of the standard deviation.

In particular, we consider a residential energy community equipped with distributed energy generation sources and service-based energy storage. The actors of the energy community include 10 prosumers and 8 providers. The control horizon corresponds to the entire day, equally subdivided into one-hour time slots.

Prosumers' energy generation and demand data are known parameters of the control frameworks, corresponding to the curves reported in Fig. 4. In particular, the reported data refer to a yearly report of energy consumption and production of an urban condominium [50]. The renewable source considered in the experiments is a set of 27 PV panels (PEIMAR SG300M), each generating 300 Wp and a three-phase inverter (SolarEdge SE8K), serving shared devices of the condominium, such as heat generator, water pump, lighting, and elevator.

Energy buying and selling prices are defined over the time horizon and known by all agents in both the prosumers and providers groups. In particular, the considered energy cost is related to the Italian Enel "E-Light Bioraria" tariff [51]. This billing plan divides the day into two zones:

- *Orange*: Monday to Friday, from 8.00 to 19.00. The buying energy cost C_t is € 0.0774.
- *Blue*: Monday to Friday, from 19.00 to 8.00 and the entire day during weekends. The buying energy cost C_t is € 0.0574.

The relationship between the energy buying cost (i.e., C_t) and the energy selling price (i.e., R_t) for prosumers is the following:

$$R_t = \epsilon C_t, \quad \epsilon \in [0, 1] \tag{23}$$

where ϵ is the increment due to exogenous factors (e.g., taxes). As for the storage service pricing (i.e., L_t), for the sake of simplicity, a weighted average of the buying and selling price is considered:

$$L_t = \beta C_t + (1 - \beta) R_t \tag{24}$$

with $\beta \in [0, 1]$ being an arbitrary weight. By tuning the value of β, a large number of policies can be experimented, independently from the energy buying and selling price curves.

Finally, in Table 1 we report the tuning parameters of the proposed algorithms, as well as the technological parameters of the ESSs. In particular, the technological coefficients are sampled from normal distributions and the charge level of ESSs are set to zero at the beginning of the day.

Since our work is focused on transactive control frameworks for energy communities, for the sake of assessing the performance of the proposed methods in a comprehensive fashion, we adopt both economic (i.e., energy cost incurred by prosumers, revenue gained by providers, and revenue gained by the retailer), energy (i.e., prosumers' energy demand and generation as well as energy bought from and sold to the retailer, energy charged and discharged by the ESSs as well the storage state), and control/computational (i.e., residual of the coupling constraints for convergence and run time for scalability purpose) performance evaluation indicators.

Figure 5 reports the evolution of the energy flow variables over the control horizon. It is apparent that prosumers buy most of the energy during the early hours of the day, when the autonomous generation is at the lowest level, and sell the surplus during the middle hours of the day. It is worthwhile noting the effects of the storage service at the latest hours: the amount of bought energy is lower than the demand since prosumers start to retrieve the stored energy to compensate for the low autonomous production. As for the sold energy, the main volume is located, as expected, during the middle hours of the day. Furthermore, it can be noticed that the global amount of energy stored in the case of coordinated and uncoordinated frameworks is lower than in the centralized one. Moreover, its variance is narrower in the non-centralized frameworks, indicating that the storage service demand is uniformly distributed among providers.

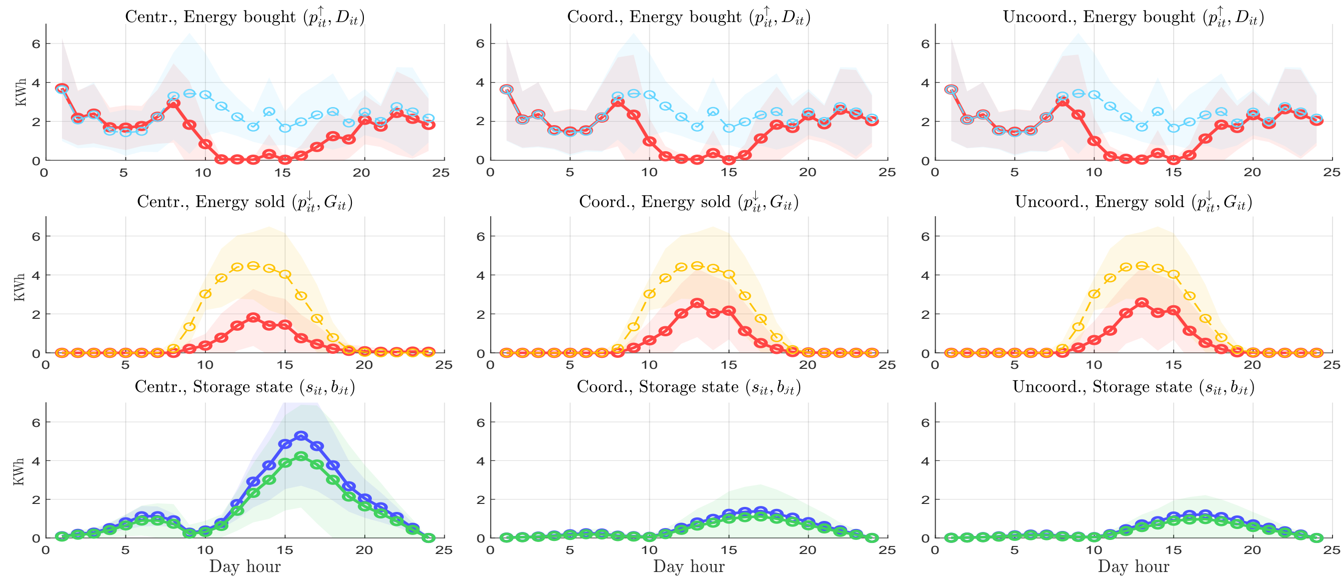


Figure 5: Energy transfer dynamics: the first, second, and third subplots column refers to the centralized, coordinated, and uncoordinated framework, respectively. The first subplots row shows the profile of prosumers demand D_{it} (cyan) and the profile of energy bought from the retailer $p^{\uparrow}_{it}$ (red). The second subplots row represents the profile of prosumers generation G_{it} (yellow) and the profile of energy sold to the retailer $p^{\downarrow}_{it}$ (red). The third subplots row shows the profile of prosumers stored energy s_{iht} (green) and the profile of providers charge level b_{kjt} (blue). In all subplots Lines corresponds to the values averaged over the involved agents, while the corresponding shaded areas are the bounds of the standard deviation.

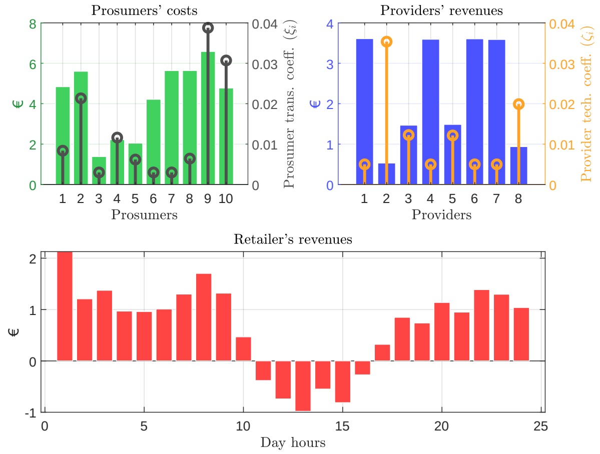
Table 2: Total costs and revenues for the group of prosumers, the groups of providers, and the retailer for each control framework.

		Cost of bought energy [€]	Revenues of sold energy [€]	Cost of storage service [€]	Cost of inefficiency* [€]	Community costs† [€]	Total costs§ [€]
Centralized	**Prosumers**	21.41	5.00	19.15	7.35	42.93	
	Providers	-	-	-19.15	0.34	-18.81	**7.70**
	Retailer	5.00	21.41	-	-	-16.42	
Decentralized	**Prosumers**	23.62	7.05	3.81	8.91	29.30	
	Providers	-	-	-3.81	0.014	-3.80	**8.93**
	Retailer	7.05	23.62	-	-	-16.57	
Distributed	**Prosumers**	23.83	7.31	1.70	9.51	27.77	
	Providers	-	-	-1.70	0.0035	-1.69	**9.51**
	Retailer	7.31	23.83	-	-	-16.57	

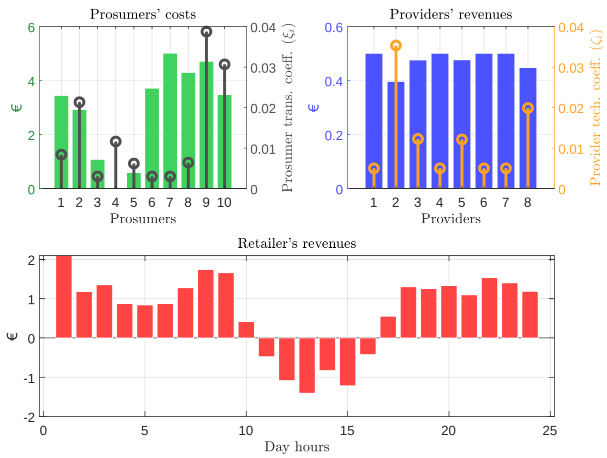
* Value related to the quadratic term in eq. (*) and eq. (3) for prosumers and providers, respectively.
† Value computed as: (Cost of bought energy) + (Cost of storage service) + (Cost of inefficiency) − (Revenues of sold energy).
§ Sum of the terms in the "Community cost" column.

Figures 6a, 6b, and 6c graphically summarize the costs and revenues sustained by each agent over the control horizon. Providers' revenues are negatively correlated with ζ, since such a coefficient indicates the tendency of ESSs to deteriorate. Some considerations related to the energy flow dynamics directly follow from the above reported findings: the middle hours of the day are the less profitable ones for the retailer, which buys energy from the prosumer, instead of selling it. The retailer achieves the highest profit in the early morning when the solar generation is at the minimum level. During the latest hours of the day, revenues are still positive, although prosumers start using the stored surplus to satisfy the demand. An important aspect is that, for all the considered frameworks, the distribution of the economic curves follows the same trend. This implies that solving the optimization problem with a particular framework does not alter *fairness*, at least at the community level, i.e., no participant in the groups of prosumers or providers can strongly benefit from changing its strategy while compromising others' welfare. Also, it can be noticed that the distribution of the revenues for the providers becomes more homogeneous as we move from the centralized solution to the coordinated one, while the largest uniformity is obtained in the uncoordinated case. This is a consequence of the perfect competition hypothesis and the non-cooperative behavior of agents. Table 2 reports the revenues and the costs for the groups of prosumers and providers, as well as for the retailer. In particular, the "Total costs" column indicates the sum of the costs of all participants, including both the groups of prosumers and providers and the retailer. For the centralized case, it corresponds to the optimal value determined as a result of (6), whilst in the uncoordinated and coordinated cases it is the sum of the optimal values determined as results of (10). It can be noticed that the total cost value increases moving from the centralized to the uncoordinated through the coordinated approach. From the prosumers' perspective, this means that the lowest total cost is achieved in the uncoordinated

(a) Centralized



(b) Coordinated



(c) Uncoordinated

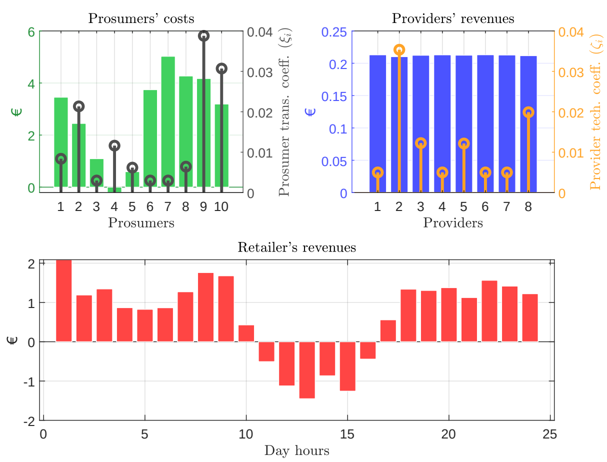
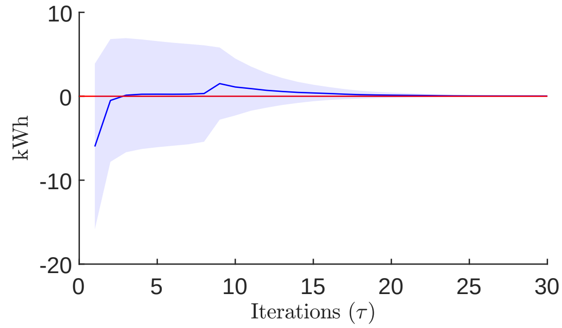


Figure 6: Economic results for the centralized (a), coordinated (b), and uncoordinated (c) framework. Total daily prosumers costs (green bars) and providers revenues (blue bars) are reported on a single agent basis. Retailer revenues (red bars) are indicated on a time slot basis. The brown and orange stems denote the values of the technological coefficients ξ_i and ζ_j over prosumers and providers, respectively.

(a) Coordinated



(b) Uncoordinated

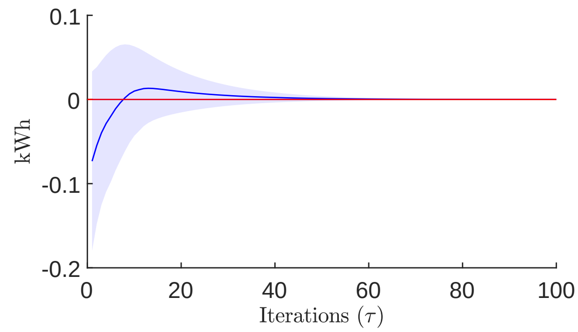


Figure 7: Convergence of the coordinated (a) and the uncoordinated (b) algorithm. The blue line indicates the average over the residual of (18) and (7) for the coordinated and the uncoordinated case, respectively. The shaded area is the bound of the standard deviation.

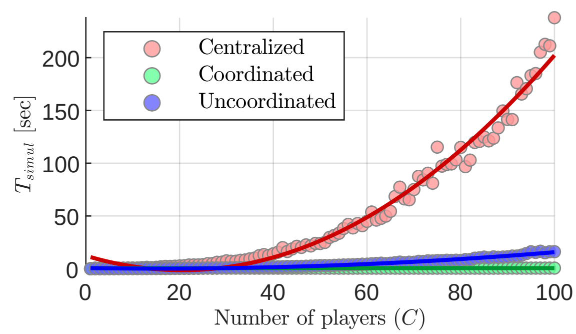


Figure 8: Run time versus number of agents (up to 100) for each framework. Curves represent polynomial fitting.

framework, whereas the lowest profit is made by providers. Retailer revenues are added for completeness's sake in Table 2, being itself part of the economic frame, even if we consider it as a passive agent.

Figures 7a and 7b report the residual value of the coupling constraints over iterations respectively for the coordinated and the uncoordinated algorithm, thus showing that convergence is ensured for both the proposed frameworks.

Finally, Fig. 8 reports the run time required by each framework. For the uncoordinated framework, the communication graph (Fig. 2) has been considered as *complete*, since it is the worst-case scenario from a computational perspective. For the non-centralized frameworks, simulation time T_{simul} is calculated as

$$T_{\text{simul}} = \max\left(T_{\mathcal{P}}, T_{\mathcal{S}}\right) \cdot N_{\text{iter}} \tag{25}$$

with $N_{\text{iter}} \approx 150$ being the number of iterations and $T_{\mathcal{P}}$ and $T_{\mathcal{S}}$ being the average simulation time for prosumers and providers, respectively. From Fig. 8 it is evident that T_{simul} approaches a sublinear trend $o(C)$ for the coordinated case and the uncoordinated case, while the centralized case shows the polynomial trend $\mathcal{O}(C^2)$. As a result, the inevitable economic performance loss occurring in the coordinated and uncoordinated frameworks comes with operational advantages from a computational point of view.

6 Conclusions and Future Works

In the last decade, distributed energy generation and storage have significantly contributed to the spread of energy communities. This increasing trend makes it necessary to develop suitable control strategies, in order to efficiently exploit the generation and storage capabilities of the energy community. For the sake of satisfying such a need, in this paper we propose two novel transactive control schemes for energy communities –namely, the coordinated and the uncoordinated frameworks– with the following objectives:

- formulating of a scalable energy management architecture for communities equipped with multiple prosumers and independent ESS service providers;
- assessing the feasibility of the underlying client-service business model by simulating the frameworks on real-case scenarios;
- improving the computational effort with respect to the optimal centralized approach, while keeping the degree of information sharing at the minimum level and with minimal loss in the economic performance.

An additional merit of the presented approaches lies in their generalizability to address different service provisioning in energy communities, for instance, in the case of optimally trading local energy exchanges at peer-to-peer level and sharing common energy resources among the involved actors.

Nonetheless, this study is not without limitations, that need to be addressed in future developments. In particular, the energy generation and demand curves, as well as energy pricing profiles, are assumed to be deterministic, whilst the control frameworks are assumed to be not affected by modeling errors and non-idealities (e.g., latency, faults, etc.). Moreover, the individual objectives of involved actors could be enhanced to include wider sustainability payoffs beyond economic benefits. Lastly, the energy distribution network ignores the constraints flow constraints regarding active and reactive power. Therefore, future works will focus on these points, by effectively dealing with the presence of the uncertainty that affects the decision parameters, and integrating additional terms in the objective functions and realistic grid in the proposed frameworks.

Acknowledgements

This work was supported in part by the Apulia Region (Italy) under the Research for Innovation (REFIN) Call (Project no. C9A3735B).

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