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An application of distributed optimisation to energy communities in Italy

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Speaker: L. Saguatti

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Outline

- Introduction
- Methodology
- Results and considerations
- Conclusions

Introduction

Italian energy communities (EC) operation cost optimisation should account for the **incentive on shared energy** recognized by GSE to the EC (60-120 €/MWh).

Thus, optimising EC's operation cost requires **coordination of the members** equipped with flexible energy assets: the optimal schedule of the single member acting alone may not coincide with the optimum of the community.

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Objective function:

$$minimize \sum_t \sum_i Cost(i,t) \ - \sum_t \pi_{inc}(t) \cdot E_{sh}(t)$$

Subject to:

- Constraints of **each** member, including **binary variables**.
- **Shared energy** definition:
  $E_{sh}(t) = \min\left\{ \sum_{i=1}^{P} E_{injected}(i,t),\ \sum_{i=1}^{P} E_{withdrawn}(i,t) \right\}$

i = 1,…,P → community members.

t = 1,…,T → timesteps of the optimization horizon.

Cost(i,t) = energy procurement cost function of each member *i* at timestamp *t.*

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Centralised problem: **MILP (nonconvex)**

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<u>Issue</u>: Centralised optimisation requires a **community manager** that:

- Collects all members' relevant information (supply contracts, asset information, forecasts…) → **Privacy** concerns!
- Determines/enforces the schedule of their systems.

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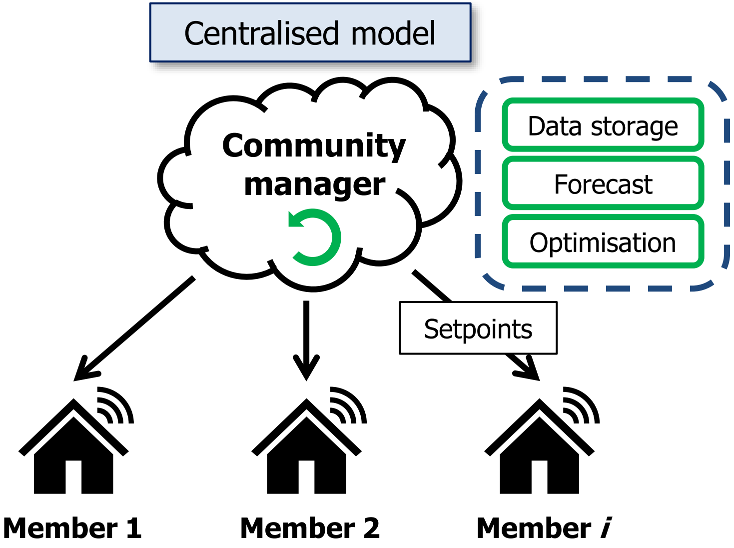
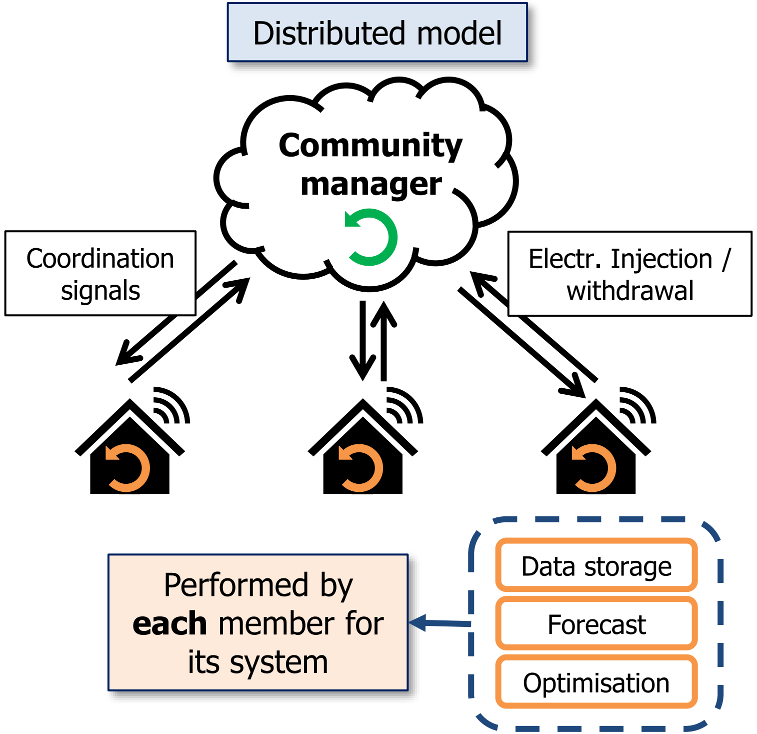
Distributed optimisation techniques allow to **split** (decompose) an optimisation problem in smaller, less complex optimisation problems.

In the paper, the **Alternating Direction Method of Multipliers** (**ADMM**) is used to decompose the EC centralised problem in:

- One **subproblem for each member**, the solution of which is iteratively coordinated.
- A **master problem** that computes the (economic) coordination signals.

Introduction





Images adapted from: https://energycommunityplatform.eu/resources/crash-course-8-energy-management-systems-for-energy-communities/

Methodology

Idea of ADMM: remove the constraint linking the variables of different agents.

Given a two-block optimisation problem:

$$\begin{aligned} \textit{minimize} \quad & f(x) + g(y) \\ \textit{subject to:} \quad & Ax + By = c \qquad\qquad (\lambda) \\ & x \in D_x \\ & y \in D_y \end{aligned}$$

$$x \in \mathbb{R}^{\mathrm{n}}, \mathrm{y} \in \mathbb{R}^{\mathrm{m}}, \mathrm{A} \in \mathbb{R}^{\mathrm{p\times n}}, B \in \mathbb{R}^{\mathrm{p\times m}}, c \in \mathbb{R}^{\mathrm{p}}$$

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&\qquad\qquad\quad \boxed{\begin{matrix} x \in D_x \\ y \in D_y \end{matrix}}
\end{aligned}
$$

Constraint preventing the two functions to be optimized independently

Dual variable of the constraint

Constraints involving only variables of one block

$$x \in \mathbb{R}^{n}, y \in \mathbb{R}^{m}, A \in \mathbb{R}^{p \times n}, B \in \mathbb{R}^{p \times m}, c \in \mathbb{R}^{p}$$

Methodology

Idea of ADMM: remove the constraint linking the variables of different agents, accounting for it with **additional terms in the objective function**.

Given a two-block optimisation problem:

Lagrangian relaxation term

Quadratic penalty term

$$\begin{aligned} minimize \quad & f(x) + g(y) + \boxed{\lambda^T(Ax + By - c)} + \boxed{\frac{\rho}{2}\|Ax + By - c\|^2} \\ subject\ to\text{:} \quad & \boxed{\cancel{Ax + By = c}} \\ & x \in D_x \\ & y \in D_y \end{aligned}$$

$$x \in \mathbb{R}^n, y \in \mathbb{R}^m, A \in \mathbb{R}^{p\times n}, B \in \mathbb{R}^{p\times m}, c \in \mathbb{R}^p$$

Methodology

The resulting function is called **augmented Lagrangian**:

$$L_\rho(x, y, \lambda) = f(x) + g(y) + \lambda^T(Ax + By - c) + \frac{\boldsymbol{\rho}}{2}\|Ax + By - c\|^2$$

Decomposition is obtained minimising the augmented Lagrangian **iteratively** in the direction of each block of primal variables.

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Issues:

- Performance of ADMM are very sensitive to the choice of the penalty parameter **ρ**
- For nonconvex problems, ADMM is not guaranteed to converge, and if it converges, it is not guaranteed to find the global optimal solution!

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Issues:

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Research question: Since the Energy Community optimisation problem is a nonconvex:

- Does ADMM converge?
- If it converges, how close is the solution to the global optimum?
- What is the influence of the penalty parameter on the model's performance?

Methodology

Test case study (fictional) – 24 hrs time horizon:

Condominium	1	2	3	4	5	6
N° of apartments	6	6	12	12	18	18
(*) Total apartments load [kWh]	48	49	106	96	156	142
Common areas load [kWh]	1.4	1.4	2.8	2.8	4.2	4.2
PV size [kWp]	6	8	13	10	16	15
Battery size [kWh]	8	10	15	11	22	19

(*) Load profiles for the apartments are the same used in: Zatti, M., et al. (2021). Energy communities design optimization in the Italian framework. Applied sciences, 11(11), 5218.

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Members' **flexibility sources**:

- **Demand shift** from consumers;
- **Batteries** connected to PV;

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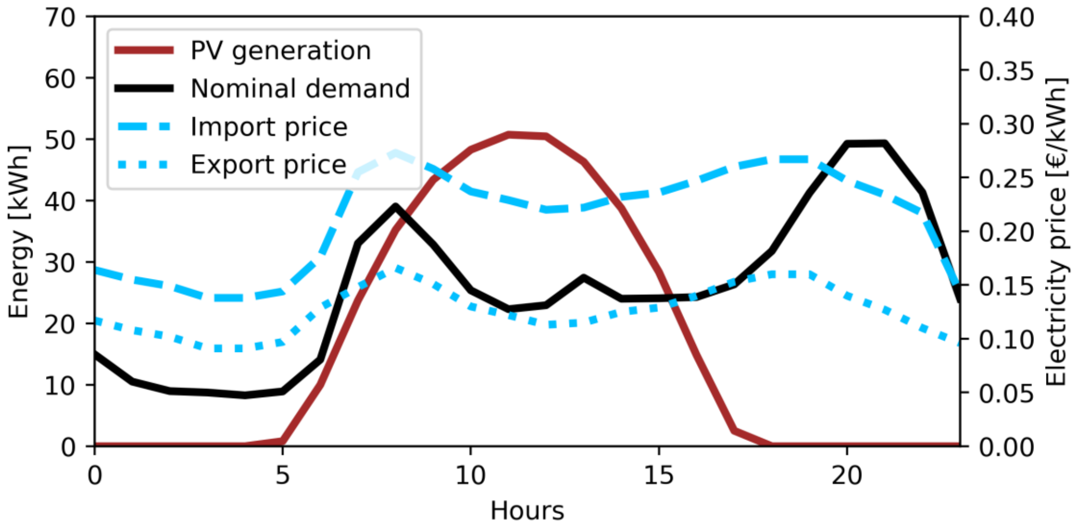
Case study:

- Aggregated EC **demand** and **production** profiles (left axis);
- **Electricity buy/sell prices** (right axis).
- **N.B.:** For the sake of simplicity, each member is subject to the same electricity prices.



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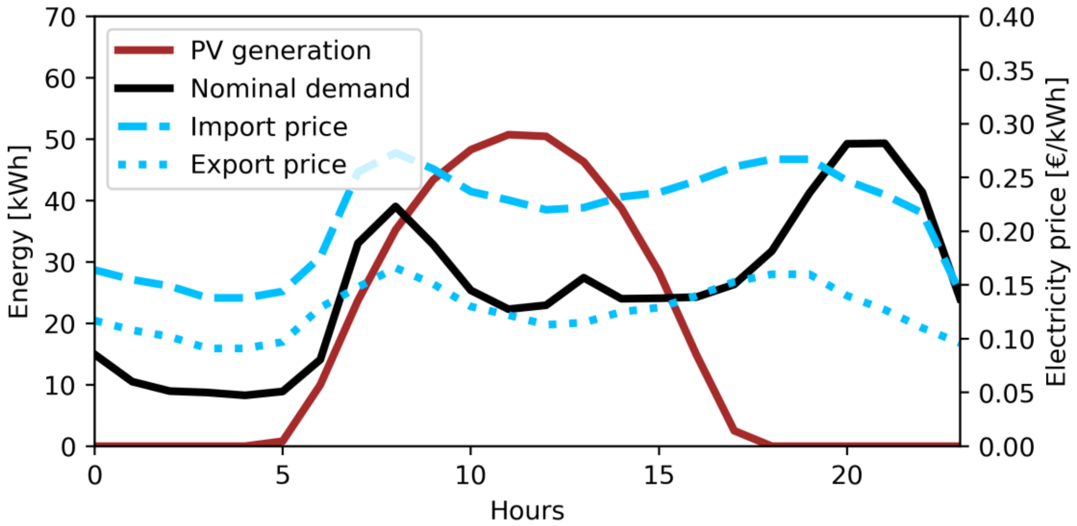

Methodology note:

Centralised model solution is **globally optimal** → **benchmark** for ADMM performance.

Results

Penalty parameter **ρ** kept **constant**, i.e, it does not change during the iterative procedure (canonical ADMM formulation for convex problems):

Outcome

- ADMM converges **only** when ρ is large enough; the quality of the solution is "poor".
- The higher the value of ρ, the worse the solution found.
- Convergence reached in 2-3 iterations.

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RESULTS OF THE DISTRIBUTED MODEL WITH CONSTANT ρ.

ρ	Objective function	Increase
2	43.2 €	23.9 %
3	44.2 €	26.8 %
4	44.7 €	28.5 %
5	45.1 €	29.6 %

Increase of ADMM O.F. value at convergence w.r.t. the global optimal solution

Results

Penalty paraemter **ρ** **iteratively updated:** in particular, multiplied by a factor α > 1 at each iteration *k* (increase can start after *m* initial iterations):

$$\rho^{k+1} = \alpha \cdot \rho^{k} \quad \forall k > m$$

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- ADMM converges for **any** starting value of the penalty parameter ρ.
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	$\alpha = 2$		$\alpha = 1.5$		$\alpha = 1.1$	
$m = 0$	Incr.	N° iter.	Incr.	N° iter.	Incr.	N° iter.
$\rho^0 = 0.1$	7.3 %	8	5.6 %	12	1.9 %	53
$\rho^0 = 0.01$	3.3 %	12	2.1 %	19	1.1 %	77

Results

Solution **closer** to the global optimum mean the EC members' schedule found by ADMM **better approximates** the schedule found with the centralized model!

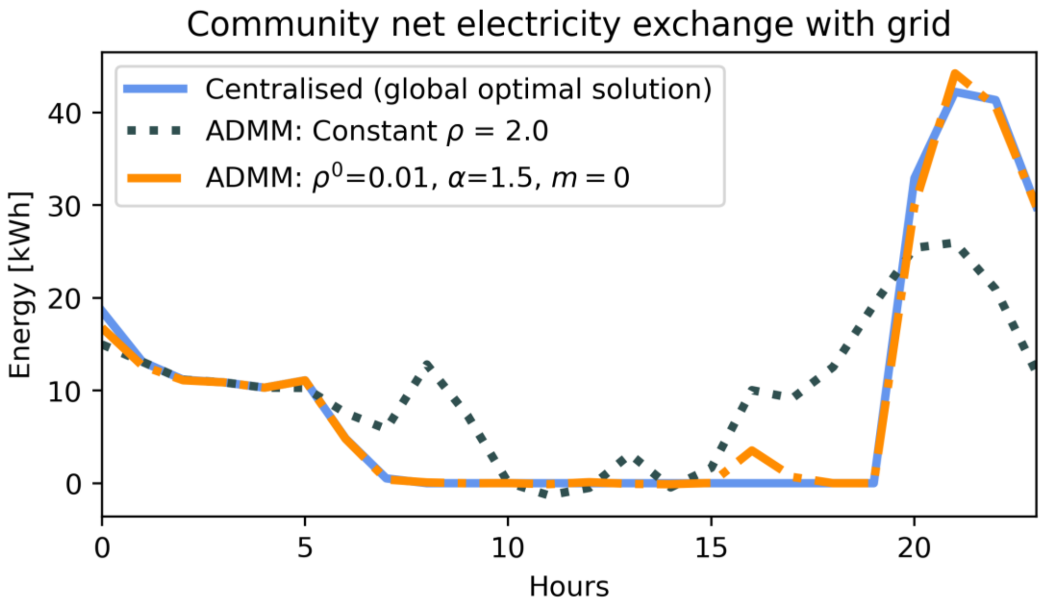
Example

ρ = 2, constant:

- OF value **+23.9 %** w.r.t. centralised model (2 iterations).

ρ^0 = 1e-3, multiplied by 1.5 at each iteration:

- OF value **+2.1%** w.r.t. centralised model (19 iterations).



Conclusions

- **Advantage**: the distributed model allows each member to optimise the schedule of its energy assets **autonomously**, sharing only their grid import/export schedule.

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Conclusions

- **Advantage**: the distributed model allows each member to optimise the schedule of its energy assets **autonomously**, sharing only their grid import/export schedule.
- **Disadvantage**: the quality of the local solution found with ADMM, in terms of distance from the global optimum, depends on the **choice** and possible **update** of the parameters of the algorithm.
- **Future improvements**: (i) modelling participation of energy communities to **local flexibility markets** (though it requires reformulating ADMM by removing the additional constraints); (ii) modeling **additional flexibility sources** (e.g., EVs); (iii) focusing on solutions to **asynchronous** subproblems behavior.

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Thank you for your attention!

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