PhD research activity

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Disclaimer

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Contents

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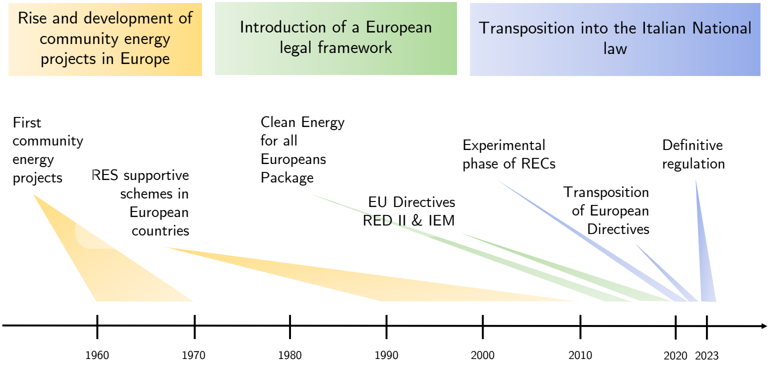
Context

Timeline

A context still in evolution...[1,2]



[1] (Hewitt, 2019) [2] (EMR, 2022)

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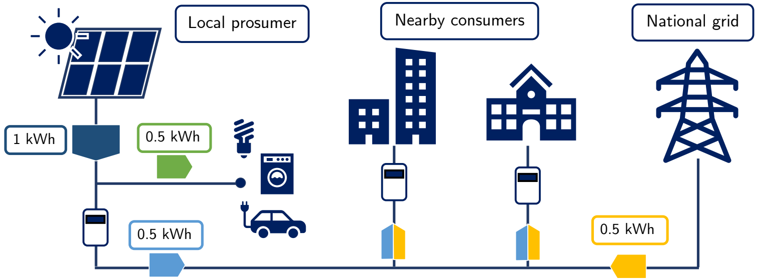
What do we mean with energy sharing? [3]



What value can it bring? [4,5]

Energy	Environment	Social
▪ Distributed generation ▪ System's efficiency ▪ Consumption habits	▪ RES penetration ▪ CO2 and local pollutant emissions reduction	▪ Energy justice & democracy ▪ Low-income families ▪ Social acceptance

[3] (CEER, 2019) [4] (Caramizaru, 2020) [5] (Bauwens, 2016)

Energy sharing (cont'd)

Comparison between Italy and France [6,7]

	Comunità Energetiche Rinnovabili	*Autoconsummation Collective*
Grid connected	Yes	
Energy sharing	Through the public distribution grid (virtual)	
Formal entity	Yes	
Internal financials	Delegated to the community	
Perimeter limitation	Technical (same MV distribution grid)	Geographical (1 km distance)
Time limitation	1 hour	30 minutes
Grid fees on shared energy	No	Reduced
Economical advantages	Shared energy is incentivized (*a posteriori*)	Shared energy is not payed (*a priori*)

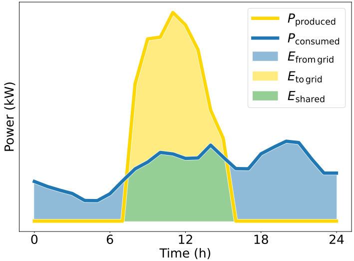
[6] (EMR, 2022) [7] (Enedis, 2021)

Motivations

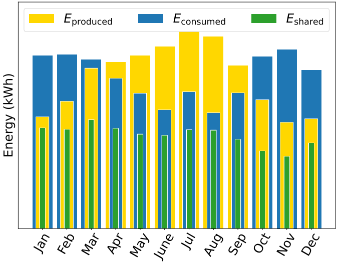
Why research on energy communities?

- *"Self-consumption is the first ingredient of local energy communities, as it brings a limited temporal scope [. . .] which is the critical link between local energy production and energy consumption. "* [8]
- **Coordination** to match RES production and end users consumption. . .

. . . hourly



. . . seasonally



[8] (Coignard, 2022)

REC optimization

How to assess RECs performances? What is their potential impact?

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Context
REC optimization
Benefits sharing
Input data
Online operation
References

Adopted workflow

Input data → Optimal hourly energy flows → Key Performance Indices → Multi-objective analysis

1. RES generation (specific) and end-users demand considered as exact (**without** uncertainty)

2. Hourly energy flows within and between nodes in typical days to **achieve** optimal performances (MILP solver)

3. Energy, environmental and economic performances on a **yearly** basis (without degradation)

4. Comparison of different REC configurarions considering multiple and **contrasting** objectives

Multi-criteria assessment

Energy KPI

- Self-consumption, $SC = \frac{\text{Local self-consumption}}{\text{Total self-production}}$
- Self-sufficiency, $SS = \frac{\text{Local self-consumption}}{\text{Total consumption}}$

Environmental

- CO_2 emissions reduction, $\Delta_{CO_2} = 1 - \frac{\text{Emissions REC}}{\text{Emissions base case}}$
- Total emissions: LCA of installed technologies (PV, batteries, . . .)

Economic

- IRR, NPV, PBT, considering capital and operative expenditures, technologies lifetime, available incentives
- Consumers cost reduction, $CR = 1 - \frac{\text{Costs REC}}{\text{Costs base case}}$

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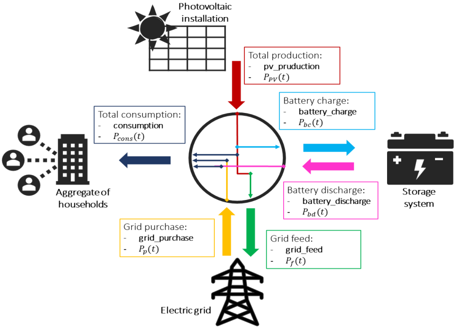
“RECopt”: a simple model for RECs[9,10,11]



- **Community** photovoltaics systems
- **Collective** energy storage
- **Aggregated** end users

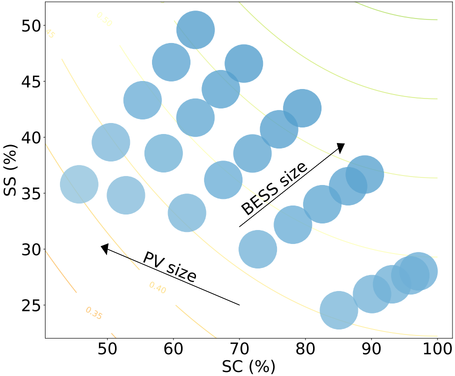
$$E_{\text{shared}} = \min\Big((P_{\text{PV}} + P_{\text{bd}} - P_{\text{bc}})\,\Delta t;\, P_{\text{cons}}\Delta t\Big)$$

→ Too far from reality…

9 (Lorenti, 2021) 10 (RECopt, 2021) 11 (Cielo, 2021)

Results snippet

Can we maximize self-sufficiency and self-consumption?



- REC with PV-battery
- Comparison base case-REC with different sizes of the technologies
- SC and SS are **conflicting** objectives
- storage systems can improve **both**

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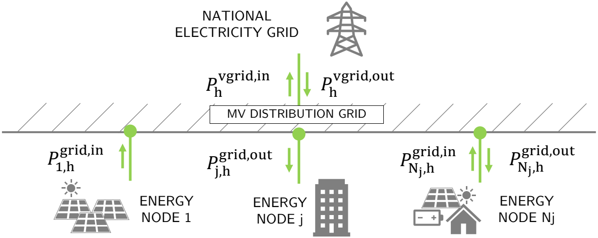
RECs as multi-node systems



- **Multiple** “nodes” exchange energy through the MV grid
- Nodes can act individually or **collectively**
- Energy produced and not consumed **locally** is considered *injected* into the National grid (vice versa *withdrawn*)

$$E_{\mathrm{shared}} = \min\left(\sum_{\mathrm{j}} P_{\mathrm{j}}^{\mathrm{grid,in}} \Delta t; \sum_{\mathrm{j}} P_{\mathrm{j}}^{\mathrm{grid,out}} \Delta t\right)$$

Model equations

Within a single energy node

- Energy balance in storage systems

$$E^{\mathrm{stor}}_{(\mathrm{h}+1) \bmod \mathrm{N_h}} - \eta^{\mathrm{stor}} E^{\mathrm{stor}}_{\mathrm{h}} = \left(\eta^{\mathrm{in}} P^{\mathrm{in}}_{\mathrm{h}} - \frac{1}{\eta^{\mathrm{out}}} P^{\mathrm{out}}_{\mathrm{h}} \right) \Delta t$$

- Constitutive equations of conversion components

$$k^{\mathrm{conv}} P^{\mathrm{in}}_{\mathrm{h}} = P^{\mathrm{out}}_{\mathrm{h}}$$

- Energy balance of electricity

$$\left(P^{\mathrm{grid,out}}_{\mathrm{h}} - P^{\mathrm{grid,in}}_{\mathrm{h}} \right) \Delta t = \sum_{\mathrm{i} \in I^{\mathrm{in}}} P^{\mathrm{i,in}}_{\mathrm{h}} \Delta t - \sum_{\mathrm{i} \in I^{\mathrm{out}}} P^{\mathrm{i,out}}_{\mathrm{h}} \Delta t$$

- Mutual exclusivity between grid injections/withdrawals

$$\left(P^{\mathrm{grid,out}}_{\mathrm{h}} \le \delta^{\mathrm{out}}_{\mathrm{h}} \cdot P^{\mathrm{grid,out}}_{\mathrm{max}} \right) \land \left(P^{\mathrm{grid,in}}_{\mathrm{h}} \le \delta^{\mathrm{in}}_{\mathrm{h}} \cdot P^{\mathrm{grid,in}}_{\mathrm{max}} \right) \land \left(\delta^{\mathrm{out}}_{\mathrm{h}} + \delta^{\mathrm{in}}_{\mathrm{h}} \le 1 \right)$$

Between energy nodes

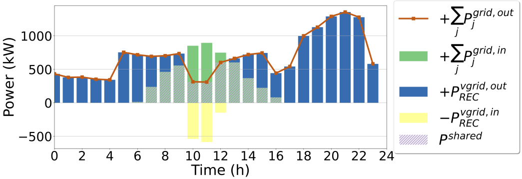
- Energy balance on the MV distribution grid (here is the shared energy)

$$\left(P^{\mathrm{vgrid,in}}_{\mathrm{h}} - P^{\mathrm{vgrid,out}}_{\mathrm{h}} \right) \Delta t = \sum_{\mathrm{j}} P^{\mathrm{grid,in}}_{\mathrm{j,h}} \Delta t - \sum_{\mathrm{j}} P^{\mathrm{grid,out}}_{\mathrm{j,h}} \Delta t$$

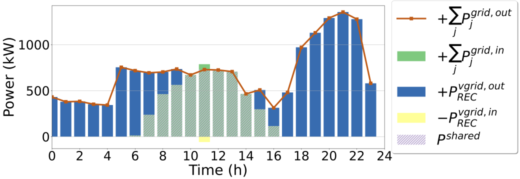
Results snippet

Coordinated vs individual optimization

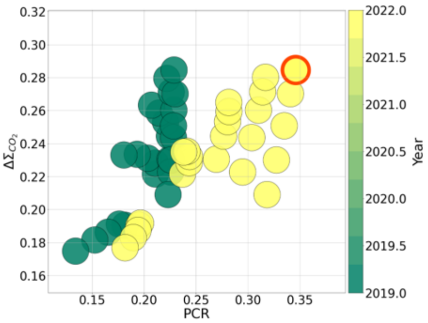
- Each node is optimized **individually**, shared energy is calculated *a posteriori*



- All nodes are optimized at the **same time**, shared energy is part of the optimization



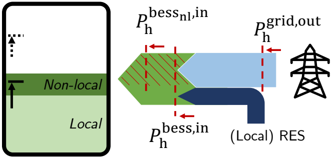
Can REC dumpen the effects of energy prices?

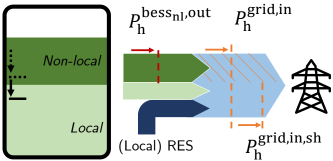


- REC with PV-battery
- Comparison base case-REC with **increasing** prices
- Better economics but improvement due to **physical** self-consumption (shared energy does not change)

REC modelling (cont'd)

Electricity storage systems (an Italian overcomplication)[12]





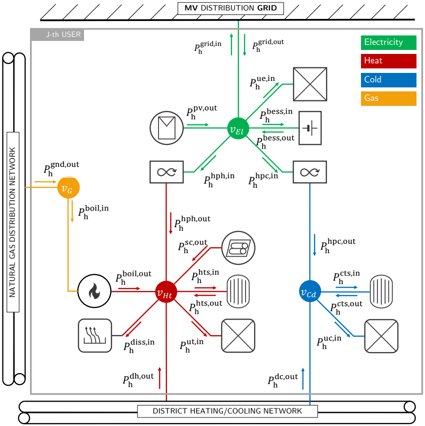
$$P_{\mathrm{h}}^{\mathrm{bess_{nl},in}} = \min\left(P_{\mathrm{h}}^{\mathrm{bess,in}}; P_{\mathrm{h}}^{\mathrm{grid,out}}\right) \qquad P_{\mathrm{h}}^{\mathrm{grid,in,inc}} = P_{\mathrm{h}}^{\mathrm{grid,in}} - \min\left(P_{\mathrm{h}}^{\mathrm{grid,in}}; P_{\mathrm{h}}^{\mathrm{bess_{nl},out}}\right)$$

- **Separation** of stored electricity into: local (same node) and non-local (from other nodes, i.e., passing through the grid)
- *Non-local* electricity is shared during the charge phase, but cannot be shared again
- Safely account storing electricity from **other** energy nodes

12 (Lazzeroni, 2022)

REC modelling (cont'd)

"RECoupled": electricity and other energy vectors[13]



- Multiple energy vectors **within** each node in a REC
- Surplus electricity can be **exchanged** among nodes through the distribution grid
- Production of other energy vectors must be consumed **locally**

→ A generalized and **flexible** model for RECs.

[13] (Gulli', 2022)

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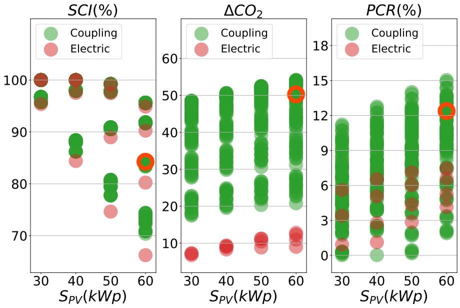
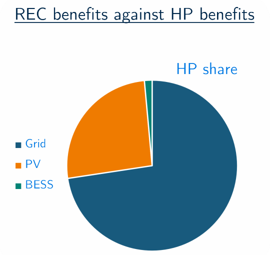
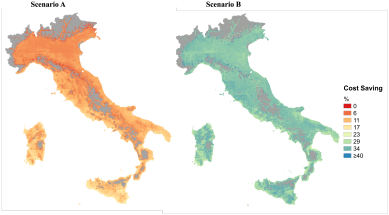
What are the benefits of sectors coupling in residential RECs?

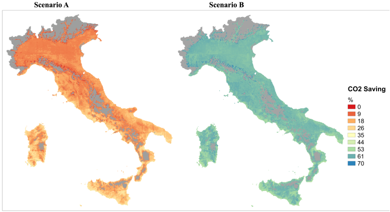
- Single multifamily building with rooftop PV system and electricity storage
- Electrification of thermal demand with heat pump and heat storage system
- **Better** economics and environmentals with sectors coupling





Analysis at national level[14]





14 (Canova, 2022)

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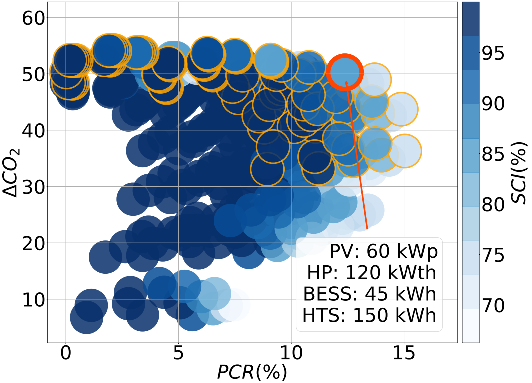
What is the impact of storage systems?



- Different objectives are **conflicting**
- Storage systems can **optimize** PV and HP sizes (and their utilization)

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Python tool “RECoupled”

INPUT LAYER

sim_config.yaml
- sim_name, str
- users, list
- economics, dict
- environmentals, dict

Users
- user1.yaml
- ...
- userj.yaml
- ...

Profiles
- user1_unit1.csv
- ...
- userj_uniti.csv
- ...

INTERNAL LAYER

Simulation
- sim_name, str
- users, list
- economics, dict
- environmentals, dict

Configuration
- users, list
- optimise()
- evaluate()
- ...

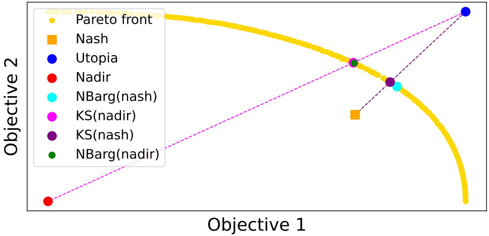
User
- unit_1
- ...
- unit_i
- ...

Unit
- inflows
- outflows
- storages
- ...

Build configuration(s) → Optimise and evaluate → Provide results

Metaheuristics and game theory in MOOP (WIP)

- Metaheuristic algorithm such as genetic or Artificial Immune Systems[15] can effectively find the Pareto front in MOOPs
- Problems of increasing size might become **unmanageable**, with many objectives the Parent front can lose meaning
- Game theory concepts can be used to **avoid** the Pareto front and find equilibrium points between conflicting objectives



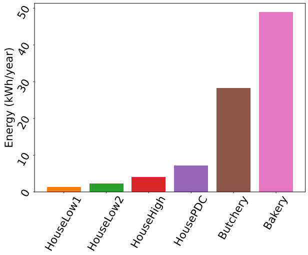
[15] (Lorenti, 2023)

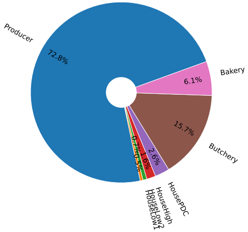
Benefits sharing

How to divide benefits among REC members?

Game theory to divide benefits between REC members[16,17]

- Each REC member is a **participant** to the game
- The **value** v is defined (e.g., yearly incomes of the REC)
- The **contribution** of participant i to total value is evaluated from the sub-coalitions S of the whole configuration N (Shapley value) $\Phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} (v(S \cup \{i\}) - v(S))$



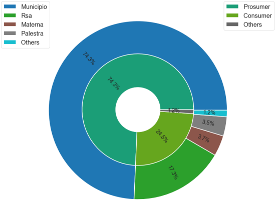


[16] (Moncecchi, 2020) [17] (Fioriti, 2021)

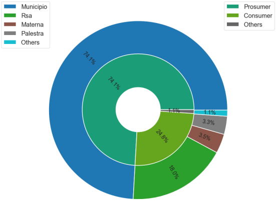
Benefits sharing (cont'd)

Is game theory always needed?

- Adoption of a heuristic distribution model, where a coefficient of division between producers and consumers is defined (β_{prod})
- The value of each participant is evaluated as the hourly contribution to the total production/consumption
- Similar results, **provided** that β_{prod} is correctly calibrated



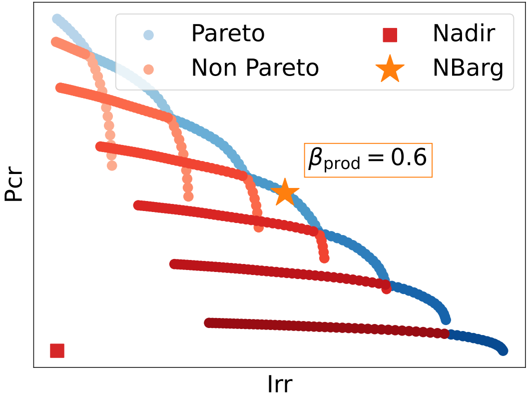
Shapley



Heuristic ($\beta_{\text{prod}} = 0.7$)

Benefits sharing in the multi-objective optimization (WIP)

- A multi-objective optimization approach can be adopted to find an **equilibrium** business model

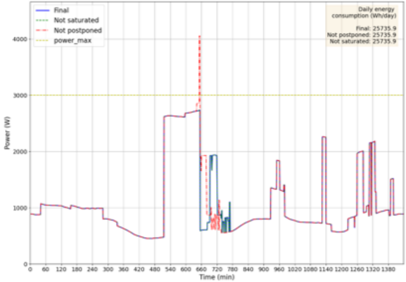


Input data

How to obtain the necessary input data? How to pre-process them?

Electricity load profiles

A probabilistic bottom-up approach[18]



- Household demand simulation from electric appliances usage in Italian families[19]
- Energy classes and statistical data of appliances distribution
- Power profiles of appliances during their working-cycles

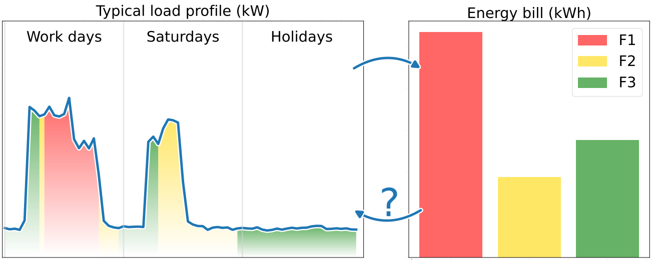
Future development: updated database[20] and "social" aspects (e.g., different family compositions) (WIP)

[18] (Cadema, 2021) [19] (MICENE, 2010) [20] (Besagni, 2020)

Electricity load profiles (cont'd)

Data-driven load prediction from energy bills (WIP)

- Three **time-of-use** tariffs in the Italian electricity billing system (on-peak, F1, mid-peak, F2, off-peak, F3)
- *Can we use this data to predict hourly load from energy bills*?
- KNN-based approach to **map** an energy bill into a typical load profile using a data set of measurement



Snippet on time series clustering

Reducing the computational burden of optimization

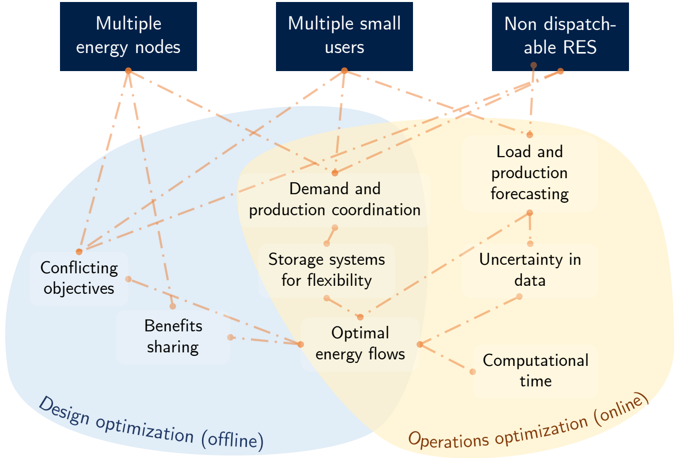
- **Typical** patterns (e.g., daily) can be found in RES production an end users consumption profiles
- Clustering algorithms (unsupervised learning) can be used to find these typical patterns or groups of end users
- The computational burden of optimization procedures is *safely* reduced by considering only a certain amount of data which are however **representative**

Online operation

What are the main issues? What are our future perspectives?

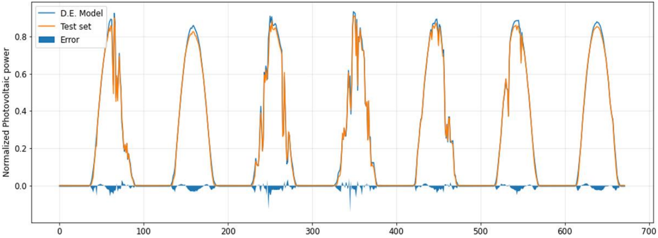
Online operation

What are the features of online vs offline optimization?



Prediction of PV production with artificial neural networks[21]

- Artificial Neural Networks for prediction of PV production from weather data (irradiance, temperature)
- Differential Evolution algorithm for ANN training
- Competitive performance with state-of-the-art Adam algorithm in terms of error but more stable
- “Late” finding: simple task, ANN may be overqualified

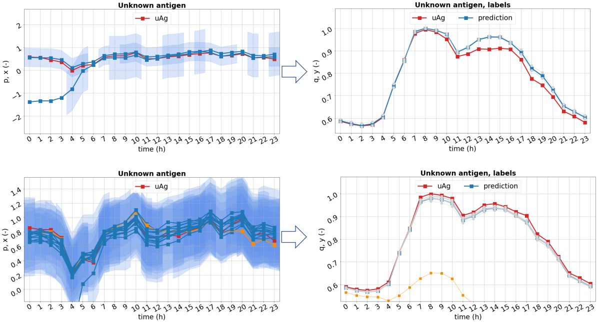


[21] (Lorenti, 2022)

Load forecasting

Forecasting of electric load[22] (implementation exercise)

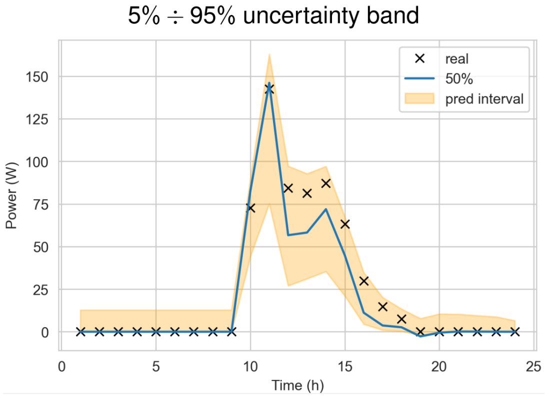
- Artificial Immune System for day-ahead forecasting trained on 1-years data of previous-next day pairs (aggregated data)
- 4.3% average MAPE on test set



[22] (Dudek, 2008)

Can we include uncertainty in our predictions? (WIP)

- Quantile linear auto-regression for a PV module production forecasting
- Predictions can be extended to a confidence interval



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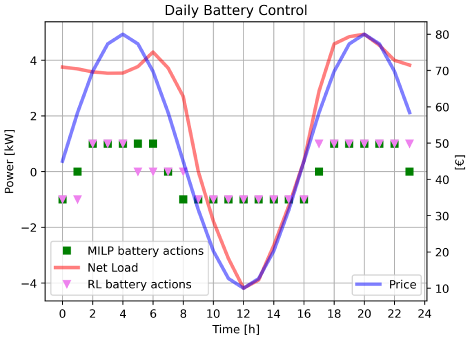
Can RL be implemented into real time operations?[23]

- Training of a model-free RL algorithm to manage the on-off status of a battery storage coupled with a PV system
- Nearly-optimal control, but on synthetic and stationary data



[23] (Repetto, 2022)

Future perspectives

What are the possible directions for future works?

- Online optimization of the energy flows is **crucial**:
  1. when passing from design (offline) to operation
  2. to assess real performance (probably, **suboptimal**) during design
- The same REC model and MILP solver can be turned into a model **predictive** control (MPC) algorithm to optimize energy flows in a sliding window fashion (*how to react to forecasting errors?*)
- Stochastic programming might be a viable option to include **uncertainty** in input data (also in offline design)
- Computational complexity and **feasibility** of the control must be taken into account (how to communicate data from a multitude of nodes?)

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Merci de votre attention!

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