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Privacy-preserving energy management in local energy communities with EVs – An enhanced benders-like solution strategy

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ABSTRACT

Local Energy Communities (LECs) are collectives of prosumers collaborating to reach common goals, such as the reduction of energy procurement costs and the provision of ancillary services to the network operator. They use the flexibility of modern residential installations, including rooftop photovoltaic (PV) systems and controllable loads, such as the charging stations of electric vehicles (EVs). A central unit, called community manager, usually coordinates the actions of prosumers. However, the need for large information exchange in this multi-agent framework is a problem for the widespread adoption of such models. Data privacy concerns between prosumers and the manager may deter participation. This paper presents a novel energy management strategy for LECs with EV charging stations that protects privacy. The proposed approach only shares dual variables with the community manager, while all primal variables, such as power schedules, remain private. The method uses Benders decomposition to solve the day-ahead energy management problem, which has a separable structure. To speed up the process, a Benders-bundle algorithm has been developed, which is faster than the basic Benders method. The method also makes it easy to include network constraints, so the results can be implemented in the network without congestions or voltage problems. The method is tested on a case of a community with 14 prosumers connected to a 15-bus radial low voltage distribution network. Results show that the new proposal performs as well as a centralized approach and is characterized by a good balance between solution accuracy and privacy preservation compared to other distributed and decentralized methods.

1. Introduction

1.1. Context and motivation

The transition toward a sustainable energy system necessitates the increased electrification of multiple sectors, especially transport and heating. This change is expected to increase electricity demand, which will cause problems in local power distribution networks, particularly for voltage regulation and congestion management (Papathanassiou et al., 2014). For example, adding the charging of an electric vehicle (EV) or a heat pump can almost double a home's annual electricity consumption (Andersen et al., 2017). To address these challenges, distribution system operators (DSOs) must employ optimal strategies for the utilization of distributed energy resources (DERs). As identified in Hennig et al. (2023), congestion management in distribution networks can be pursued through three main approaches: smart network tariffs, market-based mechanisms, and direct control of flexible loads.

At the distribution level, Local Energy Communities (LECs) can combine and manage flexibility from residential prosumers (households with local generation) (Danish Energy Agency, 2021). These prosumers often have rooftop photovoltaic (PV) systems and can trade electricity with other members of the community through Peer-to-Peer (P2P) exchanges. In the meantime, as the installation of domestic charging infrastructure for EVs is increasing (International Energy Agency, 2024), the optimal scheduling of EV charging can significantly improve the flexibility that prosumers provide to the distribution network operator.

The optimal management of DERs within LECs can help to improve the operational efficiency and reliability of distribution networks. Existing studies have examined the role of smart tariffs and market-based mechanisms in the context of LECs (Crowley et al., 2025; M. Tostado-Véliz et al., 2025). Despite the conceptual simplicity of direct

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Nomenclature

Indices (sets)

t ($\mathscr{T}$)	Time
i ($\mathscr{I}$)	Prosumer
j, k ($\mathscr{J}$)	Network node
Ω_j	Prosumers connected to the j^{th} node in the network
Ψ_j	Downstream nodes from the j^{th} node in the network
n ($\mathscr{N}$)	Breakpoints for linearization of second-order conic constraints
J	Upstream node from the j^{th} node in the network
Θ_i	Plug-in time window of the electric vehicle of the i^{th} prosumer

Superscripts and operators

im/ex	Imported/exported
NS	Non-served
DN	Distribution network
PV	Photovoltaic
$EV, c/d$	Electric vehicle in charging/discharging mode
D	Demand
$\underline{(\cdot)}/\overline{(\cdot)}$	Minimum/maximum value of a variable or parameter
(ϱ), (υ)	Iteration counter
$\widehat{(\cdot)}$	Given value
$\Vert\cdot\Vert_\infty$	Infinity norm
$\langle\cdot,\cdot\rangle$	Scalar product
$\Vert\cdot\Vert$	Euclidean norm

Parameters

TOU	Time-of-use tariff (€/kWh)
c^{ex}	Feed-in tariff (€/kWh)
γ	Parameters to linearize second-order conic constraints (-)
R/X	Branch resistance/inductance (Ω)
V^0	Root node voltage (V)
σ	Active-reactive conversion factor (kvar/kW)
η^{EV}	Efficiency of on-board batteries (pu)
E^0	Initial energy stored in the electric vehicle (kWh)
ε	Convergence threshold (kWh)
τ	Penalty parameter (-)

Variables

p/q	Active/reactive power (kW/kvar)
f^P/f^Q	Active/reactive power flow (kW/kvar)
V	Nodal voltage (V)
y	Commitment status (binary)
E	Energy stored (kWh)
λ	Sensitivities (€/kWh)
$\boldsymbol{\delta}, \boldsymbol{\zeta}, \boldsymbol{\vartheta}, \boldsymbol{\mu}$	Auxiliary variables (kW or kWh)
β	Auxiliary variable to model non-served energy (kWh)

control strategies, their practical implementation raises privacy concerns, as prosumers may be hesitant to relinquish control over their assets to external entities such as community managers. Because of this, the development of privacy-preserving mechanisms able to exploit LEC flexibility without needing direct control is important. This paper focuses on that.

1.2. Privacy-preserving energy management methodologies

Decentralized and distributed energy management approaches leverage the inherent decentralized structure of modern energy systems. These methods allow local decisions with minimal information exchange, thereby reducing both computational complexity and communication needs. According to Kong et al. (2025), these methods can be grouped into two main categories:

- Lagrangian relaxation-based methods: these techniques exploit the decomposability of the Lagrangian function, enabling distributed optimization across multiple agents or subsystems. For example, in Wan et al. (2023), a dual decomposition approach was applied to coordinate battery-swapping stations and EV charging infrastructure in a privacy-preserving manner. However, methods based on Lagrangian relaxation may suffer from slow convergence rates and significant computational burdens. To address some of these limitations, the Alternating Direction Method of Multipliers (ADMM) has been proposed as a viable alternative, offering distributed optimization capabilities with limited information exchange (Mansouri et al., 2025). Nonetheless, ADMM does not guarantee convergence in the presence of non-convex objective functions or constraints. Other decomposition-based approaches include the Optimality Condition Decomposition (OCD), which reformulates the original problem into a set of smaller subproblems solvable through their Karush-Kuhn-Tucker (KKT) conditions (Avila & Chu, 2019). However, the applicability of OCD is limited by its reliance on a continuous formulation, which restricts its use in problems involving binary variables. Approaches based on the Dual Projection Subgradient method, which is particularly effective in addressing Mixed-Integer Linear Programming (MILP) problems (Ge et al., 2020), are typically characterized by slow convergence or the need for second-order derivatives of the objective functions, limiting their practical applicability in some cases.
- Decomposition-based methods: these methodologies break the original optimization problem into smaller and more manageable subproblems that can be solved in a decentralized manner. These methods can be broadly classified into primal and dual-based decomposition techniques. Primal-based methods share primal information between the master and subproblems. Among them, the Column-and-Constraint Generation Algorithm (C&CGA), which has been extensively applied in robust optimization (Li et al., 2024), is one of the most popular. Nevertheless, its suitability for privacy-aware frameworks is limited, as primal information is incorporated into the master problem through explicit primal constraints. This structure entails direct control by the master problem and, in consequence, privacy is no longer preserved. On the other hand, Benders decomposition, which is one of the most used dual-based decomposition techniques (Conejo et al., 2006). It helps to reduce the computational complexity of large-scale or stochastic formulations (Constante-Flores & Conejo, 2024). Benders decomposition achieves privacy protection since only dual variables are communicated between the subproblems and the central coordinating entity. However, Benders decomposition is known to exhibit slow convergence, and improving its speed is still an active topic of research and algorithmic refinement (Brandenberg & Stursberg, 2021). Another method, Dantzig-Wolfe decomposition, has seen limited application in the energy domain. One example of its use is in Contreras-Ocaña et al. (2018), where it is applied for the coordinated management of building energy systems and EV charging points.

In the context of LECs, various privacy-preserving methodologies have been proposed. Notably, Lilla, Orozco et al. (Lilla et al., 2020; Orozco et al., 2022) use ADMM for P2P energy exchanges. However, ADMM does not fully guarantee user privacy, as it requires the exchange of primal information (power). Furthermore, the convergence of ADMM is highly sensitive to the selection of algorithmic parameters, which must be set carefully for each case and may hinder its practical applicability (Kargarian et al., 2018). An additional challenge associated with ADMM is the incorporation of the network model. While a network representation is proposed in Lilla et al. (2020) and can be integrated into the ADMM iterative procedure, this integration occurs ex-post and is not embedded within the optimization framework.

Several studies by Dolatabadi et al. (Dolatabadi & Siano, 2020; Dolatabadi et al., 2023) address the challenge of privacy-preserving energy management in LECs through various approaches. In Dolatabadi and Siano (2020), different distributed algorithms are proposed and compared. These algorithms offer an advantage over ADMM by relying solely on Linear Programming (LP) formulations, thereby avoiding the computationally more intensive quadratic programming required by ADMM. The methods reformulate the original MILP models for day-ahead scheduling into LP problems using the Variable Neighborhood Search approach. Although these strategies alleviate the computational burden, they still have similar limitations as ADMM in terms of sharing primal information and adding community network representation. The latter issue is addressed in Dolatabadi et al. (2023), where a hybrid iterative framework combining conic and linear programming models is introduced. Nevertheless, the exchange of primal information between prosumers persists.

Other multi-stage methods have been proposed in Tostado-Véliz et al. (2022),Tostado-Véliz et al. (2023). In these approaches, each prosumer first independently solves its home energy management problem, by scheduling their own resources and appliances. Then, in the second stage, P2P exchanges are coordinated. In the third stage, collective assets (e.g., storage systems) are utilized. These algorithms facilitate the network model integration, but they do not guarantee convergence and optimality. This is because the objectives of the first and second stages are focused on minimizing the energy to be dispatched in the third stage, a strategy that may lead to sub-optimal solutions.

1.3. Specific contributions and paper organization

This study addresses several challenges associated with privacy-preserving energy management approaches. It focuses on three main points: avoiding the exchange of primal information among agents, the integration of network constraints in the procedure, and the reduction of computational burden. To tackle these issues, a novel P2P coordination strategy for LECs is developed, based on Benders decomposition. This method ensures privacy preservation by sharing only dual information with a central entity and not sharing any data among peers. The presence of a central entity facilitates the integration of network constraints. To address the slow convergence of conventional Benders methods, a hybrid Benders-bundle method is proposed. As detailed in Mitridati et al. (2020), although a quadratic programming (QP) model must be solved in each iteration, this approach significantly improves the convergence rate. The proposed strategy is tested on a LEC with 14 prosumers connected to a 15-bus network, incorporating PV systems and EV charging stations. Its performance is compared with both a centralized approach and other distributed and decentralized methods. A case study is also presented to show the effect of ensuring privacy on economic and energy indicators.

The rest of the paper is organized as follows: Section 2 describes the background and the centralized solution of the problem. Section 3 describes the proposed decentralized solution algorithm, based on Benders decomposition and its improvement introducing bundle regularization. Section 4 presents a case study with results and discussion. Finally, the main conclusions are drawn in Section 5.

2. Background

2.1. Local energy communities (LECs)

We consider a LEC formed by domestic prosumers installing rooftop PV and charging points for EVs. The prosumers in the community are connected to the same low voltage network, which has a radial topology and is assumed to be three-phase balanced, and are located close to each other. It is noteworthy that these are typical assumptions in the context of LECs (Vespermann et al., 2021). Furthermore, since the individual consumption levels of prosumers are generally low in comparison with the network capacity, potential phase imbalances arising during the coordination of P2P energy exchanges are not considered significant.

Each prosumer is responsible for meeting its own demand, including EV charging requirements as well as the consumption of other devices such as domestic appliances or thermostatically-controlled loads. Local demand can be satisfied through PV self-generation or P2P exchanges within the community. These power transactions are coordinated by a central entity referred to as the community manager, who also ensures the reliable operation of the community network.

We also assume that EVs can partially discharge their on-board batteries to support either local consumption or energy exports to the community via vehicle-to-grid (V2G) capabilities. Likewise, the community is connected to an upscale system (e.g. distribution network) at a single root node ($j = 0$), which allows it to import and export at retail tariffs. Fig. 1 illustrates the community model and the main notation used in the mathematical formulation for centralized community management.

2.2. Formulation of the centralized model

Below, we present the centralized operational model for the LEC under study. This model assumes that the community manager has direct control over all the DERs deployed across the community. We assume an hourly day-ahead model with $t \in \mathcal{T} = 24$ time intervals. The community is formed by $i \in \mathcal{I}$ prosumers connected to a network with $j \in \mathcal{J}$ nodes.

2.2.1. Objective function

The community manager has the objective of meeting local demand at minimum cost. The cost of exchanging energy with the distribution network can be expressed as follows:

$$CC = \sum_{t \in \mathcal{T}} \{ \mathrm{TOU}_t p_t^{im} - c^{ex} p_t^{ex} \} \tag{1}$$

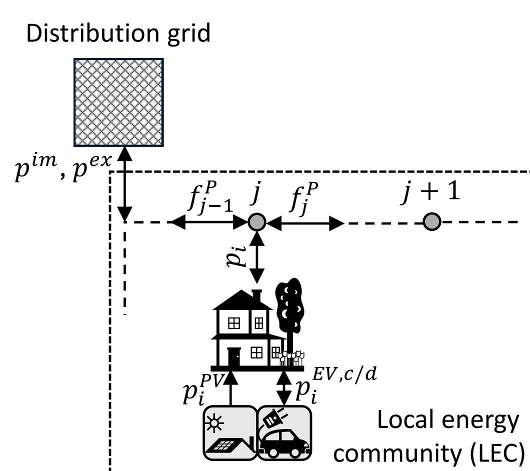

Fig. 1. Sketch of the community model considered in this paper. For simplicity, the dependence of time in the notation was omitted in this figure.

In (1), it is assumed that the community agrees on a dynamic time-of-use tariff (TOU) with the local retailer, while exports are priced under a constant feed-in tariff, as commonly in a number of commercial electricity tariffs enabling power exports (ENDESA, 2025). Nevertheless, other pricing mechanisms could be incorporated easily.

On the other hand, unserved energy is penalized by incorporating it as a part of the objective function. The total unserved energy for the i^{th} prosumer in the community is given by:

$$U_i = \sum_{t \in \mathcal{T}} p_{i,t}^{NS}; \forall i \in \mathcal{I} \tag{2}$$

2.2.2. Community-level constraints

The power exchanged with the distribution network may be constrained by either physical or contractual limits, as said (3). Similarly, the community can exchange reactive power with the distribution network, whose transactions are limited by (4).

$$0 \le p_t^{im}, p_t^{ex} \le \overline{p}^{DN}; \forall t \in \mathcal{T} \tag{3}$$

$$0 \le q_t^{im}, q_t^{ex} \le \overline{q}^{DN}; \forall t \in \mathcal{T} \tag{4}$$

Binary variables are not included in (3) and (4), as simultaneous imports and exports represent suboptimal solutions that are inherently disregarded by the solver (if the feed-in tariff is lower than the TOU one).

The community network is modelled using the LinDistFlow approach (Wang et al., 2023), which provides an appropriate representation of radial distribution networks and facilitates the inclusion of voltage constraints. Following this approach, active and reactive power flows at the root node are given by (5) and (6), respectively, whereas (7) and (8) calculate power flows for the rest of the nodes in the network.

$$p_t^{im} - p_t^{ex} = f_{(j=0),t}^P; \forall t \in \mathcal{T} \tag{5}$$

$$q_t^{im} - q_t^{ex} = f_{(j=0),t}^Q; \forall t \in \mathcal{T} \tag{6}$$

$$f_{j,t}^P = \sum_{i \in \Omega_j} p_{i,t} + \sum_{k \in \Psi_j} f_{k,t}^P; \forall j \in \mathcal{J} \wedge t \in \mathcal{T} \tag{7}$$

$$f_{j,t}^Q = \sum_{i \in \Omega_j} q_{i,t} + \sum_{k \in \Psi_j} f_{k,t}^Q; \forall j \in \mathcal{J} \wedge t \in \mathcal{T} \tag{8}$$

Power flows through network branches are bounded by the thermal limits of lines, which are calculated by the following second-order cone constraint.

$$\sqrt{\left(f_{j,t}^P\right)^2 + \left(f_{j,t}^Q\right)^2} \le \bar{f}_j; \forall j \in \mathcal{J} \wedge t \in \mathcal{T} \tag{9}$$

Although advanced commercial solvers are capable of handling conic constraints efficiently, (9) is linearized to preserve the linearity of the model. To this end, the inner polygon approach is employed (Dvorkin et al., 2021), by which (9) is replaced by a set of $\mathcal{N}$ linear constraints of the form of:

$$\gamma_n^P f_{j,t}^P - \gamma_n^Q f_{j,t}^Q - \gamma_n^f \bar{f}_j \le 0; \forall j \in \mathcal{J} \wedge t \in \mathcal{T} \wedge n \in \mathcal{N} \tag{10}$$

where the value of the γ's can be found in (Akbari & Bina, 2016). Note that increasing the number of linear constraints enhances the accuracy of the approximation. However, a satisfactory level of accuracy can be achieved with a relatively small number of constraints. In particular, $\mathcal{N} = 12$ was selected as a suitable trade-off.

Voltages throughout the network can be calculated as a function of power flows and branch parameters, as said (10), while the voltage at the root node is considered fixed in (11). Finally, voltage levels need to remain within safe limits, as enforced by (12).

$$V_{j,t} = V_{J,t} - \frac{R_j f_{j,t}^P + X_j f_{j,t}^Q}{V^0}; \forall j \in \mathcal{J} \backslash \{0\} \wedge t \in \mathcal{T} \tag{11}$$

$$V_{(j=0),t} = V^0; \forall t \in \mathcal{T} \tag{12}$$

$$\underline{V} \le V_{j,t} \le \overline{V}; \forall j \in \mathcal{J} \wedge t \in \mathcal{T} \tag{13}$$

2.2.3. Prosumer-level constraints

The power balance (14) for each prosumer in the community needs to be met, accounting for local generation through rooftop PV, P2P exchanges and EV with V2G capability. Moreover, (14) includes local demand (i.e. $p_{i,t}^D$) and non-served power (i.e. $p_{i,t}^{NS}$). In line with (Crowley et al., 2025), a constant power factor ($\sigma_i = 0.15; \forall i$) is considered for each prosumer in (15).

$$p_{i,t} + p_{i,t}^{NS} + p_{i,t}^{PV} + p_{i,t}^{EV,d} - p_{i,t}^D - p_{i,t}^{EV,c} = 0; \forall i \in \mathcal{I} \wedge t \in \mathcal{T} \tag{14}$$

$$q_{i,t} = \sigma_i p_{i,t}; \forall i \in \mathcal{I} \wedge t \in \mathcal{T} \tag{15}$$

PV generation is primarily constrained by weather-related parameters such as solar irradiance and temperature (M. Tostado-Véliz et al., 2025). These parameters inherently introduce uncertainty into the problem, which can be addressed through various modeling approaches (Roald et al., 2023). However, the treatment of uncertainties falls outside the scope of this paper, and deterministic conditions are assumed throughout the model. Under this assumption, the PV output is constrained by its instantaneous power limit, as defined in Eq. (16). Additionally, Eq. (17) ensures that non-served energy remains non-negative.

$$0 \le p_{i,t}^{PV} \le \overline{p}_{i,t}^{PV}; \forall i \in \mathcal{I} \wedge t \in \mathcal{T} \tag{16}$$

$$0 \le p_{i,t}^{NS}; \forall i \in \mathcal{I} \wedge t \in \mathcal{T} \tag{17}$$

Each prosumer is equipped with an EV charging point that supports bidirectional power flow. The maximum charging and discharging power levels are constrained by physical limits, as defined in Eqs. (18) and (19), respectively.

$$0 \le p_{i,t}^{EV,c} \le y_{i,t}^{EV} \overline{p}_i^{EV}; \forall i \in \mathcal{I} \wedge t \in \mathcal{T} \tag{18}$$

$$0 \le p_{i,t}^{EV,d} \le \left(1 - y_{i,t}^{EV}\right) \overline{p}_i^{EV}; \forall i \in \mathcal{I} \wedge t \in \mathcal{T} \tag{19}$$

Unlike the case of (3) and (4), avoiding simultaneous charging-discharging in storage systems requires the use of binary variables in (18) and (19), as discussed in (Arroyo, 2022) and illustrated in the Appendix. The instantaneous energy stored in on-board batteries can be modelled according to (20), as a function of the previous state-of-charge and the total energy exchanged.

$$E_{i,t}^{EV} = E_{i,t-1}^{EV} + p_{i,t}^{EV,c} \eta_i^{EV} - p_{i,t}^{EV,d} \Big/ \eta_i^{EV}; \forall i \in \mathcal{I} \wedge t \in \mathcal{T} \backslash \{0\} \tag{20}$$

For the sake of simplicity, we assume that EVs are only allowed to charge/discharge at the beginning of the time window (i.e. at 0:00 h). This implies that all the EVs are plugged at night and are equipped with a timer switch to prevent charging during peak-price periods. Consequently, the amount of energy stored at $t = 0$ is given by (21) and treated as a parameter dependent on the trips completed during the previous day.

$$E_{i,(t=0)}^{EV} = E_i^0; \forall i \in \mathcal{I} \tag{21}$$

EV users desire to get the on-board batteries fully charged prior to departure, as represented in (22). In this paper, Θ_i denotes the set of time intervals during which the EV of the i^{th} prosumer is plugged in, and therefore $\Theta_i[end]$ represents the departure time. Accordingly, charging and discharging are restricted to periods when the EV is connected to the charging point, as enforced by (23).

$$E_{i,(t=\Theta_i[end])}^{EV} = \overline{E}_i^{EV}; \forall i \in \mathcal{I} \tag{22}$$

$$p_{i,t}^{EV,c} = p_{i,t}^{EV,d} = 0; \forall i \in \mathscr{I} \wedge t \notin \Theta_i \quad (23)$$

2.3. Compact form of the centralized model

For convenience, the centralized community operational model is written in compact form, below.

$$\min_{x^C, p_{i,t}, x_i, y_{i,t}^{EV}} CC(x^C) + \sum_{i \in \mathscr{I}} U_i\left(p_{i,t}^{NS}\right) \quad (24a)$$

Subject to:

$$h^C(x^C) = 0 \quad (24b)$$

$$g^C(x^C) \le 0 \quad (24c)$$

$$h_i(x_i) = 0; \forall i \in \mathscr{I} \quad (24d)$$

$$g_i\left(x_i, y_{i,t}^{EV}\right) \le 0; \forall i \in \mathscr{I} \quad (24e)$$

$$y_{i,t}^{EV} \in \{0, 1\}; \forall i \in \mathscr{I} \wedge t \in \mathscr{T} \quad (24f)$$

where $x^C \triangleq \left[p_t^{im}, p_t^{ex}, q_t^{im}, q_t^{ex}, f_{j,t}^P, f_{j,t}^Q, V_{j,t}\right]; \forall j \in \mathscr{I} \wedge t \in \mathscr{T}$ and $x_i \triangleq \left[p_{i,t}^{NS}, p_{i,t}^{PV}, p_{i,t}^{EV,c}, p_{i,t}^{EV,d}, E_{i,t}^{EV}\right]; \forall \in \mathscr{T}$.

The objective function (24a) includes the cost of exchanging energy with the distribution network plus the penalization for unserved energy. In the set of constraints, (24b) and (24c) are the community-level equality and inequality constraints. Likewise, (24d) and (24e) incorporate equality and inequality constraints for each prosumer. Finally, (24f) declares binary variables.

3. The proposed privacy-preserving solution strategy

3.1. On privacy issues of (24) and other distributed/decentralized approaches

In its current form, model (24) requires the community manager to exercise direct control over prosumer-owned assets. This centralized control approach may raise significant privacy concerns, as prosumers could be hesitant to allow external entities to manage their personal energy resources directly. Such concerns may represent a substantial barrier to the practical implementation of the centralized model (24).

To overcome privacy concerns, distributed models may be adopted, as reviewed in Section 1.2. Among the most widely applied distributed methodologies in the context of LECs is ADMM (Lilla et al., 2020; Orozco et al., 2022), and its derived variants (Dolatabadi & Siano, 2020; Dolatabadi et al., 2023), while decentralized multi-stage strategies can be found in (Tostado-Véliz et al., 2023; Mitridati et al., 2020). In ADMM-based approaches, the role of the central coordinator is restricted to updating the Lagrange multipliers. As a result, only limited information is exchanged directly among prosumers, who iteratively adjust their net power profiles until consensus is achieved. While this setup preserves confidentiality from the central entity, it may still pose privacy risks, as the values of primal variables are exposed to other prosumers. OCD method presents a valuable alternative to ADMM, as it requires the exchange of only dual information (i.e., prices) among users within the considered framework (Nogales et al., 2003). In this context, price signals are generated independently by each subproblem (corresponding to individual prosumers in the case of Local Energy Communities LECs) without the need for a centralized coordinating entity (Conejo et al., 2002). Nonetheless, as with ADMM, the incorporation of network-level constraints remains an open challenge in OCD and other Lagrangian-based approaches. The methods proposed in (Tostado-Véliz et al., 2023; Mitridati et al., 2020) also raise privacy concerns, as they require users to exchange boundary information with the central manager, thus presenting privacy concerns similar to the centralized model (24).

3.2. Foundations of the proposed solution strategy

The main aim of this paper is to overcome the privacy issues of (24) as well as those in other distributed or decentralized approaches. In this context, Benders decomposition offers a promising framework for decentralized optimization that does not require the exchange of primal variables among agents. Traditionally, Benders decomposition has been employed to reduce computational complexity in optimization problems with a decomposable structure (Conejo et al., 2006). A detailed analysis reveals that the model described in equation (24) exhibits such a structure, thereby supporting the direct application of Benders decomposition.

Benders decomposition partitions optimization problems into a master problem and a set of subproblems. In the iterative Benders procedure, the subproblems communicate dual information to the master problem, which approximates the contribution of the subproblems to the overall objective function through the progressive addition of Benders cuts. For a comprehensive overview of Benders decomposition and its variants, the reader is referred to the extensive literature on the topic, e.g., (Conejo et al., 2006; Constante-Flores & Conejo, 2024; Brandenberg & Stursberg, 2021).

In the context of local energy communities (LECs), Benders decomposition is particularly well-suited to their operational structure. Specifically, the community manager naturally assumes the role of the master problem within the Benders framework, while the subproblems correspond to the individual prosumers. In this configuration, prosumers exchange only dual information with the community manager, and no direct communication occurs between prosumers, thereby preserving a high degree of privacy. Moreover, this structure facilitates the inclusion of network-related constraints directly within the master problem. For simplicity, Fig. 2(a) illustrates the core concept of the proposed solution strategy, where the λ's represent the dual variables (sensitivities) shared by prosumers with the manager while $\widehat{p}_i$ are P2P coordination signals sent by the manager.

Fig. 2(a) is compared with Fig. 2(b), which shows the information exchange in primal-based decomposition methods, such as C&CGA (Li et al., 2024). Specifically, prosumers share their primal information with the community manager, rather than solely sharing dual variables. This primal information is then embedded into the master problem as explicit primal constraints. Consequently, implementing C&CGA necessitates adding the prosumers' subproblem formulation (24d)-(24f) into the master problem, thereby leading to a non-compromised privacy framework.

3.3. Formulation of the proposed privacy-preserving solution strategy

3.3.1. Subproblems

In the proposed solution framework, $\mathscr{I}$ subproblems are solved, one for each prosumer. The subproblem for the i^{th} prosumer in the community for the ϱ^{th} iteration reads as:

$$\min_{p_{i,t}, x_i, y_{i,t}^{EV}} U_i\left(p_{i,t}^{NS}\right) \quad (25a)$$

Subject to:

$$h_i(x_i) = 0 \quad (25b)$$

$$g_i\left(x_i, y_{i,t}^{EV}\right) \le 0 \quad (25c)$$

$$y_{i,t}^{EV} \in \{0, 1\}; \forall t \in \mathscr{T} \quad (25d)$$

$$p_{i,t} = \widehat{p}_{i,t}^{(\varrho)} : \lambda_{i,t}^{(\varrho)}; \forall t \in \mathscr{T} \quad (25e)$$

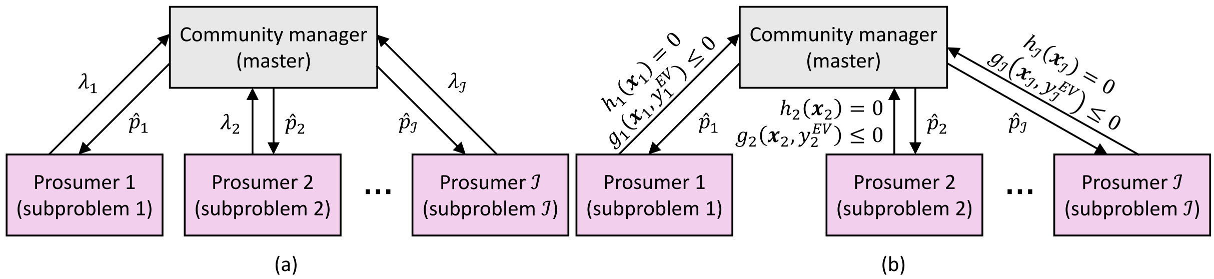

Fig. 2. Sketch of the proposed privacy-preserving solution approach (a) and an equivalent framework using C&CGA (b). For simplicity, dependence of time in the notation is omitted.

As seen, each prosumer aims to minimize its unserved energy in (25a), while satisfying its own operational constraints (25b)–(25d). The coupling variables $p_{i,t}$ are coordination signals provided by the master problem in (25e). This coupling enables the derivation of sensitivities (λ) as dual variables, which are then communicated to the master problem to construct Benders cuts. However, model (25) presents two key challenges in its current form. First, the presence of binary variables complicates the computation of sensitivities, as dual variables associated with (25e) may not be well-defined in a mixed-integer formulation (Kazempour & Conejo, 2012). Note that binary variables are essential as the objective function of (25) is not purely economic. Without them, batteries might follow unrealistic schedules where charging and discharging happen at the same time, as further discussed in (Arroyo, 2022) and the Appendix. Second, the model may become infeasible for certain values of $\widehat{p}_{i,t}$.

To address the first issue, (25) is solved in two stages. Initially, it is solved as a MILP to determine the optimal values of the binary variables, namely $\widehat{y}_{i,t}^{EV}$. These binary decisions are then fixed in a second-stage LP, which allows for the derivation of valid dual sensitivities. To address potential infeasibility, an alternative always-feasible model (26) is introduced and solved in place of (25), ensuring that Benders iterations proceed without interruption.

$$\lambda_{i,t}^{(\varrho)} \in \arg \min_{\substack{p_{i,t}, \boldsymbol{x}_i, \\ \boldsymbol{\delta}_i, \boldsymbol{\zeta}_i, \vartheta_i, \boldsymbol{\mu}_i}} F_i^{(\varrho)} = \sum \{\boldsymbol{\delta}_i + \boldsymbol{\zeta}_i + \vartheta_i + \boldsymbol{\mu}_i\} \tag{26a}$$

subject to:

$$h_i(\boldsymbol{x}_i) = \boldsymbol{\delta}_i - \boldsymbol{\zeta}_i \tag{26b}$$

$$g_i\left(\boldsymbol{x}_i, \widehat{y}_{i,t}^{EV}\right) \leq \vartheta_i - \boldsymbol{\mu}_i \tag{26c}$$

$$p_{i,t} = \widehat{p}_{i,t}^{(\varrho)} \ : \ \lambda_{i,t}^{(\varrho)}; \forall t \in \mathscr{T} \tag{26d}$$

$$0 \leq \boldsymbol{\delta}_i, \boldsymbol{\zeta}_i, \vartheta_i, \boldsymbol{\mu}_i \tag{26e}$$

where the slack variables $\boldsymbol{\delta}_i, \boldsymbol{\zeta}_i, \vartheta_i, \boldsymbol{\mu}_i$ have dimension $\mathscr{T}$ and are enforced to be non-negative in (26e). It is noteworthy that, due to binary variables are taken as fixed parameters, (26) is a LP that allows deriving valid sensitivities in (26d).

3.3.2. Master problem

In the proposed Benders' framework, the master problem encrypts the role of the community manager, including cuts to progressively approach the lower-level objective functions. Thus, the master problem for the ϱ^{th} iteration reads as:

$$\widehat{p}_{i,t}^{(\varrho)}, \beta_i^{(\varrho)} \in \arg \min_{\boldsymbol{x}^C, p_{i,t}, \beta_i^{(\varrho)}} CC\left(\boldsymbol{x}^C\right) + \sum_{i \in \mathscr{I}} \beta_i^{(\varrho)} \tag{27a}$$

subject to:

$$h^C\left(\boldsymbol{x}^C\right) = 0 \tag{27b}$$

$$g^C\left(\boldsymbol{x}^C\right) \leq 0 \tag{27c}$$

$$0 \leq \beta_i; \forall i \in \mathscr{I} \tag{27d}$$

$$F_i^{(\upsilon)} - \sum_{t \in \mathscr{T}} \left\{ \lambda_{i,t}^{(\upsilon)} \left(p_{i,t} - \widehat{p}_{i,t}^{(\upsilon)} \right) \right\} \leq \beta_i; \forall i \in \mathscr{I} \wedge \upsilon \in \{1, 2, \ldots, \varrho\} \tag{27e}$$

The master problem shares the same objective function as the centralized model, while the lower-level objective is represented through the auxiliary variable β_i. This variable is approximated via optimality cuts (27e), which incorporate information derived from the subproblems. Additionally, since subproblems of the form (26) are always feasible, feasibility cuts (27d) can also be employed to enrich the approximation of the β's. The remaining constraints (27b) and (27c) mirror those in the community-level model, primarily encompassing network-related constraints. P2P coordination signals $p_{i,t}$ are decision variables in the master problem; hence, their values are determined by the central manager. However, the information exchanged from the prosumers (subproblems) to the master problem is restricted to dual variables (i.e. $\lambda_{i,t}$) and objective values (i.e. F_i), thereby preserving the confidentiality of their primal decision variables.

A privacy-preserving solution can be achieved by developing an appropriate algorithm that iteratively updates the sensitivities, objective values, and coordination signals until a predefined convergence criterion is satisfied. Various convergence indicators may be defined; in this study, we consider the solution to be sufficiently accurate when the following condition is met:

$$\| \beta_i^{(\varrho)} \|_\infty \leq \varepsilon \tag{28}$$

where $\varepsilon \geq 0$ is a convergence threshold.

Condition (28) indicates that the amount of unserved energy across the community is negligible, which is a reasonable assumption in most LECs, where local generation and network capacity are typically sufficient to meet demand. However, Benders-like algorithms may exhibit slow convergence or become trapped in suboptimal solutions, particularly during the initial iterations when the information provided by optimality cuts is poor. To address this, the following subsection introduces an accelerated version of the proposed Benders algorithm.

3.3.3. The proposed benders-bundle model

Bundle methods are recognized as one of the most effective approaches for addressing nonsmooth optimization problems (Bagirov et al., 2014). The core concept behind these techniques is to approximate the subdifferential of the objective function by aggregating information from previous iterations, i.e., previously computed solutions. This approach was employed by Mitridati et al. (Mitridati et al., 2020) to enhance the convergence of Benders decomposition. The underlying idea is to utilize information from prior iterations to prevent the algorithm from exploring solutions that deviate significantly from earlier steps, thereby mitigating the oscillatory behavior commonly observed during the initial iterations (Lamontagne et al., 2024). Although conceptually simple, this strategy is computationally powerful and can substantially accelerate the convergence of the original Benders algorithm.

Applying the bundle trick in the proposed algorithm leads to modify the master problem (27) slightly, as follows:

$$\widehat{p}_{i,t}^{(\varrho)}, \beta_i^{(\varrho)} \in \arg \min_{\boldsymbol{x}^C, p_{i,t}, \beta_i^{(\varrho)}} CC\left(\boldsymbol{x}^C\right) + \sum_{i\in\mathcal{I}} \left\{ \beta_i^{(\varrho)} + \sum_{t\in\mathcal{T}} \frac{\tau_i}{2}\left(p_{i,t} - \widehat{p}_{i,t}^{(\varrho-1)}\right)^2 \right\} \tag{29a}$$

subject to:

$$h^C\left(\boldsymbol{x}^C\right) = 0 \tag{29b}$$

$$g^C\left(\boldsymbol{x}^C\right) \le 0 \tag{29c}$$

$$0 \le \beta_i; \forall i \in \mathcal{I} \tag{29d}$$

$$F_i^{(\upsilon)} - \sum_{t\in\mathcal{T}} \left\{ \lambda_{i,t}^{(\upsilon)} \left(p_{i,t} - \widehat{p}_{i,t}^{(\upsilon)}\right) \right\} \le \beta_i; \forall i \in \mathcal{I} \wedge \upsilon \in \{1, 2, \ldots, \varrho\} \tag{29e}$$

where $\tau_i > 0; \forall i \in \mathcal{I}$ is often called penalty parameter in the literature (Bonnans et al., 2006).

As observed, formulation (29) closely resembles (27), with the key difference being the inclusion of an additional term in the objective function. This term is designed to keep the current value of the coordination signals close to the one obtained in the previous iteration. The influence of this term is governed by a penalty parameter, namely τ, which must be appropriately updated as the algorithm progresses (Bonnans et al., 2006). Several update rules for τ have been proposed in the literature (e.g., (Bonnans et al., 2006; Rey & Sagastizábal, 2002)). In this study, we adopt the update rule proposed in (Bonnans et al., 2006), owing to its simplicity and strong theoretical foundation. Accordingly, starting from the second iteration, the penalty parameter is updated as follows:

$$\frac{1}{\tau_i} = \frac{1}{\tau_i} + \frac{\left\langle \widehat{p}_{i,t}^{(\varrho)} - \widehat{p}_{i,t}^{(\varrho-1)}, \lambda_{i,t}^{(\varrho)} - \lambda_{i,t}^{(\varrho-1)} \right\rangle}{\| \lambda_{i,t}^{(\varrho)} - \lambda_{i,t}^{(\varrho-1)} \|^2}; \forall i \in \mathcal{I} \tag{30}$$

Penalty parameter τ should not be updated frequently to avoid being trapped in a local optimum, therefore the penalty parameter is only updated if the residual increases between two consecutive iterations. After introducing the proposed bundle trick, the master problem becomes a quadratic programming problem, which can be handled efficiently by a variety of commercial solvers.

3.3.4. Overall solution algorithm

The multi-step procedure in Algorithm 1 describes the developed algorithm for the privacy-preserving solution of the centralized model (24), using the proposed Benders-bundle algorithm.

4. Case study

This section presents a case study with several results. The optimization models described in this paper were coded under Matlab R2021b and solved using Gurobi (Gurobi Optimization, LLC, 2024) on an Intel® Core™ i7–8750H CPU @ 2.20 GHz with 16.0 GB RAM.

4.1. Description of case study and input data

The developed solution strategy is applied for a single operational day on a 400 V, 15-bus radial community network as studied in (Mitridati et al., 2020) and depicted in Fig. 3. We consider one prosumer per node, with the exception of the root node ($j = 0$), where the community can exchange energy under the retailer tariff shown in Fig. 4, with a feed-in price of 0.06 €/kWh (ENDESA, 2025). In line with (Vespermann et al., 2021), we consider a LEC as a group comprising a relatively small number of prosumers connected to the same low voltage network, operated by the LEC. In this context, the majority of related studies typically consider communities consisting of between 3 and 15 prosumers (e.g. in (Lilla et al., 2020; Orozco et al., 2022; Tostado-Véliz et al., 2022; Tostado-Véliz et al., 2023; Mitridati et al., 2020)), with larger-scale cases being relatively uncommon. Therefore, the size of the case study of Fig. 3 is deemed appropriate.

Hourly demand and maximum PV generation were generated using the CREST demand model (McKenna et al., 2020). Rooftop PV panels are distributed across the community with peak powers in the range 1–3 kWp. Each prosumer can exchange 20 kW/kvar with the community, and the thermal limit of branches is set at 20 kVA. Voltage is enforced to

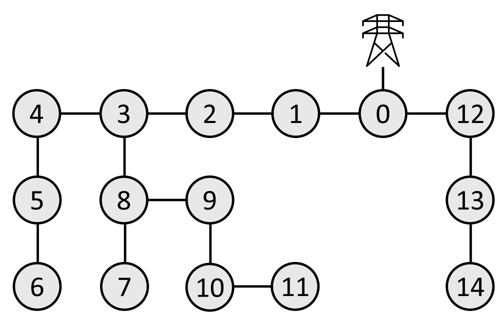

Fig. 3. Diagram of the 15-node network considered in simulations.

Algorithm 1
Privacy-preserving solution of (24).

Step 0. Read input data and initialize $\tau_i = 1; \forall i \in \mathcal{I}$, $\varrho = 0$, $\widehat{p}_{i,t}^{(\varrho)} = 0; \forall i \in \mathcal{I} \wedge t \in \mathcal{T}$, $\beta_i = \infty; \forall i \in \mathcal{I}$ and ε.
Step 1. **while** $\| \beta_i \|_\infty > \varepsilon$ **do**
Step 2. **for** $i = 1$ **to** $i = \mathcal{I}$ **do**
Step 3. solve (26) to obtain $\widehat{y}_{i,t}^{EV}; \forall t \in \mathcal{T}$
Step 4. solve (26) with $\widehat{y}_{i,t}^{EV}; \forall t \in \mathcal{T}$ fixed, store the value of $\lambda_{i,t}^{(\varrho)}; \forall t \in \mathcal{T}$ and $F_i^{(\varrho)}$
Step 5. **end for**
Step 6. **if** $\varrho = 0$ **do**
Step 7. solve (27), store the value of $\widehat{p}_{i,t}^{(\varrho)}; \forall i \in \mathcal{I} \wedge t \in \mathcal{T}$ and $\beta_i^{(\varrho)}; \forall i$
Step 8. **else**
Step 9. solve (29), store the value of $\widehat{p}_{i,t}^{(\varrho)}; \forall i \in \mathcal{I} \wedge t \in \mathcal{T}$ and $\beta_i^{(\varrho)}; \forall i$
Step 10. **if** $\| \beta_i^{(\varrho)} \|_\infty > \| \beta_i^{(\varrho-1)} \|_\infty$
Step 11. update $\tau_i; \forall i \in \mathcal{I}$ using (30)
Step 12. **end if**
Step 13. **end if**
Step 14. $\varrho \leftarrow \varrho + 1$
Step 15. **end while**

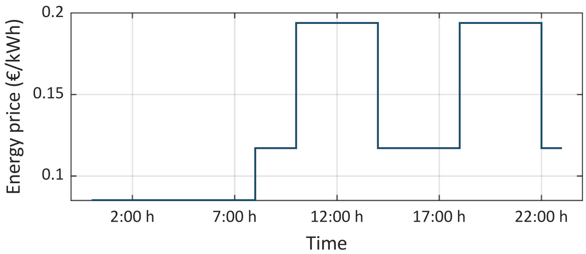

Fig. 4. TOU tariff considered in simulations.

be within the range 95–105 % of the rated value. The convergence threshold is taken to be equal to 10^{-3} kWh.

We assume that each prosumer owns an EV unless stated otherwise. Each EV on-board battery is charged with 95 % efficiency through a 7.4 kW charging point. EV battery capacities range from 60 to 100 kWh, with initial energy between 85 and 95 % of that capacity. Departure times are randomly chosen between 6:00 and 21:00. EVs cannot be discharged below 20 % of their nominal capacity. To ease reproducibility, codes and data used in simulations are freely available at (M. Tostado-Véliz et al., 2025).

4.2. Basic comparison with the centralized model at the community level

We begin by comparing our proposed solution strategy with the centralized model (24), which is used as the benchmark. Fig. 5 shows the net power exchange of the community for both approaches. The two approaches differ mainly during two periods: at night and around midday. These periods match with EV charging schedules and peak PV generation, respectively. Despite these differences, the total daily cost for the community is similar: €16.80 for the centralized model and €17.17 for the proposed privacy-preserving approach. Consequently, in this case study, preserving user privacy increases the cost by only €0.37 per day. Over one year, this adds up to about €135.05 for the whole community or about €9.65 per prosumer. Fig. 5 shows that during the rest of the day (morning and evening periods) both approaches yield nearly identical results.

Furthermore, Fig. 6 presents similar results to Fig. 5, but assuming EVs do not have V2G capability. The same conclusions apply. In the centralized solution, most of the EV charging happens during the initial hours of the scheduling horizon. In the proposed strategy, charging is more evenly spread over the early morning. Since energy prices are constant from 00:00 to 08:00, both approaches yield comparable costs for the community. The centralized approach results in a total daily cost of €16.80, and the proposed privacy-preserving strategy gives €17.47. To compare both methods further, Fig. 7 shows the total net energy exchange, with and without V2G capabilities. As seen, the aggregated energy profiles are very similar, with marginal differences of about 0.83 %, which explains the close alignment in the corresponding economic outcomes.

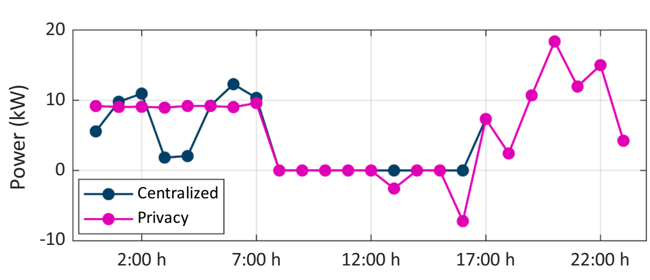

Fig. 5. Net power exchanged by the community with the distribution network using the centralized model (24) and the developed solution strategy.

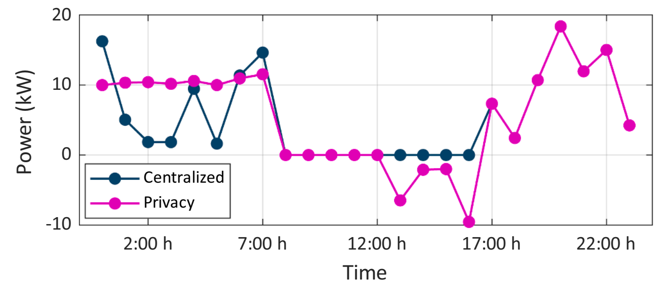

Fig. 6. Net power exchanged by the community with the distribution network using the centralized model (24) and the developed solution strategy, neglecting V2G capability of EVs.

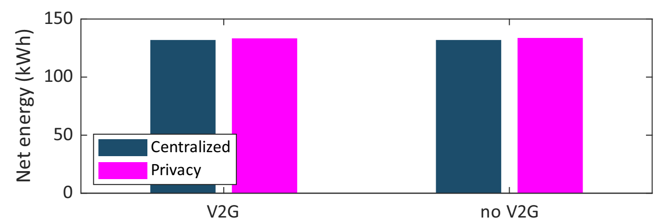

Fig. 7. Community net energy in different scenarios using the centralized model (24) and the developed solution strategy.

4.3. Prosumer-level analysis

Next, we analyze the results for each prosumer. Fig. 8 compares the net power profiles for each prosumer under the centralized and privacy-preserving optimization models. The biggest differences occur at night and midday, which match the trends previously identified at the community level. In most cases, these differences are just shifts in time between hours with the same energy prices. As a result, the total net energy consumption remains largely unchanged, as illustrated in Fig. 9, which compares individual net consumption for both optimization approaches. These findings help explain why, despite the instantaneous power differences observed in Fig. 8, the overall economic outcomes at the community level remain comparable in both models.

Fig. 10 compares the energy stored in EVs under the centralized and the proposed privacy-preserving strategies. The proposed approach tends to promote slower and more distributed charging profiles compared to the centralized model, which often results in higher and more concentrated charging demands. Additionally, V2G functionality is activated more frequently under the privacy-preserving strategy. These differences arise from the mathematical structure of the subproblem's objective function in the proposed approach, wherein discharging EVs helps reduce the value of the slack variables in (26). In contrast, the centralized model typically does not invoke EV discharging, as it yields no substantial economic advantages.

Network modeling has a strong impact on V2G behavior. Specifically, when the centralized model is executed without considering network constraints, the total energy discharged from EVs increases by 176.7 kWh. This shows the importance of an accurate model of the community network when EVs are present, as their potentially high-power demand and generation can cause bottlenecks or voltage issues. This aspect warrants further investigation in future studies.

The number of charging-discharging cycles completed under the different scheduling strategies can have an impact on the lifetime of the batteries (Alsaidan et al., 2018). Let us define the number of charging-discharging cycles as

$$CD_i = \frac{\sum_{t\in\mathcal{T}}\left\{p_{i,t}^{EV,c} + p_{i,t}^{EV,d}\right\}}{2\cdot\overline{E}_i^{EV}} \tag{31}$$

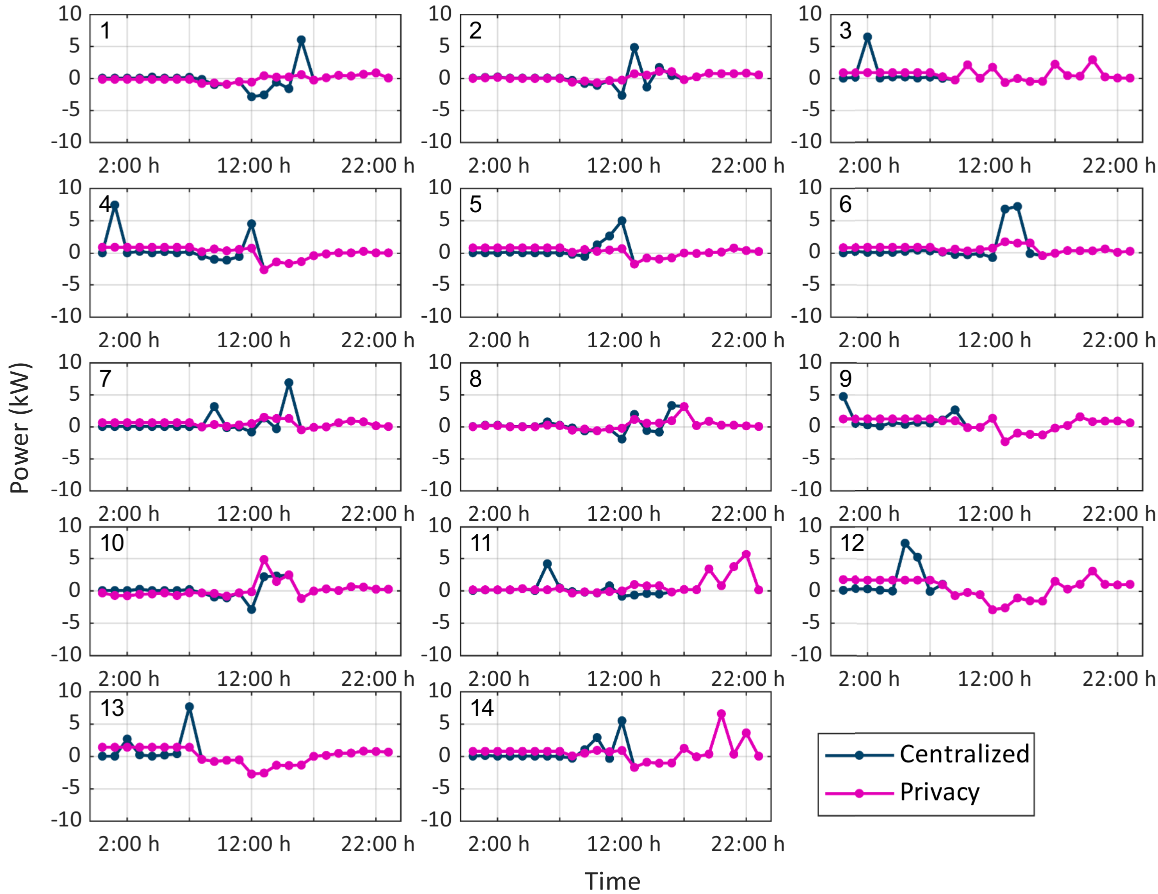

Fig. 8. Prosumer net power using the centralized model (24) and the developed solution strategy.

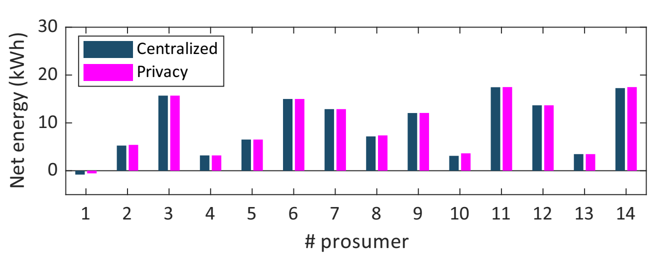

Fig. 9. Prosumers net energy using the centralized model (24) and the developed solution strategy.

Fig. 11 presents a comparison of the total number of charge-discharge cycles for each prosumer under both the centralized and the proposed privacy-aware scheduling strategies. While the majority of prosumers experience a comparable number of charge-discharge cycles across both strategies, certain prosumers (e.g., Prosumers 8 and 10) exhibit a noticeable increase in cycling frequency when the privacy-aware approach is employed. However, since the total number of cycles per day remains relatively low, this increase does not represent a significant drawback of the proposed method. As indicated in (Alsaidan et al., 2018), lithium-ion batteries with an 80 % depth-of-discharge can handle around 2500 cycles over their lifespan. If we extend the results from Fig. 11 to a typical operational horizon (e.g., 10 year period), it appears that the total number of charge-discharge cycles is not a critical factor in battery aging. Instead, other factors, such as charging power levels or calendar aging, are likely to have a greater impact on battery longevity.

4.4. Assessing the impact of the number of EVs

The results discussed in the previous subsections suggest that the largest scheduling mismatches occur when higher flexibility is introduced, particularly during the early hours of the day when EV charging or discharging is permitted. To validate this hypothesis, Fig. 12 presents a comparison of the total community cost for varying numbers of EVs within the community. In this analysis, EVs were randomly assigned to prosumers with characteristics consistent with those used in previous simulations.

Notably, when no EVs are present, the results obtained using the centralized approach and the proposed privacy-preserving strategy are nearly identical. This observation confirms that the developed methodology is well-suited for largely passive communities, providing privacy preservation without incurring additional economic costs. As the number of EVs increases, the outcomes derived from the privacy-preserving strategy begin to diverge from those of the centralized model. Nevertheless, the deviations remain within acceptable bounds, thereby reinforcing the robustness and scalability of the proposed approach under increasing levels of flexibility.

4.5. Evaluating the performance of the proposed benders-bundle method

Fig. 13 compares the value of the residual (i.e. $\| \beta_i^{(e)} \|_\infty$) obtained using the conventional Benders (27) and the proposed Benders-bundle methodology (29). As illustrated, while the conventional Benders method tends to become rapidly trapped in a local region, the proposed bundle-based approach demonstrates a more effective convergence behavior, reaching a solution within a reasonable number of iterations. These findings further support the efficacy of bundle-like strategies in

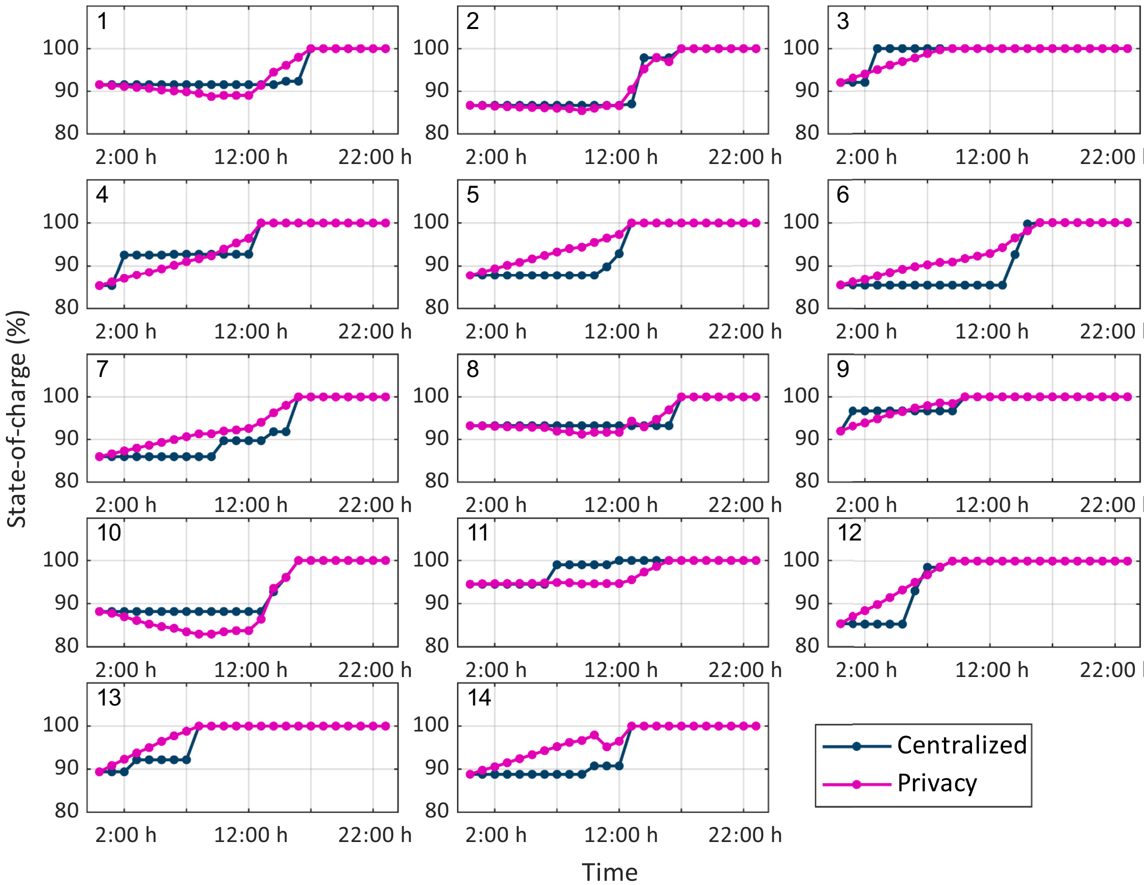

Fig. 10. Energy stored in EVs using the centralized model (24) and the developed solution strategy.

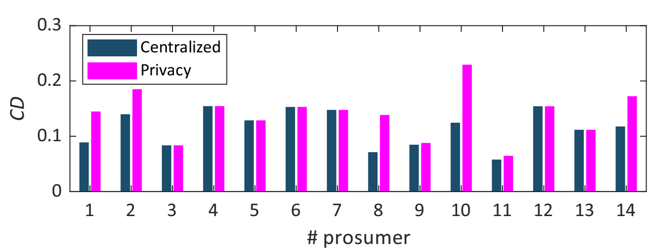

Fig. 11. Total number of charging-discharging cycles using the centralized model (24) and the developed solution strategy.

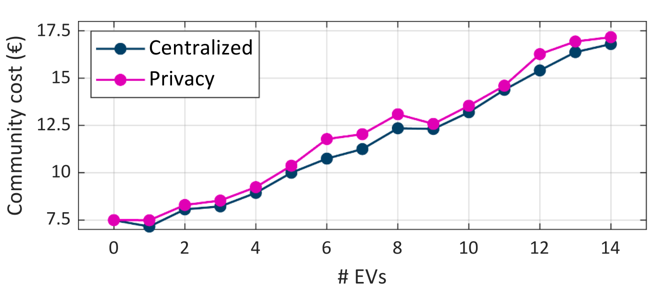

Fig. 12. Total community cost using the centralized model (24) and the developed solution strategy for different numbers of EVs in the community.

enhancing the convergence performance of Benders decomposition, as previously suggested in (Mitridati et al., 2020). Future research should explore this direction further by applying bundle-based techniques to a broader range of Benders-type algorithms.

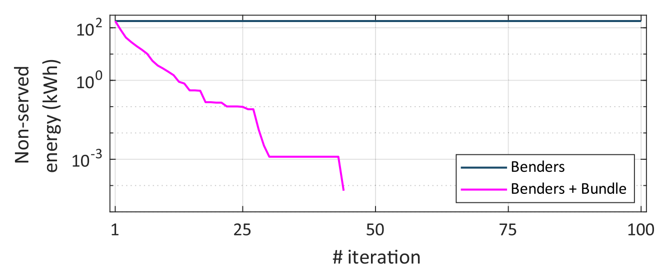

Fig. 13. Evolution of the residual employing the conventional Benders (27) and the proposed Benders-bundle approach (29).

4.6. Comparison with other solution methodologies

Finally, Table 1 compares the proposed privacy-preserving strategy with several alternative approaches from the literature. These include the centralized approach (24), the individual optimization strategy in which no P2P energy exchanges occur among prosumers, the ADMM-

Table 1
Comparison of different solution methodologies.

Method	Comm. cost (€)	Cost of privacy (€)	Runtime (s)
Centralized (24)	16.80	–	3.44
Individual	18.94	–	2.41
ADMM (Lilla et al., 2020)	17.00	0.20	119.09
Algorithm (Tostado-Véliz et al., 2022)	19.95	3.15	25.56
Developed	17.17	0.37	259.90

based method introduced in (Lilla et al., 2020), and the algorithm presented in (Tostado-Véliz et al., 2022).

As expected, enabling P2P energy exchanges contributes to reducing the total community cost, as evidenced by the comparison between the individual and centralized optimization outcomes. In this specific case study, the ADMM-based method yields the lowest community cost among the privacy-preserving strategies, resulting in a cost of privacy (defined as the difference between the centralized community cost and the cost achieved by the method) of €0.20. However, as previously discussed, this approach does not explicitly model the distribution network, which may lead to solutions that are infeasible under realistic operating conditions.

The algorithm proposed in (Tostado-Véliz et al., 2022) incorporates network constraints, thereby ensuring operational feasibility. Nevertheless, the results it provides exhibit a significant deviation from the benchmark centralized case. Moreover, both the ADMM and the algorithm in (Tostado-Véliz et al., 2022) require the exchange of primal variables (e.g., power schedules) either among prosumers or with a centralized entity.

The proposed privacy-preserving strategy offers a well-balanced trade-off between solution accuracy and privacy preservation. It achieves a cost of privacy of only €0.37 while maintaining network feasibility and minimizing the exposure of sensitive information.

From a computational efficiency perspective, the centralized and individual strategies are the fastest, as they compute the solution directly without requiring iterative procedures. Among the privacy-preserving solution methods, the algorithm proposed in (Tostado-Véliz et al., 2022) demonstrated the highest computational efficiency. However, its results show a significant deviation from the benchmark centralized solution.

In contrast, both the ADMM approach and the proposed privacy-preserving strategy achieved satisfactory solutions within a few minutes, which is acceptable for day-ahead operational planning. These results indicate that the computational requirements of the proposed method are not a limiting factor for its practical implementation. Furthermore, it is important to highlight that, unlike ADMM, the proposed solution procedure is inherently parallelizable at the subproblem level, offering additional potential for reducing computation time and improving scalability.

5. Concluding remarks

This paper has presented a novel privacy-preserving energy management strategy for LECs. The new proposal leverages the inherently decomposable structure of the community energy management problem to apply Benders decomposition, enabling a fully decentralized solution approach. The proposed strategy requires only the exchange of dual variables with the community manager, while all primal information remains confidential and is not disclosed to either the manager or other prosumers. Furthermore, the formulation incorporates EV charging schedules and network constraints, enabling the efficient calculation of accurate and feasible solutions.

The new methodology has been tested in a 14-prosumer LEC connected to a 15-bus radial distribution network. The results obtained allow to conclude that:

- Although discrepancies in instantaneous power schedules are observed between the decentralized and centralized solutions, the total energy consumption within the community remains comparable. As a result, the economic outcomes are also similar, with only marginal differences in the order of euro cents.
- The level of flexibility impacts the accuracy of the proposed privacy-preserving solution strategy. Nevertheless, the proposed approach consistently yields accurate results across varying numbers of EVs, thereby demonstrating its scalability and robustness.
- The inherent limitations of the conventional Benders decomposition approach have been effectively addressed through the development of a novel Benders-bundle methodology. This enhanced technique demonstrates a strong ability to overcome convergence issues and avoid entrapment in suboptimal local solutions.
- Although certain tailored algorithms (Tostado-Véliz et al., 2022) demonstrate higher computational efficiency, their solutions exhibit significant deviations from ground-truth benchmarks. Conversely, ADMM (Lilla et al., 2020) achieves slightly higher accuracy, but its implementation necessitates the exchange of primal information and presents challenges in incorporating network-related constraints. Thus, the proposed methodology offers the most favorable trade-off between solution accuracy and privacy preservation.

The obtained results demonstrate the effectiveness of Benders decomposition in delivering privacy-preserving solutions within multi-agent energy systems. The approach is especially useful for LECs and can be extended to broader contexts, such as coordinated EV charging in parking lots or multi-microgrid systems. Future research will focus on improving the computational performance of Benders-like methodologies, with the objective of enabling their deployment in real-time energy management scenarios.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to enhance readability and language. The authors reviewed and edited the content as needed and take full responsibility for the final published version of the article.

CRediT authorship contribution statement

Marcos Tostado-Véliz: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Alberto Borghetti:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Formal analysis. **Pierluigi Siano:** Writing – review & editing, Visualization, Validation, Data curation. **Francisco Jurado:** Supervision, Resources, Project administration, Formal analysis, Conceptualization.

Declaration of competing interest

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

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Appendix. On the necessity of binary variables

This appendix shows the necessity of incorporating binary variables into the mathematical models presented in this paper, to prevent simultaneous charging and discharging in energy storage systems. Some studies, such as (Wen et al., 2016), suggest that setting battery efficiencies below 100 % can discourage these unrealistic schedules. The rationale is that charging and discharging at the same time is economically inefficient, so optimization solvers aiming to minimize cost will avoid it. However, as shown in (Arroyo, 2022), including battery losses alone is insufficient to guarantee the feasible results when the objective function is not only a pure cost minimization, as in (26). In such cases, the solution can include simultaneous charging and discharging because it is mathematically optimal, despite being physically infeasible. Therefore, binary decision variables are added to prevent such behaviour.

Fig. 14 compares the outcomes of the developed privacy-aware strategy in two formulations: one with binary variables and another one without binary them. Specifically, we consider the case of Prosumer 11 during the second iteration of the solution algorithm. As observed, when binary variables are omitted, simultaneous charging and discharging frequently occur, since the model only aims to minimize power mismatches as defined in constraint (26a). This non-physical schedule is avoided when disjunctive constraints involving binary variables, such as (18) and (19), are included. Without binary variables, the value of the objective function (i.e., total power mismatches) is 12.30 kWh. When binary variables are included, the value increases to 16.97 kWh. This difference indicates that solutions involving simultaneous charging and discharging are optimal from a mathematical standpoint, despite being physically infeasible. Consequently, binary variables are essential to ensure the physical realizability of the schedules obtained by using the developed model.

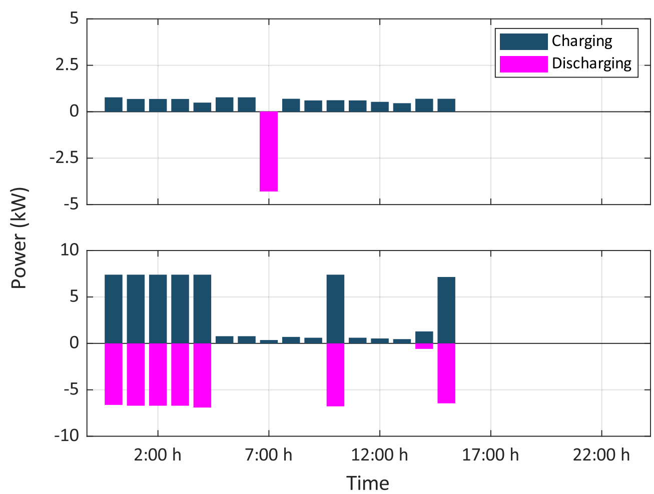

Fig. 14. EV scheduling for prosumer 11 at the second iteration with binary variables (top) and without binary variables (bottom). Discharging power is plotted as negative values.

Data availability

I have shared the link to my data/code

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