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On the Applicability of the Alternating Projections Method for Privacy-preserving Scheduling in Local Energy Communities

Abstract: Local energy communities enable proper infrastructure and management mechanisms to empower final users to partake actively in the operation of electrical systems while sharing resources to pursue common objectives. As an aggregated structure, suitable energy management and scheduling tools need to be developed and tested to ensure that local resources are properly operated to maximize the economy and efficiency of energy communities. However, final electricity users may be reluctant to share confidential information, which needs to be taken into account when developing novel computational tools for energy communities. This paper applies the well-known Alternating Projection Method (APM) and differential privacy (DP) to the day-ahead scheduling problem in energy communities. As a result, two novel iterative methodologies are proposed enabling decentralized privacy-aware resolution in energy communities. Different numerical results are discussed on 100 different community instances, analyzing both economic and energetic indicators. Specifically, with no added noise ($\sigma = 0$) APM is numerically identical to the centralized benchmark across all cases . Additionally, for $0 < \sigma \leq 1$, the mean absolute percentage error in imported energy remains less than 20%. Results reveal that the application of the APM is capable of reproducing exactly the results of the centralized approach, while the application of differential privacy may lead to large errors, especially regarding economic results when exportable capacity is large. Moreover, results reveal that the computational burden of the new methodologies is reasonable and therefore does not pose a barrier to their implementation. Indeed, as all steps in our implementation rely on Linear Programming (LP) and as there are many stable LP solvers (both open-source and commercial) it is easy for practitioners to deploy our approach for real-life scenarios. Our numerical experiments show that the considered privacy-aware techniques were quite efficient, achieving the solution in less than a minute in all cases. Moreover, the considered privacy-aware APM presents a highly parallelizable structure which allows the results to be even further improved.

Keywords. Alternating projection method; Local energy communities; Differential privacy.

1 - Introduction

1.1 - Context and motivation

With the deregulation of power systems, new businesses and management strategies arise intending to empower final users [1]. In this context, Local Energy Communities (LECs) appear as a valuable framework to collectivize energy assets installed by residential users. Thus, a LEC can be conceived as an aggregation of residential electric consumers, who seek to improve their levels of efficiency and self-sufficiency, while enabling their participation in different activities like local markets or flexibility provision [2].

Therefore, different consumers (prosumers, normally) partake within the community exchanging resources to reduce their dependency on the main grid (e.g. the distribution network). In this context, privacy concerns may arise due to the information that prosumers need to exchange among them. In this way, such concerns need to be solved in energy management tools, when implemented in LECs. This paper focuses on this issue.

1.2 – Literature review

Prosumers within communities can exchange different data depending on the objectives pursued. The most common way to manage LECs is through a central agent called the community manager. This agent could have access to the different resources throughout the community and manage them in order to optimize a predefined objective. This option ensures that common objectives are optimized but implies the direct action of the manager in individual assets. Within this category, one can find different works. For instance, Feng et al. [3] propose a coalitional game model to form coalitions of prosumers in communities. De Grève et al [4] develop different machine learning techniques to improve self-consumption in highly renewable LECs, while Brusco et al [5] focus on sharing energy storage, for which a tailored day-ahead scheduling tool is proposed. Mustika et al [6] propose a two-stage management model for LECs, where a central manager is responsible for coordinating peer-to-peer (P2P) transactions and allocating costs among prosumers. Likewise, Wu and Conejo [7] develop an equilibrium model for local price clearing in LECs. Cheng and Ruiz [8] propose a bi-level management strategy for communities where the manager acts as the leader with prosumers as followers. On the other hand, other works simply assume that the central manager has full access to controllable assets installed by community members such as [9-11].

The references above propose different energy management or market models for LECs that imply sharing information among prosumers or with the manager. In some cases, the manager is responsible for managing controllable appliances or battery energy storage systems directly [11]. Therefore, although these tools ensure optimum reachability, their implementation in real-life cases entails privacy concerns due to the data revealed and even the direct action of the manager. The former can be solved by using distributed or decentralized algorithms. These solution techniques enable individual solutions to the corresponding optimization problems. For example, in LECs, each prosumer is responsible for solving its home energy management problem. Then, the global solution is reached by exchanging only boundary information, such as the individual net power profile.

Different distributed and decentralized methodologies have been proposed for energy management in LECs. Zhou et al [12] proposed a reinforcement learning model for coordinating P2P transactions within communities. Each prosumer decides on the energy shared with the community as a response to individual learning models. This way, each prosumer individually optimizes its responses, limiting the information shared with other agents. The alternating direction of multipliers method (ADMM) enables a decentralized solution of power scheduling in LECs. By using this approach, each prosumer solves its energy management model, while exchanging only boundary information with the other prosumers until reach an agreement. This algorithm has been employed in LECs in [13, 14]. In particular, Lilla et al. [13] develops a decentralized algorithm for day-ahead scheduling in LECs, using ADMM, while power losses are included once the algorithm has converged and P2P exchanges are revealed. Likewise, ADMM is employed in [14], but provides intraday responses within the community, thus resulting in a multi-stage decision-making framework. Dolatabadi et al [15] solved day-ahead scheduling in LECs in a privacy-preserving decentralized way by decoupling the problem into a linear programming (LP) problem plus a conic projection (CP), in which solving LP only requires matrix-vector multiplications.

Alternatively, tailored algorithms have been proposed for decentralized energy management in LECs, by which the different agents exchange only boundary information following a multi-stage solution strategy. For example, the algorithms in [16, 17] consider the individual home energy management solution in the first stage, seeking to maximize the participation of prosumers in P2P transactions. Then, the second stage clears P2P exchanges among prosumers considering net profiles calculated in the first stage, looking to minimize the total energy deficit. Finally, the manager exchanges power with the upscale network to attend to the local demand. Thereby, the manager has only access to the aggregated net demand in the community. It is worth noting that while Tostado-Véliz et al [16] collectivize some assets such as flexible loads or storage, Tostado-Véliz et al [17] consider the installation of a collective hydrogen system for energy storage and production. Furthermore, Tostado-Véliz et al [18] propose a similar algorithm but include coordinated actions with intelligent parking lots.

The distributed algorithms revised above suppose a powerful tool to avoid disclosing internal data of prosumers, such as inflexible demand, battery settings or controllable appliances. However, prosumers need to exchange real boundary information with the other prosumers in the community (typically their net demand). In this sense, prosumers might still be reluctant to share such kind of information. Alternatively, some papers have proposed energy or market tools by which prosumers do not exchange data with other prosumers or the manager. Instead, aggregators manage such information and transfer aggregated profiles to the manager. Thereby, only the aggregator has access to real data from prosumers. Within this category, Jo et al. [19] develop a market model for LECs for sharing battery storage. This market mechanism enables the active participation of distributed generators and the so-called storage aggregator, which gathers information on the storage assets throughout the community.

Alternatively, some recent works have proposed different types of aggregators and study their importance and behaviour in community management. Thus, Tostado-Véliz et al [20] develop a privacy-aware robust day-ahead scheduling tool for LECs, involving the presence of different aggregators such as storage, net demand and flexible demand aggregators, which ensures further privacy as information from prosumers is shared with different aggregators instead of only one collecting all the relevant information. On the other hand, a coalition model has been proposed by Tostado-Véliz et al [21], by which prosumers only share confidential information with the other prosumers in the coalition, while the manager and the rest of the community have only access to boundary information. For the sake of simplicity, Table 1 summarizes the studied literature. As it can be seen in Table 1, what sets our proposed method apart from the other methods in the literature is the fact that we do not rely on true values for shared information to be disclosed by the prosumers in our DP approach, while other methods like [12],[13],[14],[15] (and of course our APM) do. Indeed, our DP is a modification of our APM such that it works even with perturbed boundary information. The main reason why having the shared information perturbed is so crucial (in terms of privacy) is elaborated as follows:

If $p_{i,t}^{PV}$ and $p_{i,t}^{D}$ are the instantaneous PV generation and demand for the i^{th} prosumer at time t then boundary information $p_{i,t}$ satisfies in $p_{i,t} + p_{i,t}^{PV} = p_{i,t}^{D}$ (power balance constraint) where $p_{i,t}^{PV}$ is less than the PV potential $\tilde{p}_{i,t}^{PV}$. Now if $p_{i,t}^{PV}$ is estimated in some way (from knowing the amount of sunlight availability plus the physical characteristics of the solar panels) then having the true values for $p_{i,t}$ shared as boundary information will lead to the disclosure of $p_{i,t}^{D}$. In our method (DP) we propose disclosure of noisy version of $p_{i,t}$ to avoid this vulnerability. This is what makes our approach more resilient in terms of privacy. Also in the next sections we will provide in-depth analysis of the application of our methodology in LECs, with special focus on its accuracy and reliability, in order to validate it for real-life cases.

1.3 - Contributions

In the energy management of LECs, privacy consideration plays a key role and poses a major challenge. The different methodologies proposed so far ensure partial privacy, enclosing only internal data while real boundary information is still revealed to other agents within the community. As seen in Table 1, most of the existing approaches try to ensure privacy by only sharing real boundary or aggregated information. Solution approaches are mainly based on decentralized methodologies, although some references are still capable to preserve privacy by means of centralized scheduling.

This paper contributes with novel privacy-aware algorithms for energy management in LECs. Specifically, we firstly develop a simple algorithm which only requires boundary information sharing. The new approach is based on the alternating projection method (APM) and casts as a solvable LP, thus supposing the first attempt to apply this methodology in LECs, as seen in Table 1. Next, we firstly apply the well-known differentially private methodology to LECs [22]. This approach ensures that real data is not transferred and is kept enclosed for the rest of the community.

Table 1. A summary of the related literature

Ref.	Information shared	Methodology	Solution approach
[12]	Boundary real information	Fuzzy Q-learning	Decentralized
[13]	Boundary real information	ADMM	Decentralized
[14]	Boundary real information	ADMM	Decentralized
[15]	Boundary real information	Tailored algorithm	Decentralized
[16]	Aggregated real net demand	Tailored algorithm	Centralized
[17]	Aggregated real net demand	Tailored algorithm	Centralized
[18]	Aggregated real net demand	Tailored algorithm	Centralized
[19]	Boundary real information	Direct solution	Centralized
[20]	Aggregated real profiles	Direct solution	Centralized
[21]	Boundary real information	Direct solution	Centralized
This paper	Boundary real information	APM	Decentralized
This paper	Boundary perturbed information	DP	Decentralized

On the other hand, we compare how ensuring privacy may affect final results and to what point privacy can be ensured without compromising the objectives of the community. To this end, a statistical analysis is performed on 100 different instances, and the results are compared in terms of economic and energetic indicators. Our main aim is, in consequence, to demonstrate if differentially private approaches could be adopted widely in LECs ensuring effectiveness in scheduling and energy management results. Therefore, we aim to conclude if ensuring the privacy of users in LECs may result in compromising key economic and energetic indicators that may eventually lead to making wrong decisions.

In the rest of this paper, Section 2 describes the necessary background and the benchmark centralized scheduling. Section 3 develops the mathematical formulation of the different privacy-aware methodologies which are inspired by the alternating projections method (APM) and differential privacy (DP). Section 4 presents and discusses different numerical results. Finally, the main conclusions are duly drawn in Section 5.

2 – Background

2.1 – Notations

We consider a LEC formed by I prosumers indexed by $i \in \mathcal{I}$, who install individual rooftop photovoltaic (PV) arrays. Each prosumer is connected to a bus in the local network, which is assumed to be radial with J buses indexed by $j \in \mathcal{J}$. The set Θ_j collects all the prosumers connected to the j^{th} bus in the network.

The considered computational tools decide on day-ahead power scheduling throughout the community, including power flows across branches for the local network within the community. This way, decisions are taken for a time span of $T = 24$ time steps indexed by $t \in \mathcal{T}$.

We assume that powers are given in kW or kvar (active and reactive power, respectively), while prices are given in €/kWh.

2.2 – Overview of the LEC under study

Fig. 1 sketches the LEC under study. The local network is connected to an upscale system (e.g. the distribution system) at a unique root node ($j = 0$). The community can exchange power with the upscale system. The imported power is dynamically priced under a known time-of-use (TOU) tariff, while the energy exported is priced by a fixed fed-in tariff. We assume that the community manager is responsible for coordinating power transactions through the local network and the energy exchanged with the upscale system. Thus, the community manager decides on P2P exchanges. Regarding prosumers, they can generally manage their assets such as PV arrays. However, when a centralized approach is adopted, the manager has direct control over individual assets, as explained in the following subsection.

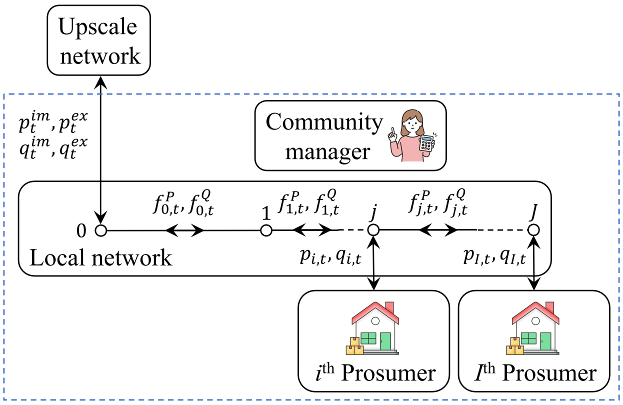

Fig. 1 – Sketch of the LEC under study and some notations used in formulation

2.3 – Centralized day-ahead scheduling

This section presents the mathematical formulation of the centralized day-ahead scheduling tool for the community described in Fig. 1. Under this approach, the manager has a direct action on all the assets installed in the community, including those installed by prosumers, in order to minimize the energy cost of the entire community, which can be expressed, as follows:

$$F^C = \sum_{t \in \mathcal{T}} \{ \mathrm{TOU}_t p_t^{im} - \zeta p_t^{ex} \} \quad (1)$$

Therefore, we define the community energy cost as the balance between the cost of imported energy and the income from exporting energy. Commonly, the fed-in tariff is lower than the minimum TOU price (i.e. $\gamma < \min_t \mathrm{TOU}_t$), to avoid incoherent practices such as importing energy just to be exported in the next time step. As seen in Section 2.1, the community can exchange power with the upscale system at the root node $j = 0$, as given by

$$p_t^{im} - p_t^{ex} = f_{(j=0),t}^P; \forall t \in \mathcal{T} \quad (2)$$

$$q_t^{im} - q_t^{ex} = f_{(j=0),t}^Q; \forall t \in \mathcal{T} \quad (3)$$

While (2) and (3) express the active and reactive power flows at the root node, (4) and (5) do it for the rest of the nodes throughout the local network.

$$f_{j,t}^{P} = \sum_{i\in\Theta_j} p_{i,t} + \sum_{k\in\mathcal{D}_j} f_{k,t}^{P} : \langle\lambda_{j,t}^{P}\rangle; \forall j \in \mathcal{J}\backslash\{0\} \wedge t \in \mathcal{T} \quad (4)$$

$$f_{j,t}^{Q} = \sum_{i\in\Theta_j} q_{i,t} + \sum_{k\in\mathcal{D}_j} f_{k,t}^{Q}; \forall j \in \mathcal{J}\backslash\{0\} \wedge t \in \mathcal{T} \quad (5)$$

Note that we consider negative net power when the prosumer is exporting energy to the network. In line with [23], we consider a constant power factor for prosumers, therefore

$$q_{i,t} = \delta_i p_{i,t}; \forall i \in \mathcal{I} \wedge t \in \mathcal{T} \quad (6)$$

where δ_i is the power factor of the i^{th} prosumer.

We adopt a linear power flow model in (4) and (5), which supposes an acceptable simplification for radial systems with short branches [24, 25], such as that typically encountered in LECs. Furthermore, $\lambda_{j,t}^{P}$ is the dual variable associated with (4), which will be useful in the proposed decentralized solution approaches. Indeed, $\lambda_{j,t}^{P}$ can be seen as the locational marginal price at node j and time t, thus representing the marginal cost of supplying the demand at node j.

Power flows through branches are bounded by the thermal limits of lines by the following second-order cone constraint:

$$\sqrt{\left(f_{j,t}^{P}\right)^2 + \left(f_{j,t}^{Q}\right)^2} \leq \overline{f}_j; \forall j \in \mathcal{J} \wedge t \in \mathcal{T} \quad (7)$$

Although second-order cone programming models can be handled by off-the-shelf solvers, we further linearize (7) in order to keep the model linear and scalable. To do this, we consider the inner polygon approximation [22, 26], which replaces (7) with a set of N linear constraints of the form of

$$\delta_n^P f_{j,t}^{P} - \delta_n^Q f_{j,t}^{Q} - \delta_n^f \overline{f}_j \leq 0; \forall j \in \mathcal{J} \wedge t \in \mathcal{T} \wedge n \in \{1,2,\ldots,N\} \quad (8)$$

where the δ's are real parameters whose values can be found in [26].

The inner polygon approach works better as more breakpoints n are taken. However, as the number of breakpoints increases, the overall computational burden grows as more constraints in the form of (8) need to be included. In our experiments, we saw that $N = 12$ often gives good results while keeping the model tractable.

Nodal voltages can be calculated using branch parameters, as follows:

$$V_{j,t} = \sum_{k\in\mathcal{U}_j} V_{k,t} - \frac{R_j f_{j,t}^{P} + X_j f_{j,t}^{Q}}{V^0}; \forall j \in \mathcal{J}\backslash\{0\} \wedge t \in \mathcal{T} \quad (9)$$

As customary, we consider that the voltage at the root node is fixed, therefore

$$V_{(j=0),t} = V^0; \forall t \in \mathcal{T} \quad (10)$$

Each prosumer needs to ensure its power balance given by

$$p_{i,t} + p_{i,t}^{PV} = p_{i,t}^{D}; \forall i \in \mathcal{I} \wedge t \in \mathcal{T} \quad (11)$$

The PV generation is limited by the PV potential $\tilde{p}_{i,t}^{PV}$, normally impacted by weather parameters, as follows

$$p_{i,t}^{PV} \leq \tilde{p}_{i,t}^{PV}; \forall i \in \mathcal{I} \wedge t \in \mathcal{T} \quad (12)$$

This paper assumes that PV potential can be forecasted with sufficient accuracy 24 hours ahead. Nevertheless, there exists a variety of approaches modelling uncertainty associated with weather parameters and how to deal with them [27, 28].

In the centralized approach, the manager is responsible for ensuring (11) and (12), thus having access to the internal data of prosumers. Finally, non-negativity needs to be imposed on some variables.

$$0 \le p_t^{im}; \forall t \in \mathcal{T} \tag{13}$$
$$0 \le p_t^{ex}; \forall t \in \mathcal{T} \tag{14}$$
$$0 \le q_t^{im}; \forall t \in \mathcal{T} \tag{15}$$
$$0 \le q_t^{ex}; \forall t \in \mathcal{T} \tag{16}$$

2.4 – Final form of the centralized day-ahead model

The day-ahead scheduling for the LEC described in Section 2.2 assuming centralized dispatch reads as

$$\min_{\boldsymbol{x}^C, p_{i,t}^{PV}} F^C \tag{17a}$$

Subject to:

$$(2)\text{-}(5), (8)\text{-}(16) \tag{17b}$$

where $\boldsymbol{x}^C$ is the community-level set of decision variables:

$$\boldsymbol{x}^C = \left[p_t^{im}, p_t^{ex}, q_t^{im}, q_t^{ex}, p_{i,t}, f_{j,t}^P, f_{j,t}^Q, V_{j,t}\right]$$

As seen, (17) ensures that the global optimum regarding energy cost minimization is achieved, as all the variables are jointly optimized. However, under this centralized approach, the community manager has control of individual assets (rooftop PV arrays in our case), which may entail privacy issues. The following section describes some alternative models to avoid sharing confidential information among prosumers and with the manager. On the other hand, (17) is an LP easy to solve with off-the-shelf solvers.

3 – Proposed Privacy-aware approaches

In this Section, we present two different methodologies to solve (17) respecting the privacy of users. The two methodologies are based on the APM, require decomposing (17) into the following two sub-problems:

<u>Prosumer problem:</u>

$$\min_{p_{i,t}^{PV}, p_{i,t}} \sum_t \lambda_{i,t}^P p_{i,t} \tag{18a}$$

Subject to:

$$(11)\text{-}(12) \tag{18b}$$

<u>Community problem:</u>

$$\min_{\boldsymbol{x}^C, p_{i,t}} F^C \tag{19a}$$

Subject to:

$$(2)\text{-}(5), (8)\text{-}(10), (13)\text{-}(16) \tag{19b}$$

where $\lambda_{j,t}^P$ is the dual variable associated with (4).

As seen, (18) solves individual problems for each prosumer in the community. The objective function (18a) accounts for the marginal cost of each node in the LEC, which reflects the cost of supplying power at the i^{th} node. This way, the consumption of each prosumer is guided by the collective bill in order to reduce it as much as possible. The problem (18) only considers two variables, namely the individual PV generation and energy exchanged with the community.

On the other hand, the community problem (19) coordinates power exchanges through the local grid, ensuring its correct operation, and determining power exchanges with the upscale system in order to reduce the collective bill, well-represented in (19a). It is worth noting that (19) does not include the individual PV generation in its decision space and therefore ensures that the community manager has no direct access to individual assets.

To solve (18) and (19) in a coordinated way, we propose a solution algorithm based on APM in the following sub-section.

3.1 – Foundations of APM

The proposed privacy-aware techniques are based on APM by Boyd et al [29]. Although the scope of this paper is not to describe in detail this methodology, let us include hereinafter some basic explanation for the sake of self-sufficiency, while an in-depth explanation of this methodology can be found in [29].

Let us assume that A and B are two closed convex sets in $\mathbb{R}^n$ such that $A \cap B \neq \emptyset$ (as shown in Fig. 2). Let us also assume that we have two generic minimization problems given by: $\min\{f(x)|x \in A\}$ and $\min\{g(x)|x \in B\}$ (where f and g are two convex functions), and we are interested in finding a common solution x for both optimization problems. To find such a solution $x \in A \cap B$ we start with any point $x_1 \in A$ (for instance $x_1 = 0$), and then try to find a solution for $\min\{f(x)|x \in A\}$ that is close to x_1 simply by penalizing $|x - x_1|$ in the objective function, as follows:

$$x_2 \in \underset{x}{\operatorname{argmin}} f(x) + \gamma|x - x_1| \tag{20a}$$

Subject to:

$$x \in A \tag{20b}$$

where $\gamma \in \mathbb{R}_+$. As a result of (20), one obtains the optimal point x_2. In the next step, the following problem is solved.

$$x_3 \in \underset{x}{\operatorname{argmin}} g(x) + \gamma|x - x_2| \tag{21a}$$

Subject to:

$$x \in B \tag{21b}$$

Thus obtaining x_3. Then, x_1 is replaced by x_3 in (20) to obtain x_4, which is sent to (21) to replace x_2, and so on, as shown in Fig. 2. This process is repeated until penalty terms in (20a) and (21a) are small enough.

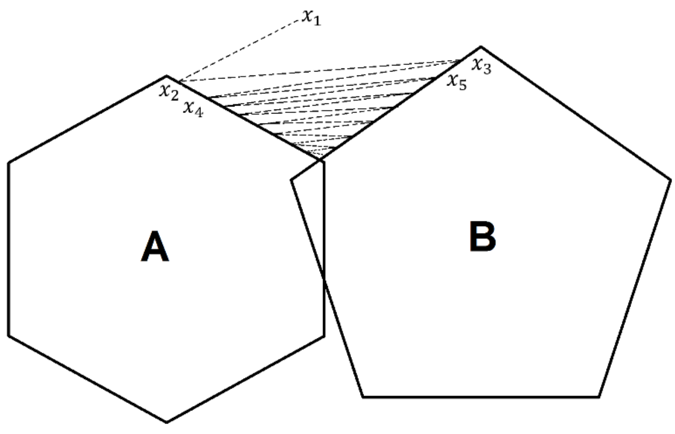

Fig. 2. Sketch of APM

It is worth noting that, if x is continuous, both (20) and (21) are LP as the absolute penalty terms can be linearized easily.

3.2 – Application of APM to LECs

This Section applies APM described in the previous sub-section to LEC scheduling as detailed in Section 2. One can find fair similitudes between the problem structure described by (18) and (19) and those in (20) and (21). Exploiting this similarity allows applying APM to the LEC problem following these steps:

1. Initialize γ and $\lambda_{i,t}^{P,(\theta)} = TOU_t; \forall i \in \mathcal{I} \wedge t \in \mathcal{T}$. Let $\theta = 0$ be the iteration counter and $\varepsilon \in \mathbb{R}_+$ the convergence threshold.
2. Solve (22) $\forall i \in \mathcal{I}$, as follows:

$$p_{i,t}^{fixed,(\theta)} \in \underset{p_{i,t}^{PV}, p_{i,t}}{\operatorname{argmin}} \sum_t \lambda_{i,t}^{P,(\theta)} p_{i,t} \tag{22a}$$

subject to:

$$(11)\text{-}(12) \tag{22b}$$

to obtain $p_{i,t}^{fixed,(\theta)}; \forall i \in \mathcal{I} \wedge t \in \mathcal{T}$

3. Solve (23), as follows:

$$p_{i,t}^{fixed,(\theta+1)} \in \underset{x^C, p_{i,t}}{\operatorname{argmin}} F^C + \gamma \sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} \left| p_{i,t} - p_{i,t}^{fixed,(\theta)} \right| \tag{23a}$$

subject to:

$$(2)\text{-}(5),\ (8)\text{-}(10),\ (13)\text{-}(16) \tag{23b}$$

to obtain $p_{i,t}^{fixed,(\theta+1)}$ and $\lambda_{i,t}^{P,(\theta+1)}; \forall i \in \mathcal{I} \wedge t \in \mathcal{T}$

4. Check convergence as:

$$\frac{\sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} \left| p_{i,t}^{fixed,(\theta+1)} - p_{i,t}^{fixed,(\theta)} \right|^2}{\sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} \left| p_{i,t}^{fixed,(\theta)} \right|^2} \leq \varepsilon \tag{24}$$

if (24) holds, then stop, else go to step 5

5. Let $\theta = \theta + 1$ and solve (25) $\forall i \in \mathcal{I}$, as follows:

$$p_{i,t}^{fixed,(\theta+1)} \in \underset{p_{i,t}^{PV}, p_{i,t}}{\operatorname{argmin}} \sum_t \left\{ \lambda_{i,t}^{P,(\theta)} p_{i,t} + \gamma \left| p_{i,t} - p_{i,t}^{fixed,(\theta)} \right| \right\} \tag{25a}$$

subject to:

$$(11)\text{-}(12) \tag{25b}$$

to obtain $p_{i,t}^{fixed,(\theta)}; \forall i \in \mathcal{I} \wedge t \in \mathcal{T}$ and go to step 3.

Note that $p_{i,t}^{fixed,(\theta)}$ in equations (23) and (25) is equivalent of what appears in equations (21) and (22) as $x_1, x_2, x_3, x_4, \ldots$ gradually converges to a point in intersection of the sets A and B.

It is worth noting that the algorithm 1-5 above solves the LEC problem in a decentralized manner, as each prosumer decides on its variables and only shares boundary information. In our experiments, we set $\varepsilon = 10^{-6}$ and $\gamma = 1$. As in all main steps (solving (22), (23) and (25)) we only use the sum of absolute values of deviations as a penalty term, we only need to solve Linear Programming (LP). Basically, the computational burden and memory requirement can be assessed based on the LPs that have to be solved. Fortunately, LP is one of the most studied problems with highly optimized mature solvers. As a result, the method works well in real-world problems. We used Linprog of Matlab as our LP solver but there are many open-source (yet robust) LP solvers in Python and C++ which makes it very easy to replicate the numerical results. Also, one very important thing is that since all of the components can be implemented in open-source environments like Python, it increases the chance of the integration of the software in pre-existing software infrastructures.

The idea behind the 1-5 algorithm above is to progressively refine the value of $p_{i,t}^{fixed}$ until reach an agreement between the prosumer and the community problems. This way, the prosumers only share the boundary variable $p_{i,t}$ with the community manager. Therefore the basic assumption in APM is that the true value for $p_{i,t}^{fixed}$is revealed. However, as the true value of this variable is still revealed, therefore this algorithm does not preserve privacy completely yet. To solve this issue, the following sub-section describes the applicability of differential privacy to LECs.

3.3 – Application of Differential Privacy to LECs

Differential privacy (DP) is a statistical method to ensure that the release of individual data (that is essential to find out the aggregate patterns of a society of people) can be done in a private way [22].

To do this, Gaussian noise is injected into statistical computations such that the mean of the aggregate noisy data remains intact while what can be inferred about any individual in the community remains limited. In general, for real numbers $x_1, \dots, x_n$ if we perturb each of them by Gaussian noise $\epsilon_1, \dots, \epsilon_n$, then

$$mean(x_1 + \epsilon_1, \dots, x_n + \epsilon_n) = \frac{x_1 + \epsilon_1 + \cdots + x_n + \epsilon_n}{n} = \frac{x_1, \dots, x_n}{n} + \frac{\epsilon_1 + \cdots + \epsilon_n}{n} \tag{26}$$

But as $\frac{\epsilon_1 + \cdots + \epsilon_n}{n}$ gets close to zero then

$$mean(x_1 + \epsilon_1, \dots, x_n + \epsilon_n) \cong mean(x_1, \dots, x_n) \tag{27}$$

This means that while what reported by entities in the community (which are $x_1 + \epsilon_1, \dots, x_n + \epsilon_n$) might be very far from true values $x_1, \dots, x_n$, but the means are the same, which means we still can do coordination even if individuals are secretive.

Applying DP to LECs is simple and only requires minor modifications on the 1-5 algorithm in Section 3.2. Indeed, after obtaining $p_{i,t}^{fixed}$ from (22) or (25), its true value is no longer revealed. Instead, a perturbed one is calculated. The basic way to report $p_{i,t}^{fixed}$ is to report $p_{i,t}^{fixed} + \epsilon_{i,t}$ where $\epsilon_{i,t} \sim N(0, \sigma^2)$ is Gaussian distribution with a mean of 0 and a standard deviation σ. But, as we might have different prosumers with different scales, we want the standard deviation to be proportional to the magnitude of $p_{i,t}^{fixed}$. For this reason, we add noise as follows:

$$p_{i,t}^{fixed} = p_{i,t}^{fixed} \times \mathrm{rand}(\sigma); \forall i \in \mathcal{I} \wedge t \in \mathcal{T} \tag{28}$$

where $\mathrm{rand}(\sigma) \sim N(1, \sigma^2)$. This way $p_{i,t}^{fixed} \times \mathrm{rand}(\sigma) \sim N(p_{i,t}^{fixed}, (p_{i,t}^{fixed}\sigma)^2)$ which means $p_{i,t}^{fixed} \times \mathrm{rand}(\sigma)$ has mean $p_{i,t}^{fixed}$ and standard deviation $p_{i,t}^{fixed}\sigma$.

In DP method, the assumption is that the noise should be Gaussian. Thereby, each prosumer reveals only the perturbed boundary value instead of its true value, ensuring the privacy of users. Intuitively, the larger the σ the higher the degree of privacy is ensured. Indeed, in APM-only approach, all the information except $p_{i,t}^{fixed}$ and $\lambda_{i,t}^{P}$ (that is shared between prosumers and community manager) are kept private. When DP is added to the pipeline, then even the true $p_{i,t}^{fixed}$ is not revealed and only a noisy version of it will be shared with the community manager. This second step makes things more privacy preserving. We protect each household's entire day-ahead profile against inference by any party observing the exchanged messages. Noise is added only to the "shared signals" (aggregates/dual variables), never to private local variables.

However, large values of σ may lead to wrong solutions with consequences in decision-making in LECs. For the sake of simplicity, Fig. 3 shows a flowchart of the developed methodology. In our experiments we vary the standard deviation σ, starting from 0 to 1 with step-size of 0.025. Also we set $\varepsilon = 10^{-6}$ (note that this ε differs from the ε in formal (ε, δ)-differential privacy and here it is just a threshold) for algorithm presented in Fig. 3. The next section discusses the implications of applying DP in LECs through simulations.

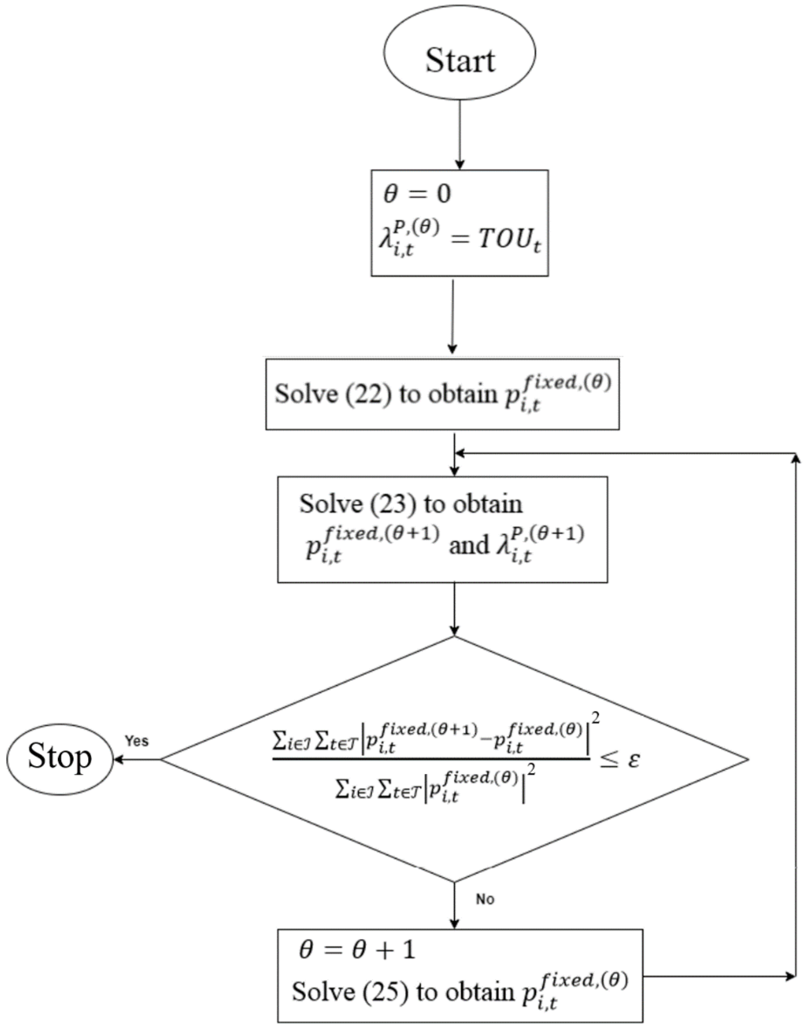

Fig 3. Flowchart of the proposed DP approach

4 – Numerical Results

This section presents different numerical results to analyse the performance of the APM described in Section 3, in comparison with the centralized scheduling strategy in Section 2, which will be taken as a benchmark. To this end, the different mathematical models described in this paper were coded under Matlab R2021b and solved using Gurobi [30].

4.1 – Description of cases

The time resolution is assumed hourly and time horizon considered 24 hours ($T = 24$). We perform in this section a statistical analysis of 100 different cases. Firstly, we consider the 15-bus network depicted in Fig. 4, which has been used in some papers related to LECs (see e.g. [20, 23]). Its nominal voltage is 400 V (three-phase) and voltage limits are 0.95-1.05 per-unit nominal voltage, common limits for safe operation of distribution networks [23]. Also, thermal limit at every node is set to 250 (kVA).

The community can exchange energy with the distribution network under known TOU tariffs. In particular, we have considered the tariff offered by Endesa in Spain [31], with 0.06 €/kW for energy exported. Specifically, tariffs are as follows: Peak is 0.21, Mid-peak is 0.16 and Off-peak is 0.13 (€/kWh).

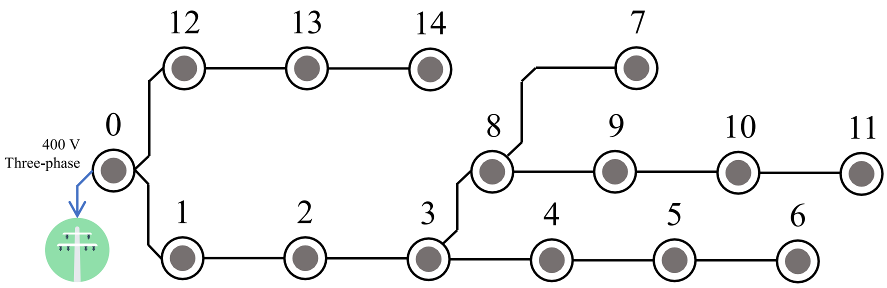

Fig. 4 – Schematic view of the community network employed in simulations

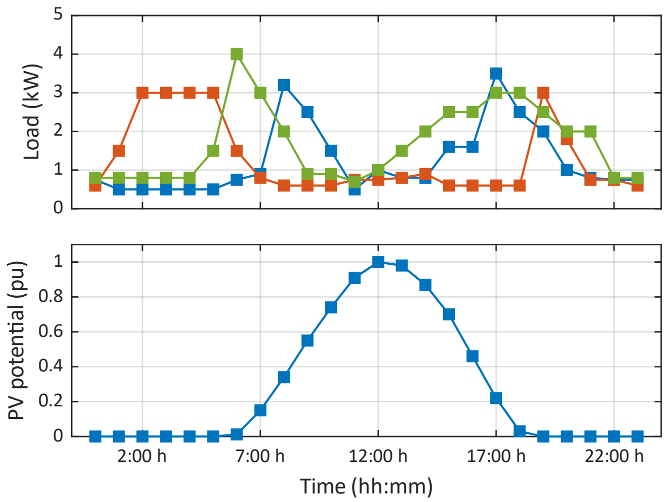

Fig. 5 – Base demand profiles (top) and PV potential (bottom) considered in simulations

The 100 cases were generated randomly. The case study does not refer to any particular location (specific city, country or coordinates) or socio-economic context (such as income of the households, family structure or employment status) and, as such, demand profiles respond to typical characteristic demand habits in residential installations as referred in [32, 33], in order to cover a wide range of scenarios. Note that this case study limits on studying the applicability of APM and does not go further in a particular case study referred to a specific geographic location or ambient conditions. The demand profiles are randomly assigned between the three base profiles in Fig. 5, which have been taken from [11]. The total number of prosumers in the community varies from 4 to 15 while the PV peak generation is in the range of 3-7 kWp, following the instantaneous potential in Fig. 5. Finally, we assume that each prosumer can exchange up to 10 kW with other peers and the reactive power consumption is 15 % of the active one [23].

4.2 – Impact on energetic indicators

Firstly, we focus on how ensuring privacy affects the expected energy exchanged with the grid. To this end, we compare the results obtained with the privacy-aware APM in Section 3 with the centralized one in Section 2 for different standard deviations (i.e. σ). To provide a fair comparison, we employ two different indexes, the mean absolute percentage error (MAPE) and the mean absolute deviation (MAD), respectively defined as:

$$MAPE = \frac{1}{M}\sum_{m=1}^{m=M}\left|\frac{\hat{y}_m - y_m}{\hat{y}_m}\right| \cdot 100 \quad (29)$$

$$MAD = \frac{1}{M}\sum_{m=1}^{m=M}|\hat{y}_m - y_m| \quad (30)$$

where M is the total number of samples, while $\hat{y}_m$ and y_m are the ground truth (from centralized approach) and calculated values of the m^{th} sample.

First, we focus on the total energy imported by the community, as shown in Fig. 6, where we compare the different values obtained using the APM, noting that $\sigma = 0$ is equivalent to the algorithm without applying DP. It is interesting to see that when DP is neglected, the algorithm calculates the same value as in the benchmark method. When the value of σ starts to increase, both the MAPE and MAD increase consequently. The mean MAPE across the different values of σ keeps below 20 %, revealing that ensuring privacy does not affect notably the estimated energy imported. It is interesting to see that the minimum MAPE is occasionally zero even for very high values of σ. On the other hand, very large errors could be induced, as expected, in some cases, reaching up to 40 %.

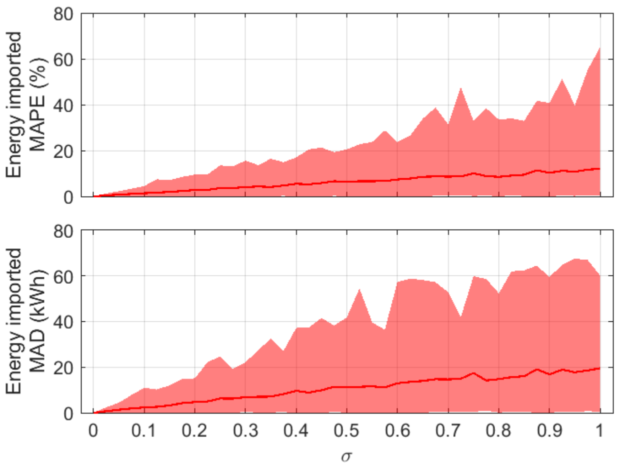

Fig. 6 – Comparison of the total energy imported by the community using privacy-aware APM

It is also interesting to see that the errors grow mostly linearly and considering standard deviations beyond $\sigma = 0.6$ does not increment the error notably. This is important since users may be interested in increasing their privacy as much as possible and the coordinator needs to know until this point the objectives of the community are not compromised. On the other hand, when comparing the MAD, one can see that it is kept below 10 kWh on average, reaching up to 30 kWh in some cases. It should be taken carefully as incrementing the demand in kWh may lead to overestimating the cost of the community and lead to wrong decisions, as discussed later.

Next, we focus on the total energy exported in Fig. 7. In contrast to the energy imported, it is interesting to see that errors keep, in general, stable for $\sigma > 0.4$. This is because energy exported is provided by PV systems and it is devoted, firstly, to satisfy the local demand through P2P exchanges. This practice follows a logical coherency of reducing imports, which are priced under the TOU tariff, which is always higher than the fed-in tariff. In other words, it is not profitable to import energy just to be exported later. Thus, the energy exported is limited by the PV capacity installed in the community and, therefore, ensuring privacy affects the final results limitedly. However, in this case, the MAD may reach high values (80 kWh in some cases). These results should be compared with other historical data regarding the total PV installed in the community, in order to filter out possible errors induced by the differentially private methodology. This topic will be studied in future works.

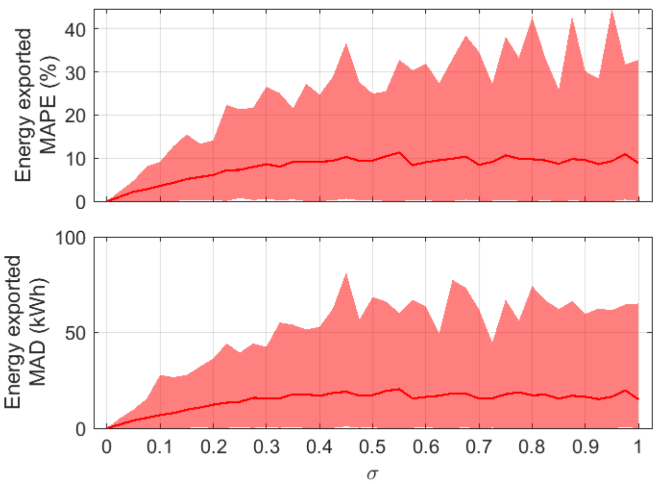

Fig. 7 – Comparison of the total energy exported by the community using privacy-aware APM

Finally, Fig. 8 is analoguous to 4 and 5 but refers to the total net consumption of prosumers. In this case, it is interesting to see how errors are always higher than zero. This aspect is important since it may lead to calculating the individual bills wrongly, as we will check later on. On the other hand, the errors increase with the value of σ as in the previous analyses.

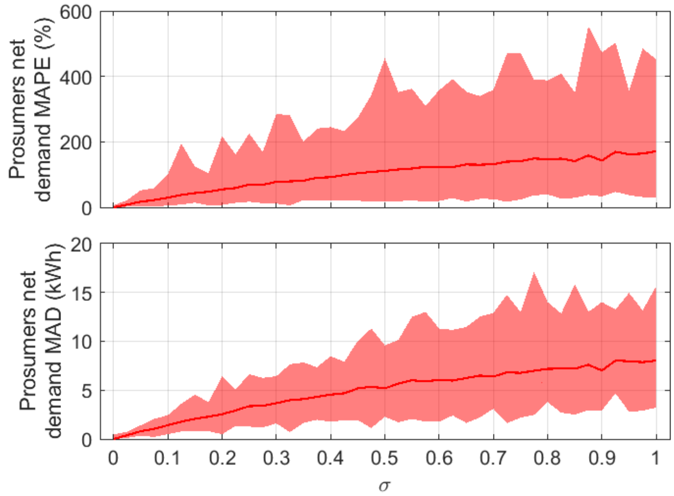

Fig. 8 – Comparison of the total prosumers' net demand using privacy-aware APM

In all cases, the errors were kept within reasonable bounds regarding energetic indicators, as you can see when observing the average errors in Figs. 6-8 are closer to the lower bound than to the higher one. It indicates that maximum errors reported were infrequent within the 100 cases studied and therefore the privacy-aware methodologies were generally well-behaved when estimating the total energy imported, exported and individual net demand. It is noteworthy that in all cases the results obtained with σ correspond faithfully to those obtained with the benchmark method. Therefore, we conclude that, at least concerning energetic indicators, the considered privacy-aware algorithm neglecting DP can be employed without compromising the fidelity of solutions.

To add more practical validations, we report the net energy ($\sum_{t\in\mathcal{T}}\{p_t^{im} - p_t^{ex}\}$) for different values for σ and different cases. As shown in bellow, for 40 out of 100 users, the x-axis represents σ and y-axis represent the net energy. In each sub-plot the red line represents the true value from centralized approach and the blue curve is the value from privacy preserving APM. It can be seen that the larger the σ, the greater the error in estimated net energy:

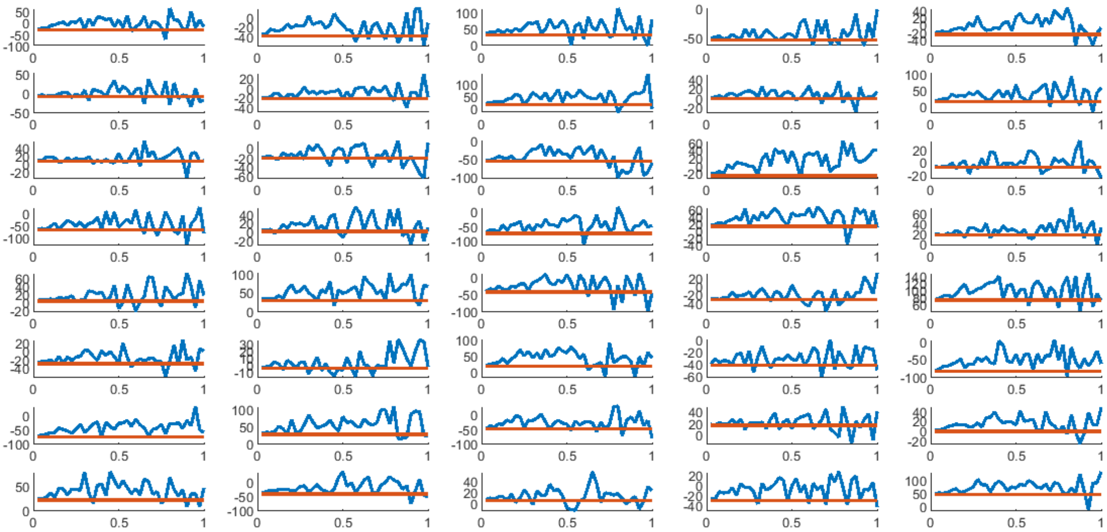

Fig. 9 – The net energy $\sum_{t\in\mathcal{T}}\{p_t^{im} - p_t^{ex}\}$ for 40 different cases with different values for σ.

4.3 – Impact on economic indicators

Now, let us focus on different economic indicators. Firstly, we analyze the impact of privacy-preserving on the total community cost in Fig. 10. As observed, errors assumed in the total community cost are very high, achieving not assumable values in percentage. Also one another point to mention is that min $\{\hat{y}_1, \ldots, \hat{y}_M\} \cong 4$ and max $\{\hat{y}_1, \ldots, \hat{y}_M\} \cong 39$. Now within this gap of €35, the MAD stays below €4 across all cases.

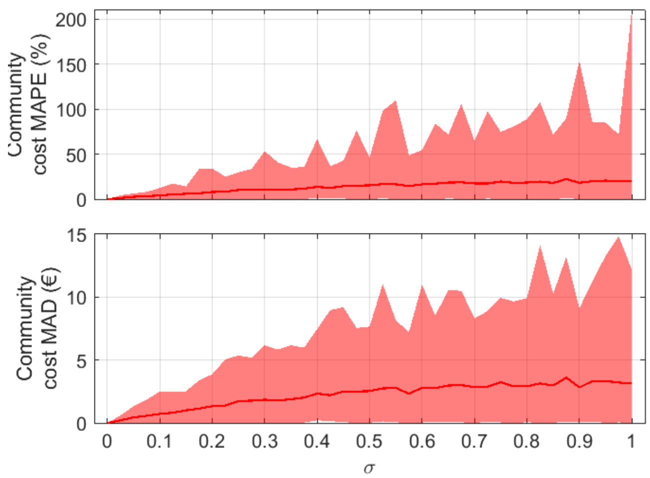

Fig. 10 – Comparison of the total community cost using privacy-aware APM

To better explain the large errors in percentage in Fig. 10, Fig. 11 plots the actual community cost using privacy-aware techniques, compared to their corresponding true value in each case studied in Fig. 11. In this figure, dots correspond to the community cost calculated for different values of σ. Indeed, darker filled dots correspond to large values of σ. In this figure, it is important to note two issues. First, the community cost does not seem to follow any pattern regarding σ, which could be also observed by analysing the MAPE in Fig. 10. On the other hand, Fig. 11 well explains the large percentage errors in Fig. 10. Indeed, in some cases the community cost is estimated positive (i.e. the community pays to the distribution network) while the true value is negative (the distribution network pays to the LEC for exporting energy). Therefore, using privacy-aware techniques may lead to considering net expenditures, when the true value reflects net incomes. Again, minimum value depicted by the blue line is min $\{\hat{y}_1, \ldots, \hat{y}_M\} \cong 4$ and the maximum is max $\{\hat{y}_1, \ldots, \hat{y}_M\} \cong 39$ and the mean deviation of the value of dots obtained by DP method from the true value is below €4 across all cases.

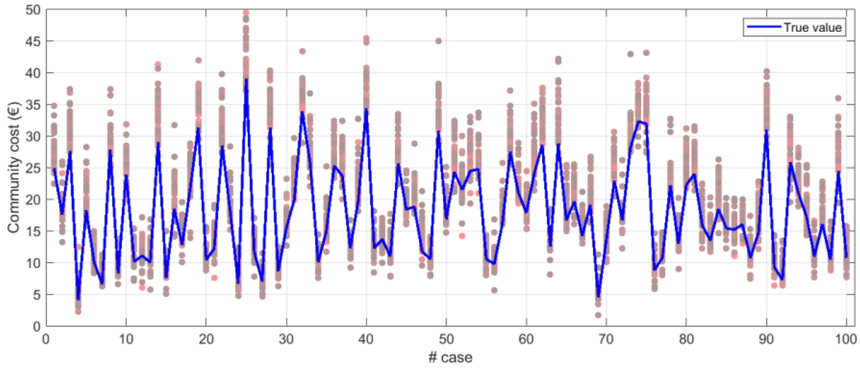

Fig. 11 – Community cost in each case compared to the true value. In this figure, dots represent those results obtained using privacy-aware techniques. Darker dots represent higher values of σ

In the following, the content of figure 11 are depicted in pictures 12-18 to better show privacy-utility trade-off, especially as σ increases**.** As it can be seen, for bigger value for σ we have big deterioration in the community cost.

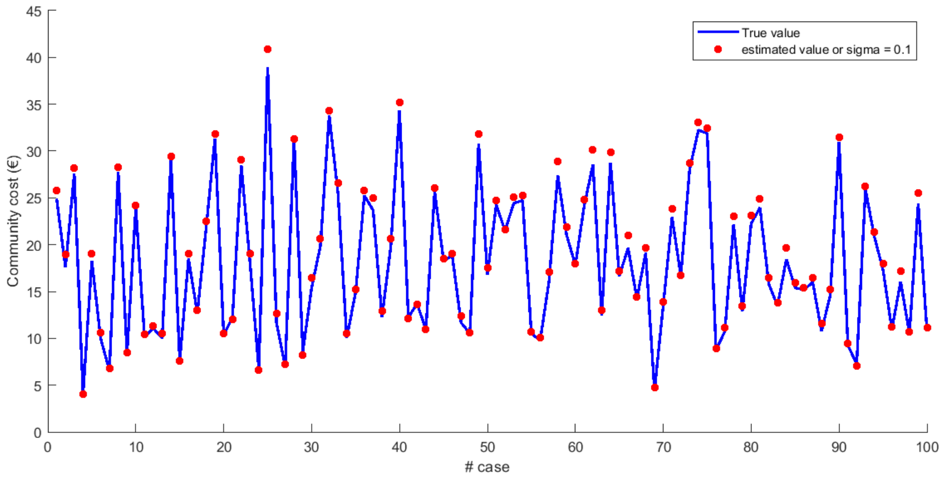

Fig. 12. Community cost in each case compared to the true value for σ=0.1

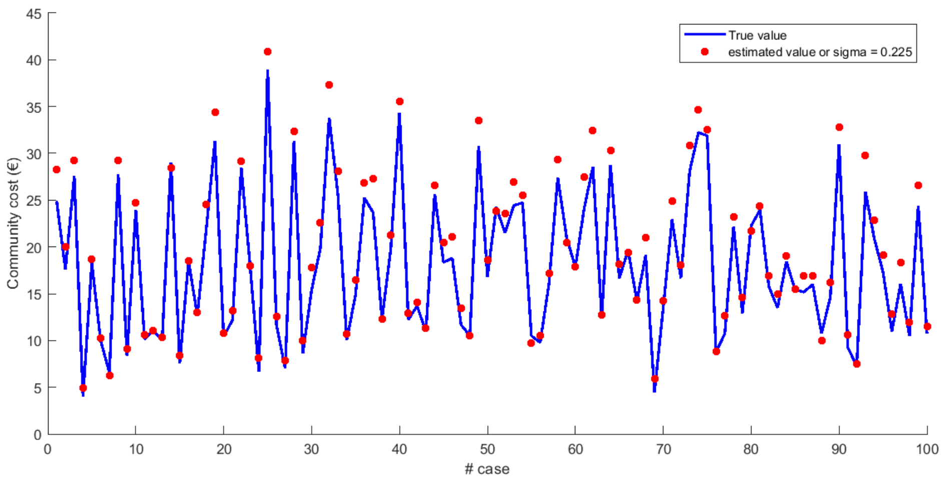

Fig. 13. Community cost in each case compared to the true value for σ=0.225

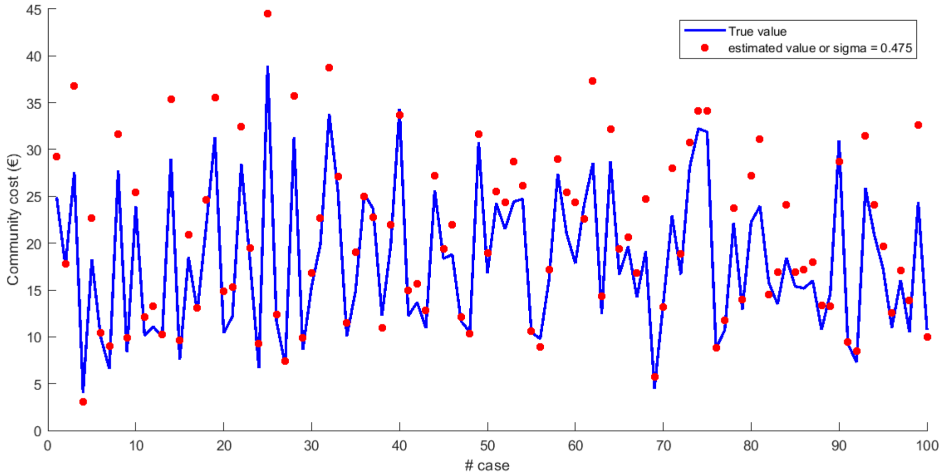

Fig. 14. Community cost in each case compared to the true value for σ=0.475

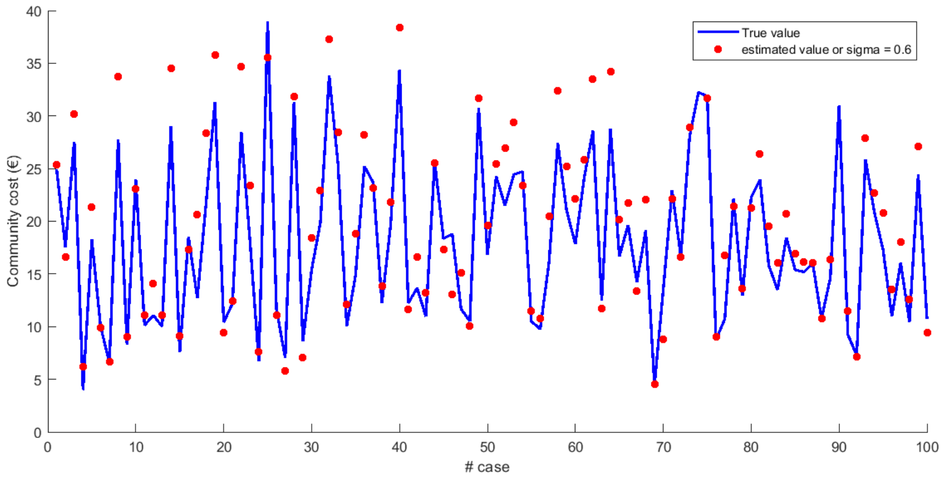

Fig. 15. Community cost in each case compared to the true value for σ=0.6

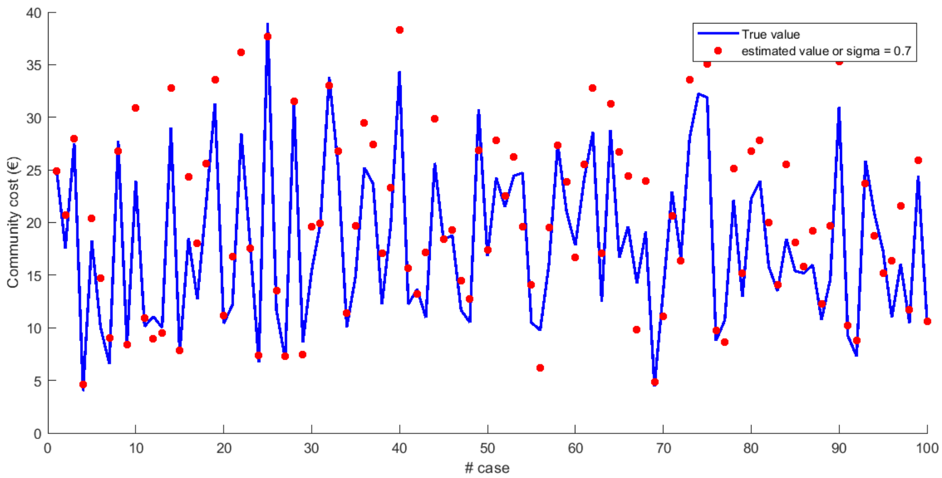

Fig. 16. Community cost in each case compared to the true value for σ=0.7

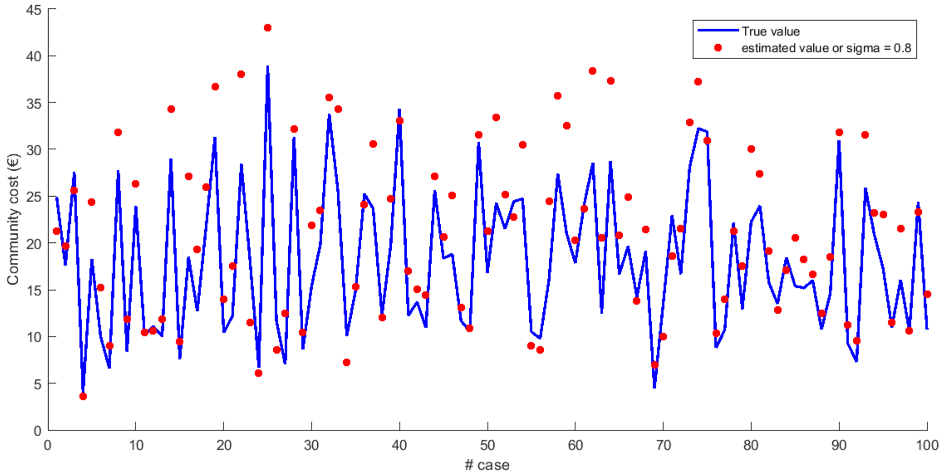

Fig. 17. Community cost in each case compared to the true value for σ=0.8

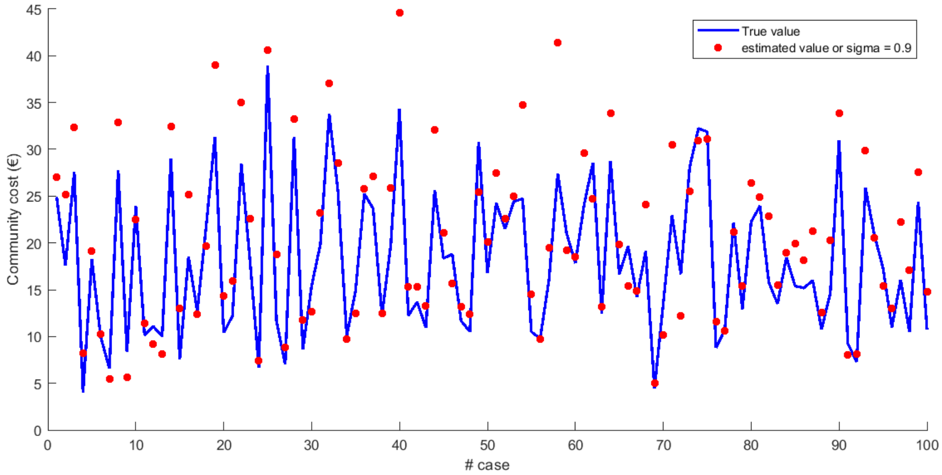

Fig. 18. Community cost in each case compared to the true value for σ=0.9

To explain these results, Fig. 19 plots the instantaneous community net power for a particular case, comparing the benchmark results to that obtained with $\sigma = 0.25$. As seen in this figure, while the power imported is practically the same in both cases, exported power notably differs. Therefore, one could attribute the difference in the community cost to the inaccuracy in calculating the exported power. Actually, for the particular case reported in Fig. 19, the total cost for importing energy was 6.05 and 6.24 € in the benchmark and privacy-aware cases, respectively, while incomes from exporting were 5.35 and 6.05 €, thus explaining the difference in the cost. Therefore, one can conclude that the high errors in Fig. 10 are attributable to the energy exported rather than to the imported. To further confirm this hypothesis, Fig. 20 analyses the error in neglecting PV systems. As seen, results in this figure confirm our supposition, since neglecting PV systems (and therefore exporting capability) maintains the average error in the community cost below 20 % in almost all cases.

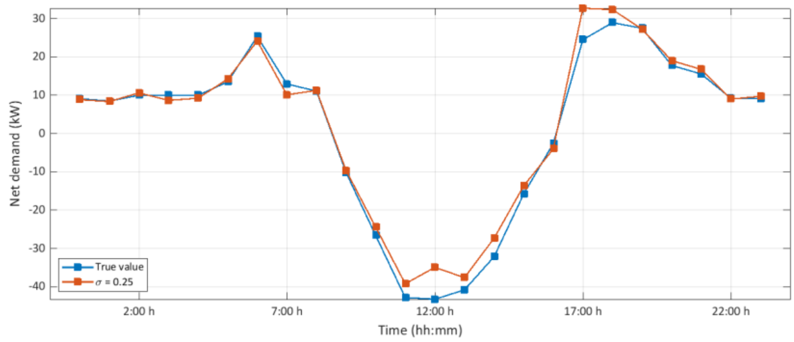

Fig. 19 – Comparison of the true community net demand and that obtained with $\sigma = 0.25$

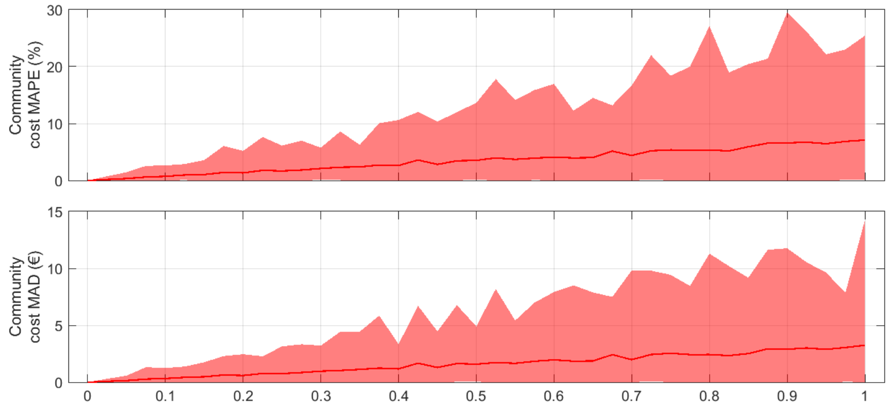

Fig. 20 – Comparison of the total community cost using privacy-aware APM and neglecting PV systems

One key result in LECs is the so-called sharing or allocation factors [6]. These parameters determine how the total community bill is allocated among prosumers in the community according to pre-established criteria. In this paper, we consider one of the most common ones, by which individual electricity bill is calculated according to the percentage of the total net demand attributable to each prosumer. Thus, the sharing factor (SF) for the i^{th} prosumer in the community can be calculated as:

$$SF_i = \frac{\sum_{t \in \mathcal{T}} p_{i,t}}{\sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} p_{i,t}}; \forall i \in \mathcal{I} \tag{31}$$

Fig. 21 analyses the error when calculating sharing factors using privacy-aware APM. As seen, the privacy-aware techniques were generally well-behaved when estimating the sharing factors, keeping the average and maximum error below 20 and 40 % respectively, in the cases studied. This result confirms that sharing factors can be effectively determined using privacy-aware approaches. Thus, the community manager could determine them to preserve the privacy of users and reveal them in advance. Thus, prosumers could self-schedule with perfect information about cost allocations in the community.

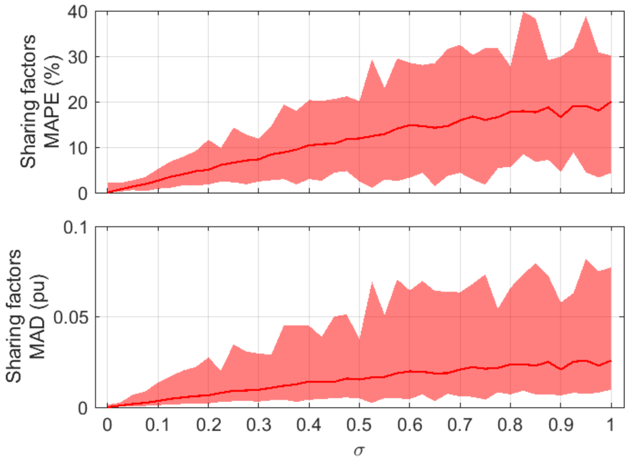

Fig. 21 – Comparison of sharing factors using privacy-aware APM

4.4 – Computational analysis

Next, we carry out a computational performance analysis. To this end, the total execution time of the different approaches considered in this paper is compared. All the simulations were performed on an Intel Core i7-10700K CPU 3.80GHz 3.79 GHz with 32 GB RAM. As expected, the privacy-aware techniques require much more time to achieve the solution than the centralized approach, which calculates it directly without iterating. Nevertheless, the considered privacy-aware techniques were quite efficient, achieving the solution below 8 seconds in almost all cases. Moreover, the considered privacy-aware APM presents a highly parallelizable structure (each prosumer can solve its problem in parallel), therefore, the results in Fig. 22 could be even further improved. Thus, we can conclude that the computational burden does not pose a barrier for implementing privacy-aware techniques in LEC scheduling.

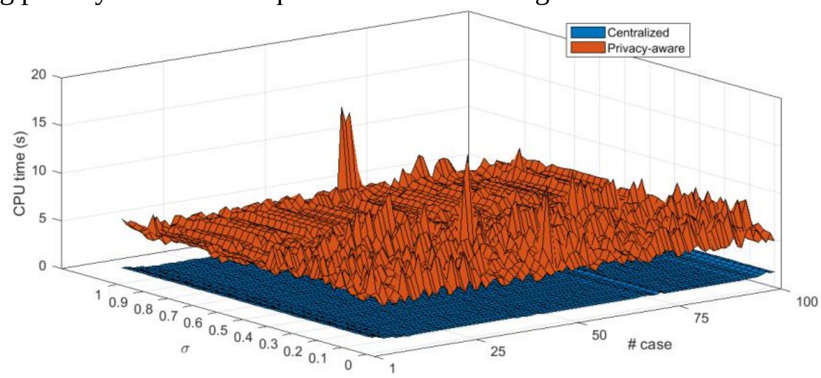

Fig. 22 – Comparison of total computational time consumed by the different approaches considered in this paper

To further illustrate the scalability of our method we set up another experiment, this time for 5-25 prosumers (intervals of 5 prosumers). We vary σ, starting from 0 to 1 with step-size of 0.1. As it can be seen in Fig. 23, Fig. 24 and Fig. 25 although there are some anomalies due to randomness of injected Gaussian noise, but on average, the time, exported energy and imported energy increase almost linearly which demonstrates scalability. In Fig. 24 and Fig. 25 the centralized solution is depicted by a solid red curve which is close (but not identical) to the case of $\sigma = 0$ (which is equivalent to APM).

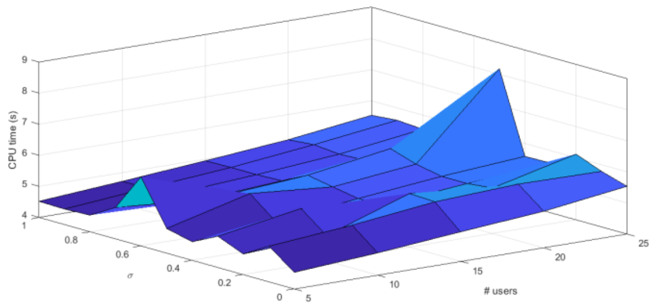

Fig. 23 – Comparison of total computational time consumed when number of prosumers varies up to 25

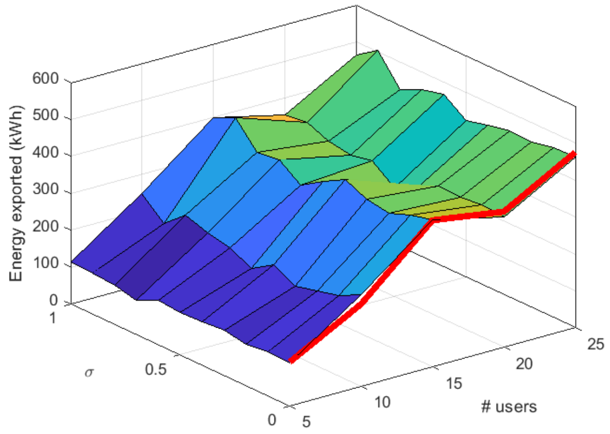

Fig. 24 – Comparison of total exported energy (the red solid curve represents the centralized case)

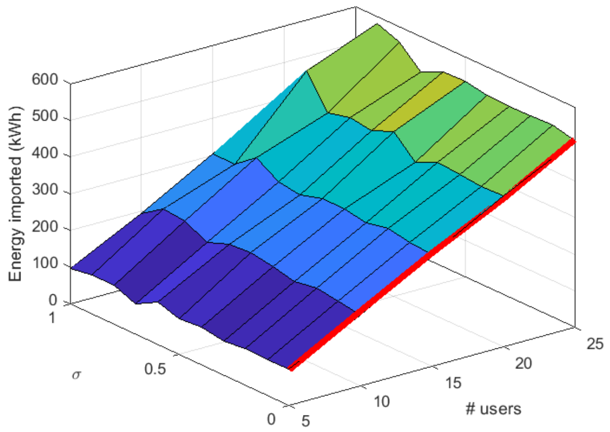

Fig. 25 – Comparison of total imported energy (the red solid curve represents the centralized case)

Also to diversify the load profiles of the prosumers and PV production profile, we take as reference the activity probability distribution in the CREST demand model [33]. We consider 5 activities with average power consumption as follows: watching TV (125 W), cooking (1750 W), laundry (900 W), ironing (2000 W) and house cleaning (950 W). To create load profiles, for any given prosumer, the 24 hour time period is divided into 144 time intervals of length 10 minutes. Then these activities are randomly distributed across 144 time windows according to occupancy probability distribution in [33] and then, energy consumption is averaged and multiplied by 6 for every hour. Also for PV, we sample every 60 minutes from the PV data in [33] to obtain hourly data. Again as it can be seen in Fig. 26, Fig. 27 and Fig. 28, although there are some anomalies due to randomness of injected Gaussian noise, but on average, the time, exported energy and imported energy increase almost linearly. In Fig. 27 and Fig. 28 the centralized solution is depicted by a solid red curve.

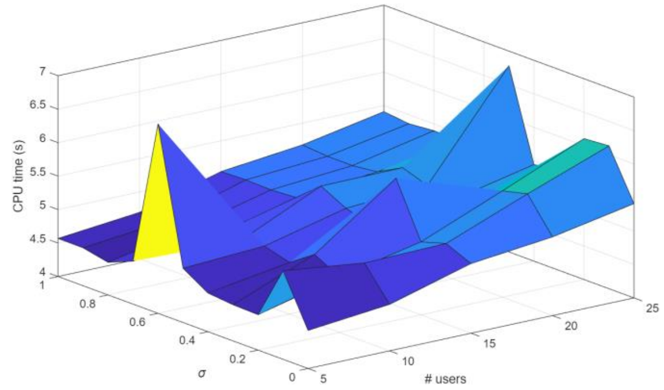

Fig. 26 – Comparison of total computational time consumed when number of prosumers varies up to 25

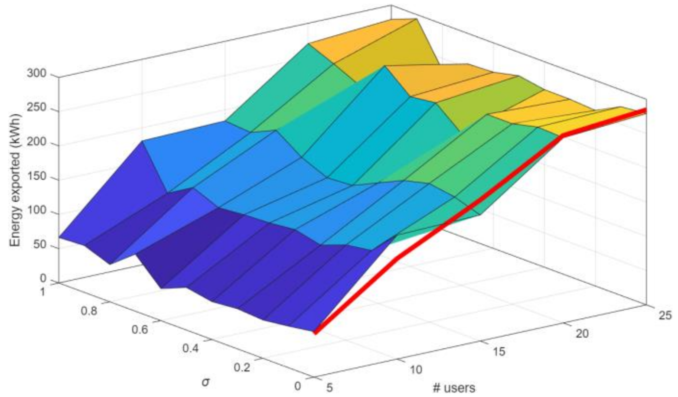

Fig. 27 – Comparison of total exported energy (the red solid curve represents the centralized case)

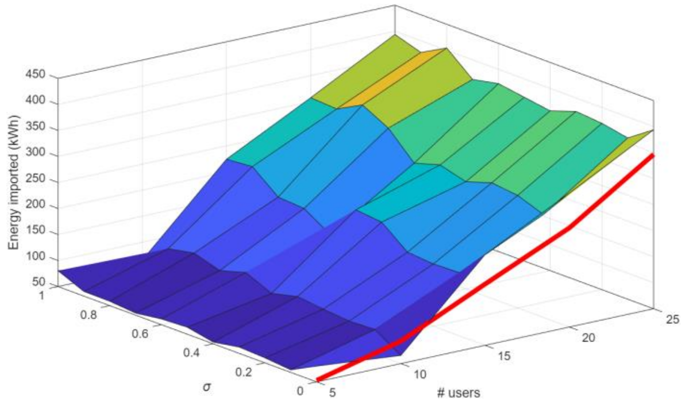

Fig. 28 – Comparison of total imported energy (the red solid curve represents the centralized case)

4.5 – Discussion

After analysing the results provided throughout Section 4, it is worth highlighting some important conclusions:

- The considered privacy-aware approach does not incur errors compared with the centralized approach with $\sigma = 0$. Under these settings ($\sigma = 0$), the prosumers only reveal boundary information (net demand) to the community manager.
- Normally, the Gaussian errors induced by the proposed privacy-aware methodologies were within reasonable bounds for $\sigma < 0.6$. This value of standard deviation could be considered enough to encrypt individual information from prosumers. Therefore, if the prosumers are reluctant to share individual information, the proposed methodologies

could be adopted with values below this threshold without producing large errors (up to 40 %.).

- Regarding the energy indicators (energy imported, exported and net demand), the considered privacy-aware methodologies performed well (keeping the error below 20 %). However, large errors were found in economic indicators (total community cost). We have confirmed that such errors are induced by significant differences in the energy exported. Therefore, if the expected energy exported is low or even null (in the absence of PV energy), the proposed methodologies could be adopted without any problem.
- Even in the presence of high exportable energy, sharing factors (boundary information) can be effectively estimated using privacy-aware techniques. In this way, the community manager could employ these methodologies to estimate the allocation factors to be revealed to prosumers in advance.
- The computational burden is not a barrier to implementing the considered privacy-aware methodologies.

4.6 – Limitations and scope

It is worth mentioning that deploying the APM-based scheduling framework in a live LEC demands a bidirectional, low-latency, and cyber-secure communication channel between the community manager and every prosumer. However, when solving (23), as the bottleneck is APM, the communication delays are negligible in both APM and DPM (in our experiments each round of local computations takes around 5 seconds while communication takes several milliseconds). In fact, the core part of computations are done locally in isolation and all communities work concurrently in parallel and do not need to receive the information from others to be able to do their turns.

Setting up and then operating this infrastructure, smart meters with two-way connectivity, PLC modems or dedicated broadband gateways, and the required cybersecurity layers-represents a considerable capital and operational expenditure that must be added to the community's business case.

Our formulation assumes a single coordinating entity that gathers the boundary information produced at each iteration, solves the community-level optimization, and redistributes updated prices. While this architecture is consistent with cooperatives that have already delegated operational control to a manager, it is less suitable for distributed peer-to-peer marketplaces. Consequently, the scope of the proposed method is limited in communities where a trusted central coordinator is acceptable.

Although Section 4.4 shows that the algorithm's computational burden scales favorably with the number of prosumers, each iteration still incurs both processing time and network latency. In practice, the accumulated turnaround time makes it difficult to provide responses within the sub-second horizons demanded by real-time flexibility services. We therefore consider the method best suited to day-ahead scheduling or, with very fast telemetry intra-day scheduling rather than hard real-time control.

5 - Conclusion

The impact of ensuring privacy in LECs has been studied in this paper. Specifically, different iterative approaches have been proposed, allowing to increment in the level of privacy ensured. In this regard, the considered methodologies are based on the well-known differentially private approach, which has been applied firstly to LECs in this paper.

The main idea is that if the instantaneous PV generation is estimated in some way (from knowing the amount of sunlight availability plus the physical characteristics of the solar panels) and the true values for boundary information $p_{i,t}$ are shared, that will lead to the disclosure of $p_{i,t}^{D}$. In our method (DP) we propose disclosure of noisy version of $p_{i,t}$ to avoid this vulnerability. This is what makes our approach more resilient in terms of privacy. This approach allows for solving the LEC scheduling problem in a decentralized manner, sharing boundary information with different levels of encryption.

The proposed methodologies have been compared in 100 community instances with the conventional centralized solution approach, in which the community manager has direct access to individual assets installed by prosumers. Different energetic, economic and computational indicators have been analysed, revealing that the considered privacy-aware approaches generally perform well and allow estimating final results accurately when the exportable capacity is not very high and the prosumers do not require a high level of privacy. This way, we can conclude that the proposed privacy-aware techniques constitute easily implementable methodologies when the privacy of users needs to be ensured.

Future research should be devoted to further developing privacy-aware methodologies for LECs that eventually could improve the results obtained by those proposed in this paper, especially when the community produces huge surplus energy and can therefore export much energy to the grid. Also we provided in-depth analysis of the method in terms of accuracy and reliability, in order to validate it for real-life cases.

References

[1] A.Q. Al-Shetwi, M.A. Hannan, H.M.K. Al-Masri, M.Z. Sujod. Latest advancements in smart grid technologies and their transformative role in shaping the power systems of tomorrow: an overview. *Progress in Energy* 2025; 7(1): 012004. 10.1088/2516-1083/ada198.

[2] European Commission. Energy Communities. Online, available at: https://energy.ec.europa.eu/topics/markets-and-consumers/energy-consumers-and-prosumers/energy-communities_en, (accessed 16 Jan. 2025).

[3] C. Feng, F. Wen, S. You, Z. Li, F. Shahnia, M. Shahidehpour. Coalitional Game-Based Transactive Energy Management in Local Energy Communities. *IEEE Transactions on Power Systems* 2020; 35(3): 1729-40. 10.1109/TPWRS.2019.2957537.

[4] Z. De Grève et al. Machine Learning Techniques for Improving Self-Consumption in Renewable Energy Communities. *Energies* 2020; 13: 4892. 10.3390/en13184892.

[5] G. Brusco, D. Menniti, A. Pinnarelli, N. Sorrentino. Renewable Energy Community with distributed storage optimization to provide energy sharing and additional ancillary services. *Sustainable Energy, Grids and Networks* 2023; 36: 101173. 10.1016/j.segan.2023.101173.

[6] A.D. Mustika, R. Rigo-Mariani, V. Debusschere, A. Pachurka. A two-stage management strategy for the optimal operation and billing in an energy community with collective self-consumption. *Applied Energy* 2022; 310: 118484. 10.1016/j.apenergy.2021.118484.

[7] X. Wu, A. J. Conejo. Distribution Market Including Prosumers: An Equilibrium Analysis. *IEEE Transactions on Smart Grid* 2023; 14(2): 1495-504. 10.1109/TSG.2022.3151338.

[8] W. Cheng, C. Ruiz. Risk management of energy communities with hydrogen production and storage technologies. *Applied Energy* 2023; 348: 121494. 10.1016/j.apenergy.2023.121494.

[9] J.L. Maldonado, M. Tostado-Véliz, H.M. Hasanien, N. Khosravi, F. Jurado. Optimal planning of collective photovoltaic arrays in energy communities through a multi-cut benders' decomposition strategy. *Sustainable Cities and Society* 2024; 104: 105307. 10.1016/j.scs.2024.105307.

[10] W. Guedes, C. Oliveira, T. Soares, B. Dias, M. Matos. Collective asset sharing mechanisms for PV and BESS in renewable energy communities. *IEEE Transactions on Smart Grid* 2024; 15(1): 607-16. 10.1109/TSG.2023.3288533.

[11] M. Tostado-Véliz, A.R. Jordehi, H.M. Hasanien, N. Khosravi, S.A. Mansouri, F. Jurado. On different collective storage schemes in energy communities with internal market. *Journal of Energy Storage* 2024; 75: 109699. 10.1016/j.est.2023.109699.

[12] S. Zhou, Z. Hu, W. Gu, M. Jiang, X.-P. Zhang. Artificial intelligence based smart energy community management: A reinforcement learning approach. *CSEE Journal of Power and Energy Systems* 2019; 5(1): 1-10. 10.17775/CSEEJPES.2018.00840.

[13] S. Lilla, C. Orozco, A. Borghetti, F. Napolitano, F. Tossani. Day-Ahead Scheduling of a Local Energy Community: An Alternating Direction Method of Multipliers Approach. *IEEE Transactions on Power Systems* 2020; 35(2): 1132-42. 10.1109/TPWRS.2019.2944541.

[14] C. Orozco, A. Borghetti, B.D. Schutter, F. Napolitano, G. Pulazza, F. Tossani. Intra-day scheduling of a local energy community coordinated with day-ahead multistage decisions. *Sustainable Energy, Grids and Networks* 2022; 29: 100573. 10.1016/j.segan.2021.100573.

[15] M. Dolatabadi, A. Borghetti, P. Siano. Scalable distributed optimization combining conic projection and linear programming for energy community scheduling. *Journal of Modern Power Systems and Clean Energy* 2023; 11(6): 1814-1826. 10.35833/MPCE.2022.000783.

[16] M. Tostado-Véliz, S. Kamel, H.M. Hasanien, R.A. Turky, F. Jurado. Optimal energy management of cooperative energy communities considering flexible demand, storage and vehicle-to-grid under uncertainties. *Sustainable Cities and Society* 2022; 84: 104019. 10.1016/j.scs.2022.104019.

[17] M. Tostado-Véliz, A.R. Jordehi, S.A. Mansouri, F. Jurado. A two-stage IGDT-stochastic model for optimal scheduling of energy communities with intelligent parking lots. *Energy* 2023; 263(D): 126018. 10.1016/j.energy.2022.126018.

[18] M. Tostado-Véliz, S.A. Mansouri, A.R. Jordehi, D. Icaza-Alvarez, F. Jurado. Information Gap Decision Theory-based day-ahead scheduling of energy communities with collective hydrogen chain. *International Journal of Hydrogen Energy* 2023; 48(20): 7154-69. 10.1016/j.ijhydene.2022.11.183.

[19] H.-C. Jo, G. Byeon, J.-Y. Kim, S.-K. Kim. Optimal Scheduling for a Zero Net Energy Community Microgrid With Customer-Owned Energy Storage Systems. *IEEE Transactions on Power Systems* 2021; 36(3): 2273-80. 10.1109/TPWRS.2020.3036077.

[20] M. Tostado-Véliz, J.S. Giraldo, D. Icaza-Alvarez, C. Cruz, F. Jurado. Robust day-ahead scheduling of cooperative energy communities considering multiple aggregators. *Sustainable Cities and Society* 2024; 116: 105878. 10.1016/j.scs.2024.105878.

[21] M. Tostado-Véliz, W.K. Meteab, P. Siano, F. Jurado. Risk-averse strategic participation of prosumers coalition in local community markets. *Sustainable Cities and Society* 2025; 118: 106035. 10.1016/j.scs.2024.106035.

[22] V. Dvorkin, F. Fioretto, P. Van Hentenryck, P. Pinson, J. Kazempour. Differentially Private Optimal Power Flow for Distribution Grids. *IEEE Transactions on Power Systems* 2021; 36(3): 2186-96. 10.1109/TPWRS.2020.3031314.

[23] B.W. Crowley, J. Kazempour, L. Mitridati. How Can Energy Communities Provide Grid Services? A Dynamic Pricing Mechanism with Budget Balance, Individual Rationality, and Fair Allocation. Available at SSRN: https://ssrn.com/abstract=4981172 or http://dx.doi.org/10.2139/ssrn.4981172.

[24] M.E. Baran, F.F. Wu. Network reconfiguration in distribution systems for loss reduction and load balancing. *IEEE Transactions on Power Delivery* 1989; 4: 1401-07. https://doi.org/10.1109/61.25627.

[25] X. Wang, F. Li, Q. Zhang, Q. Shi, J. Wang. Profit-Oriented BESS Siting and Sizing in Deregulated Distribution Systems. *IEEE Transactions on Smart Grid* 2023; 14(2): 1528-40. 10.1109/TSG.2022.3150768.

[26] T. Akbari, M.T. Bina. Linear approximated formulation of AC optimal power flow using binary discretization. *IET Generation, Transmission & Distribution* 2016; 10(5): 1117-23. 10.1049/iet-gtd.2015.0388.

[27] L. Bai, F. Li, H. Cui, T. Jiang, H. Sun, J. Zhu. Interval optimization based operating strategy for gas-electricity integrated energy systems considering demand response and wind uncertainty. *Applied Energy* 2016; 167: 270-9. 10.1016/j.apenergy.2015.10.119.

[28] L.A. Roald, D. Pozo, A. Papavasiliou, D.K. Molzahn, J. Kazempour, A. Conejo. Power systems optimization under uncertainty: A review of methods and applications. *Electric Power Systems Research* 2023; 214: 108725. 10.1016/j.epsr.2022.108725.

[29] Boyd, S., & Dattorro, J. (2003). Alternating projections. EE392o, Stanford University.

[30] Gurobi Optimization L.L.C. Gurobi Optimizer Reference Manual. 2021. Online, available at: https://www.gurobi.com, (accessed 16 Jan. 2025).

[31] Endesa. Electricity tariffs. Online, available at: https://www.endesa.com/en/catalog/light, (accessed 16 Jan. 2025).

[32] https://www.kaggle.com/datasets/taranvee/smart-home-dataset-with-weather-information

[33] Barton, J., Thomson, M., Sandwell, P., & Mellor, A. (2020). A domestic demand model for India. In Advances in Energy Research, Vol. 1: Selected Papers from ICAER 2017 (pp. 743-753). Singapore: Springer Singapore. https://repository.lboro.ac.uk/articles/dataset/CREST_Demand_Model_v2_0/2001129