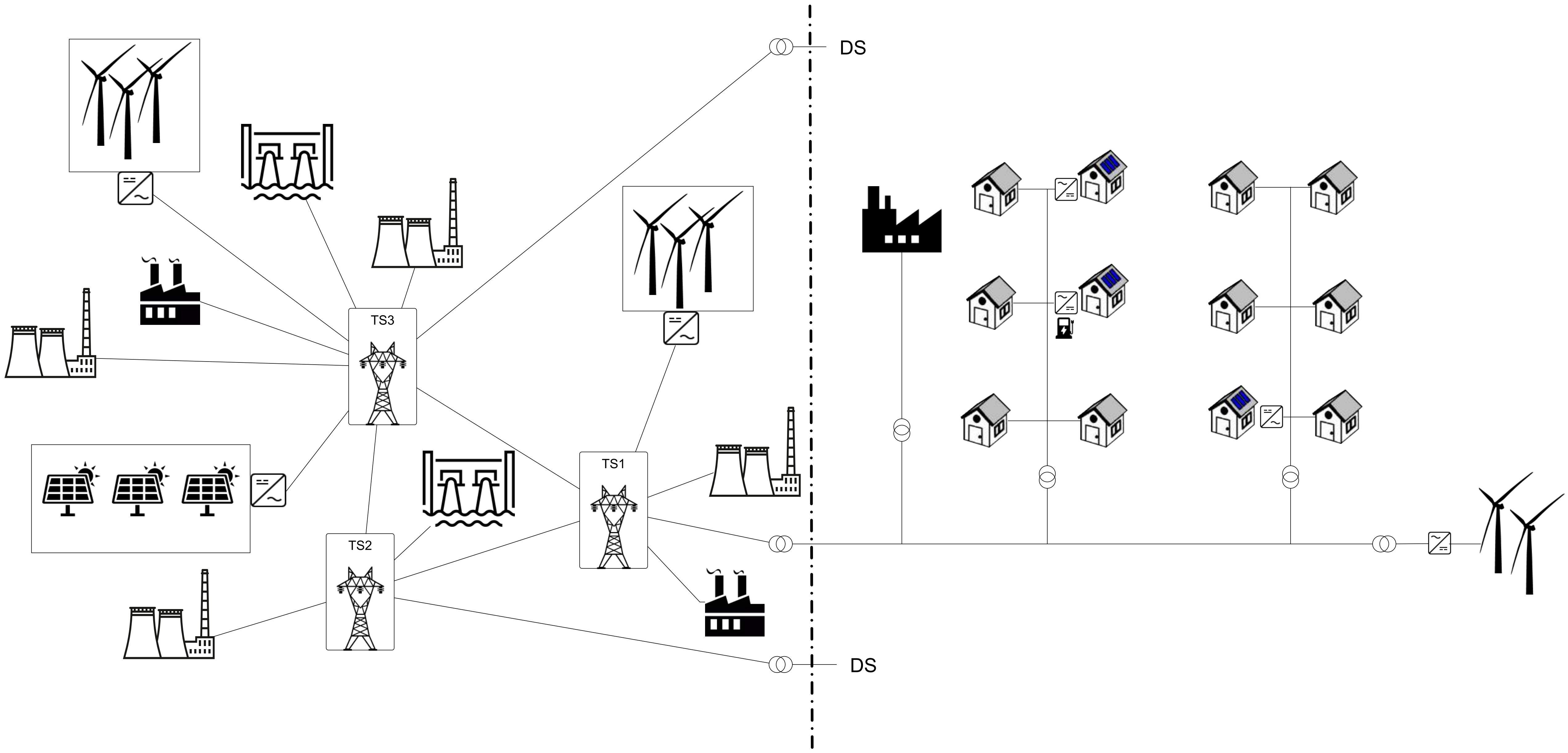
Energy communities & microgrids: current situation and perspectives

November 13th, 2019

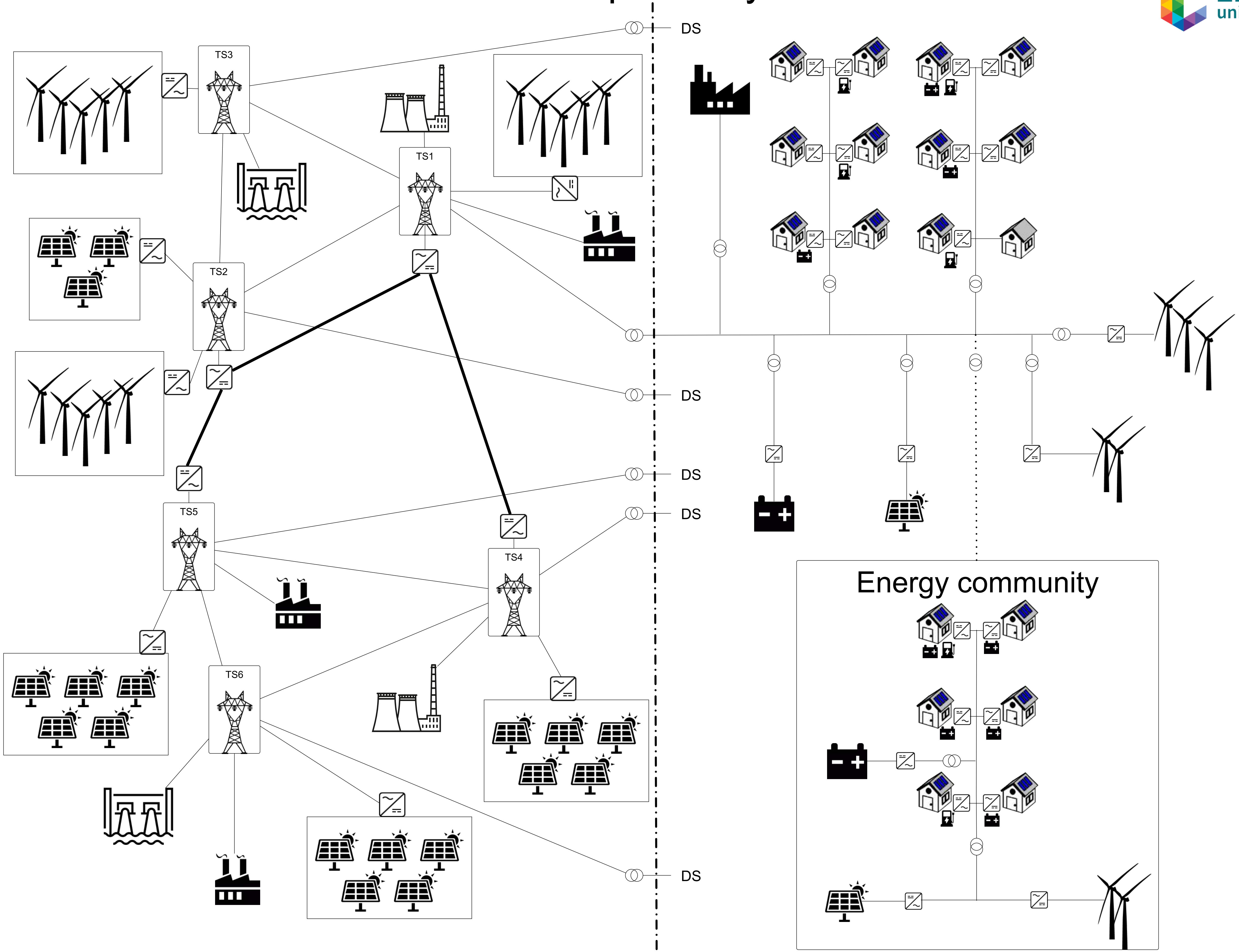
ELEC0080-1 ENERGY NETWORKS Partim1: Les systèmes d’énergie électrique

Preamble

From present...



... to future power systems.



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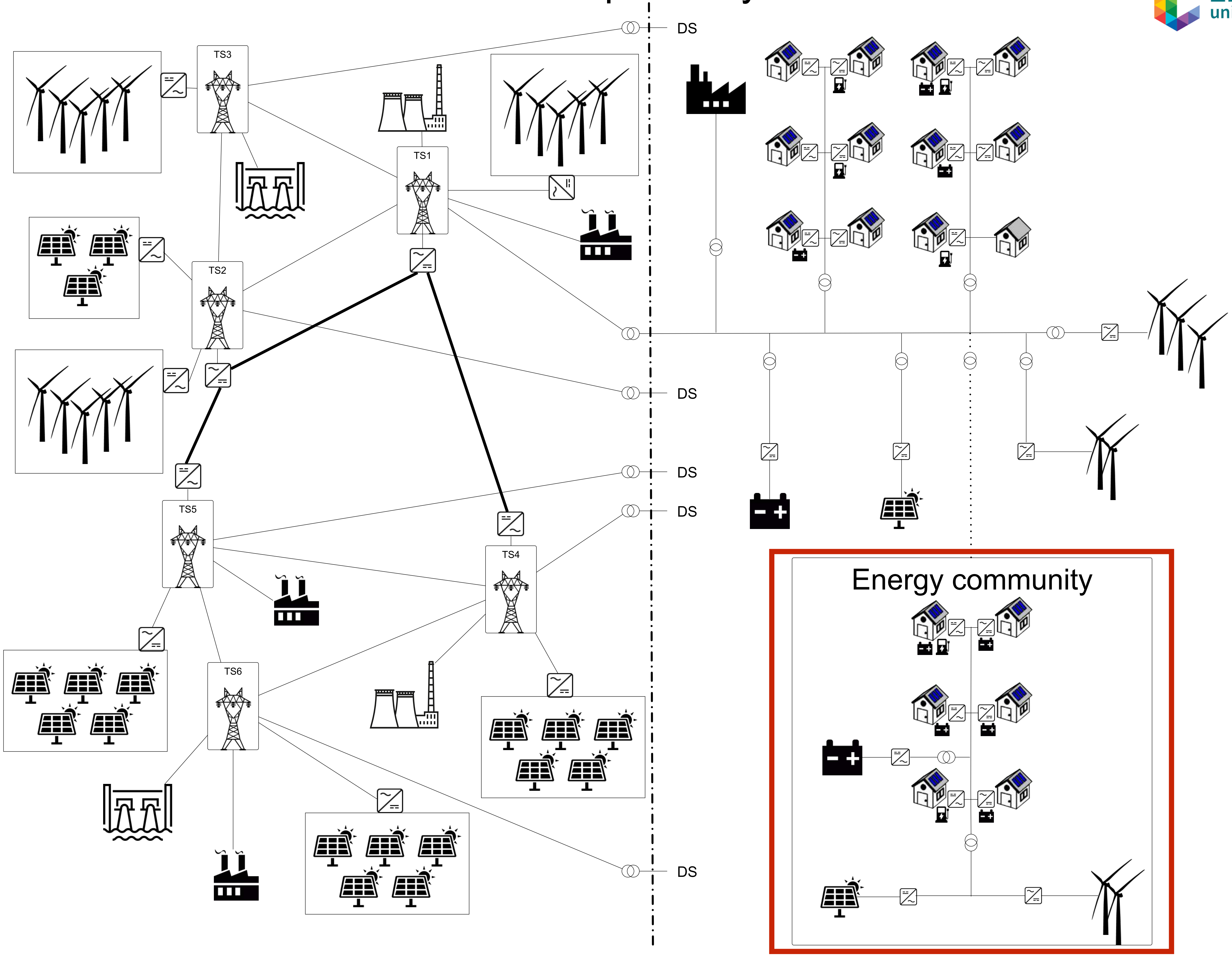


What is currently happening?

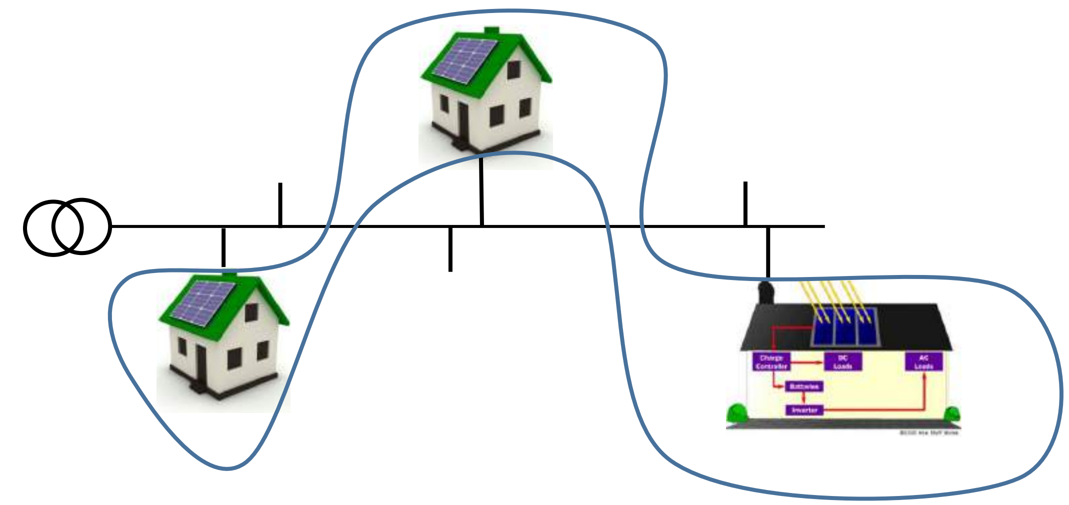
Elements of fear for the big utilities:

Cheap cost of distributed generation

Falling cost of batteries

Increase of energy efficiency

Electric cars + possible ‘uberisation’ of the grid



Community based energy solutions:

Small consumers, producers, prosumers sharing resources for their provision of energy

Made possible by exploiting the above-mentioned « elements of fear »

Rather than to oppose these community-based energy solutions, utilities should tap into the new business opportunities they represent

Energy prosumer communities

In this course, we will focus on two extreme types of energy communities, as well as on their potential interactions:

- A first community of houses connected to the same low-voltage feeder, sharing production and/or storage capacities: the **local energy community**

- A second community of electricity sellers, and electricity buyers, in particular using electric vehicles: the **mobile energy community**

Outline

I. Local energy communities

II. Mobile energy communities

III. Integrating communities?

IV. Décret “Communautés d’Energie Renouvelable”

I.
Local Energy Communities

The microgrids case

A house, some PVs, and a little storage.

There is local electricity production, and a local consumption.

There is also the possibility to locally store energy.

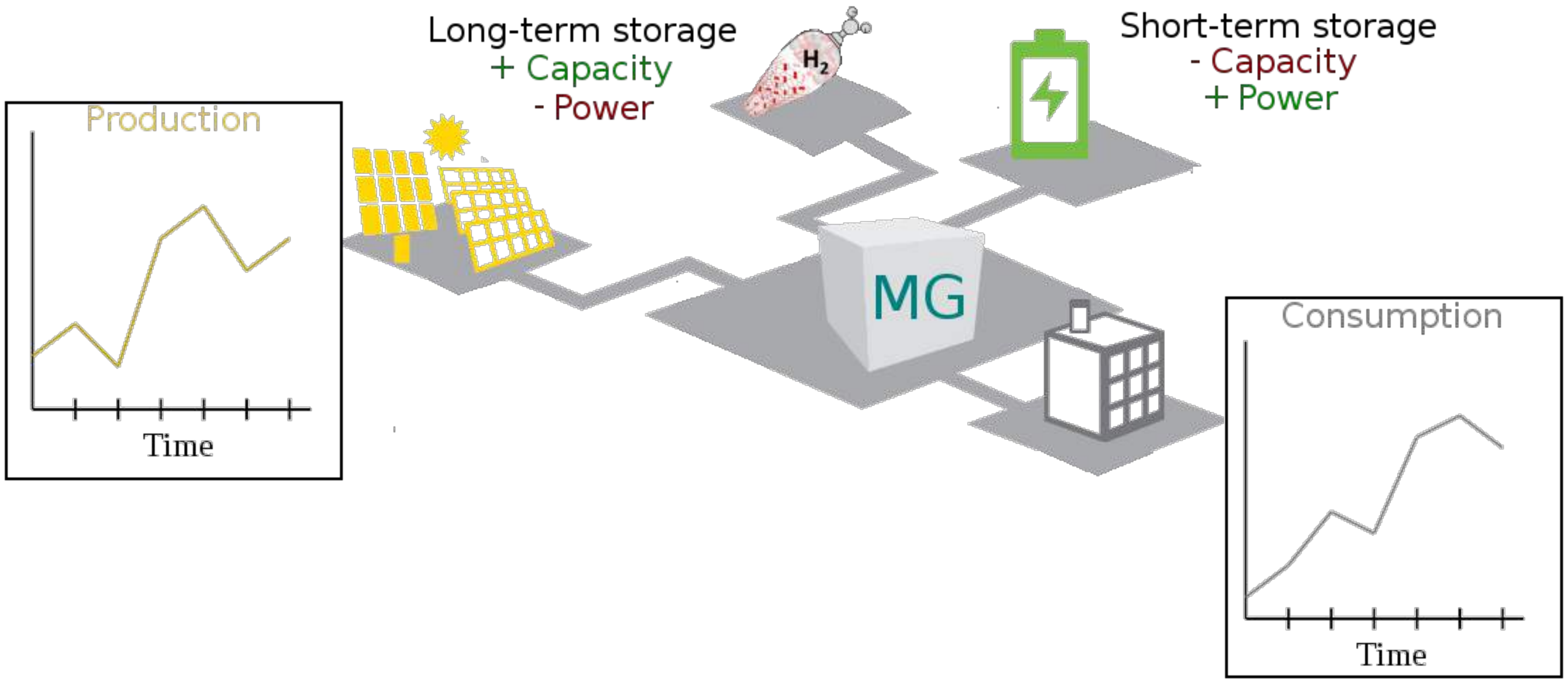
Questions :

- Is it possible to become self-sufficient ?

- What is the “best” way to size the installation ?

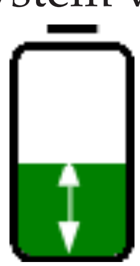
The microgrids case

Fully off-grid microgrid

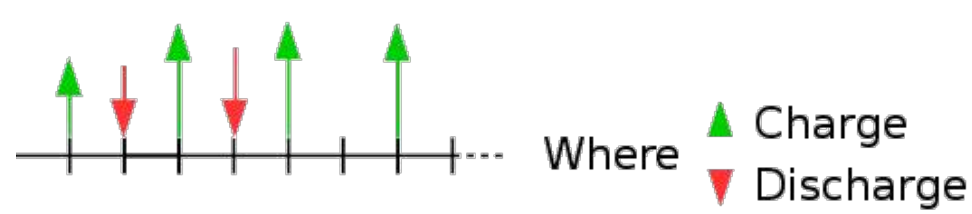


For each storage systems included in the microgrid :

State system variable



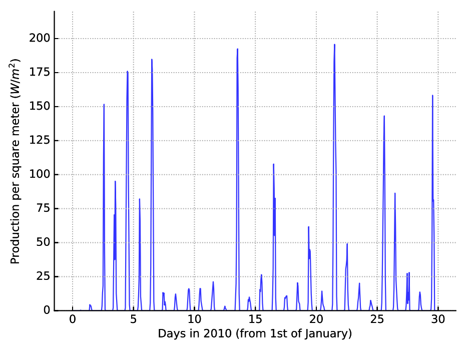
Decision making process



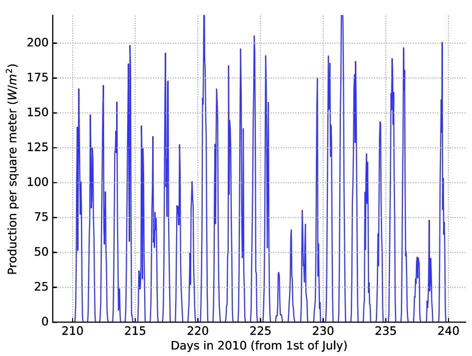
Challenge : Real-time balancing of several storage systems under uncertainties.

Operating storage devices in microgrids

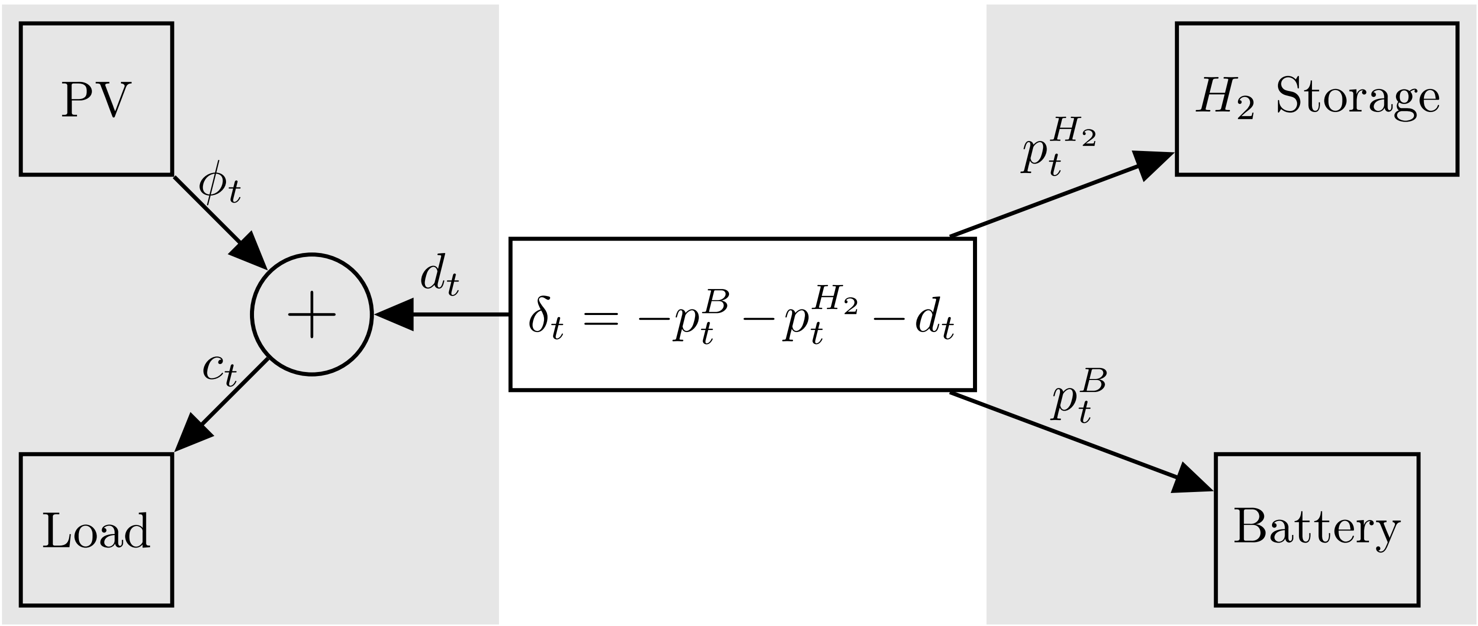
The context: imagine a microgrid (MG) featuring photovoltaic (PV) panels, with both short and long terme storage devices.

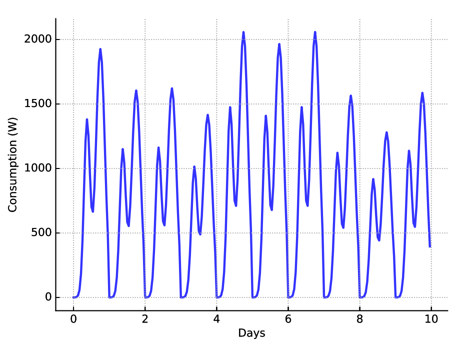


(b) Example of production in winter



(c) Example of production in summer



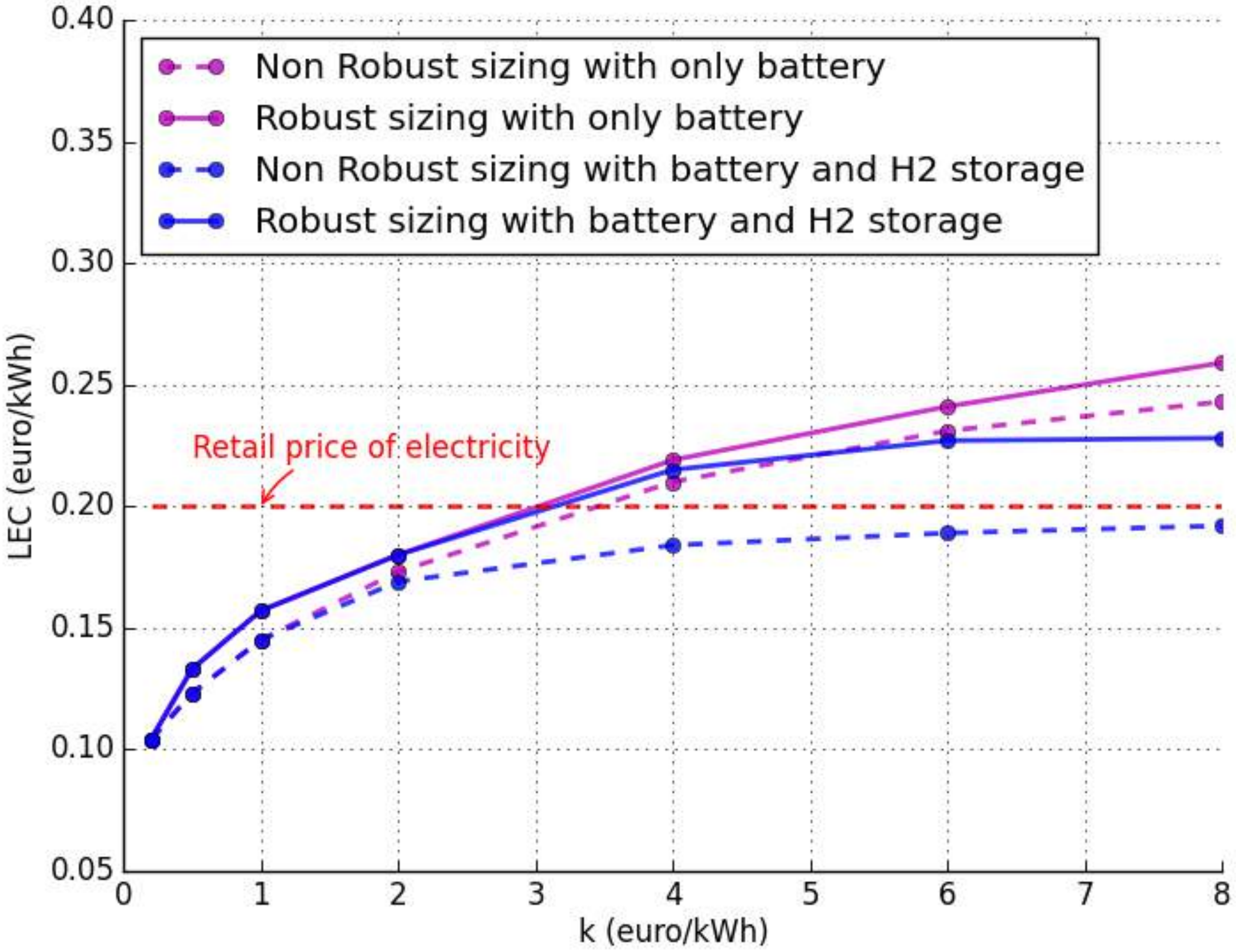


The problem: how to optimally active the storage devices so that to minimise the operating costs of the MG?

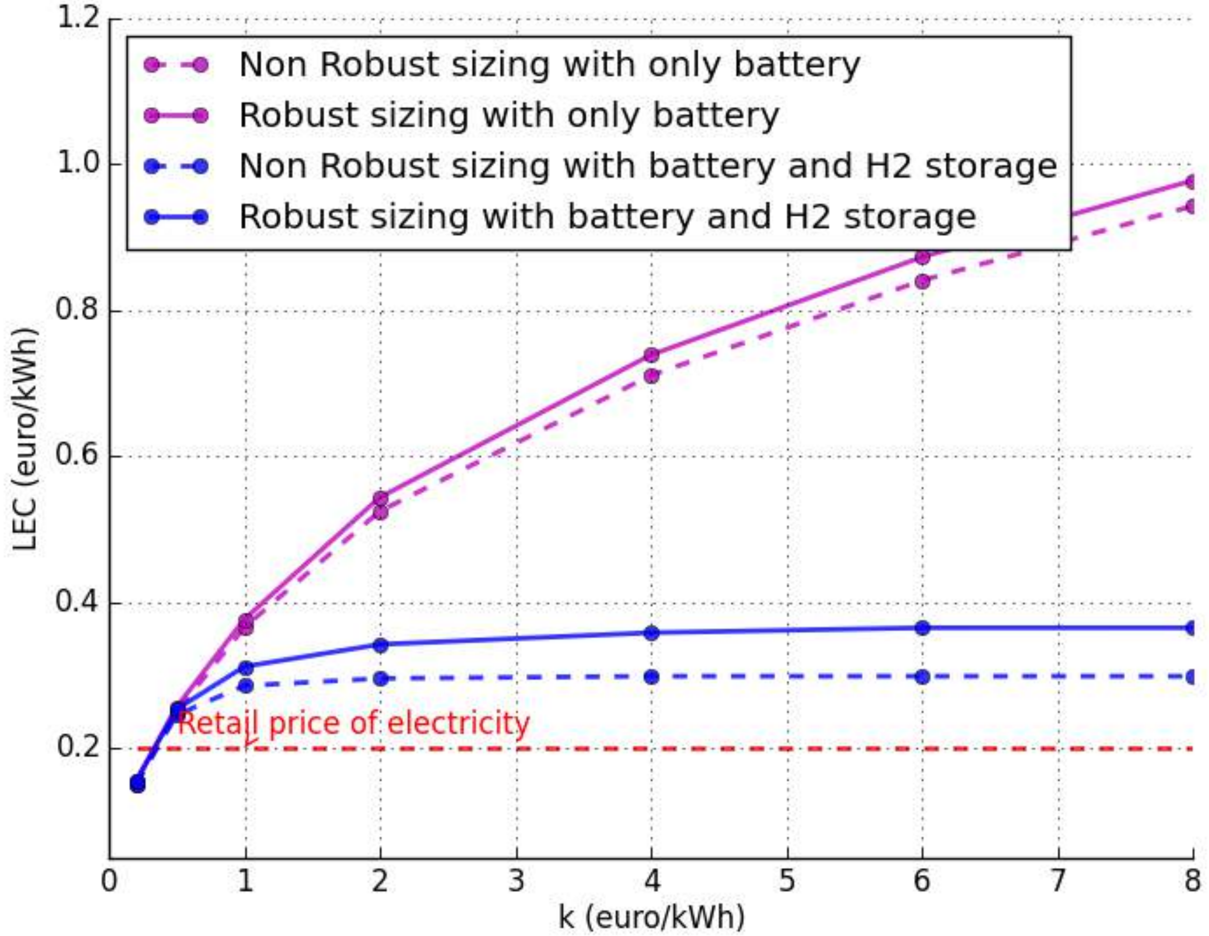
Operating storage devices in microgrids

$$
\begin{aligned}
\text{Minimize} \quad & LEC = \frac{\sum_{t=0}^{T-1} \frac{-k \;\; F_t}{(1+r)^y} + I_0}{\sum_{y=1}^{n} \frac{\epsilon_y}{(1+r)^y}} \text{ where } y = \lceil t/365 \rceil \\
\text{With} \quad & 0 \leq s_t^B \leq x^B, && \forall t \in [0, T] \\
& 0 \leq p_t^{B,+} \leq P_t^B, && \forall t \in [0, T-1] \\
& -P_t^B \leq p_t^{B,-} \leq 0, && \forall t \in [0, T-1] \\
& 0 \leq s_t^{H_2} \leq R_t^{H_2}, && \forall t \in [0, T] \\
& 0 \leq p_t^{H_2,+} \leq x^{H_2}, && \forall t \in [0, T-1] \\
& -x^{H_2} \leq p_t^{H_2,-} \leq 0, && \forall t \in [0, T-1] \\
& s_t^B = s_{t-1}^B + \eta_t^B p_{t-1}^{B,+} + \frac{p_{t-1}^{B,-}}{\zeta_{t-1}^B}, && \forall t \in [1, T] \\
& s_t^{H_2} = s_{t-1}^{H_2} + \eta_t^B p_{t-1}^{H_2,+} + \frac{p_{t-1}^{H_2,-}}{\zeta_{t-1}^{H_2}}, && \forall t \in [1, T] \\
& F_t \leq -d_t - p_t^{B,+} - p_t^{B,-} - p_t^{H_2,+} - p_t^{H_2,-}, && \forall t \in [1, T] \\
& F_t \leq 0, && \forall t \in [1, T]
\end{aligned}
$$

Operating storage devices in microgrids

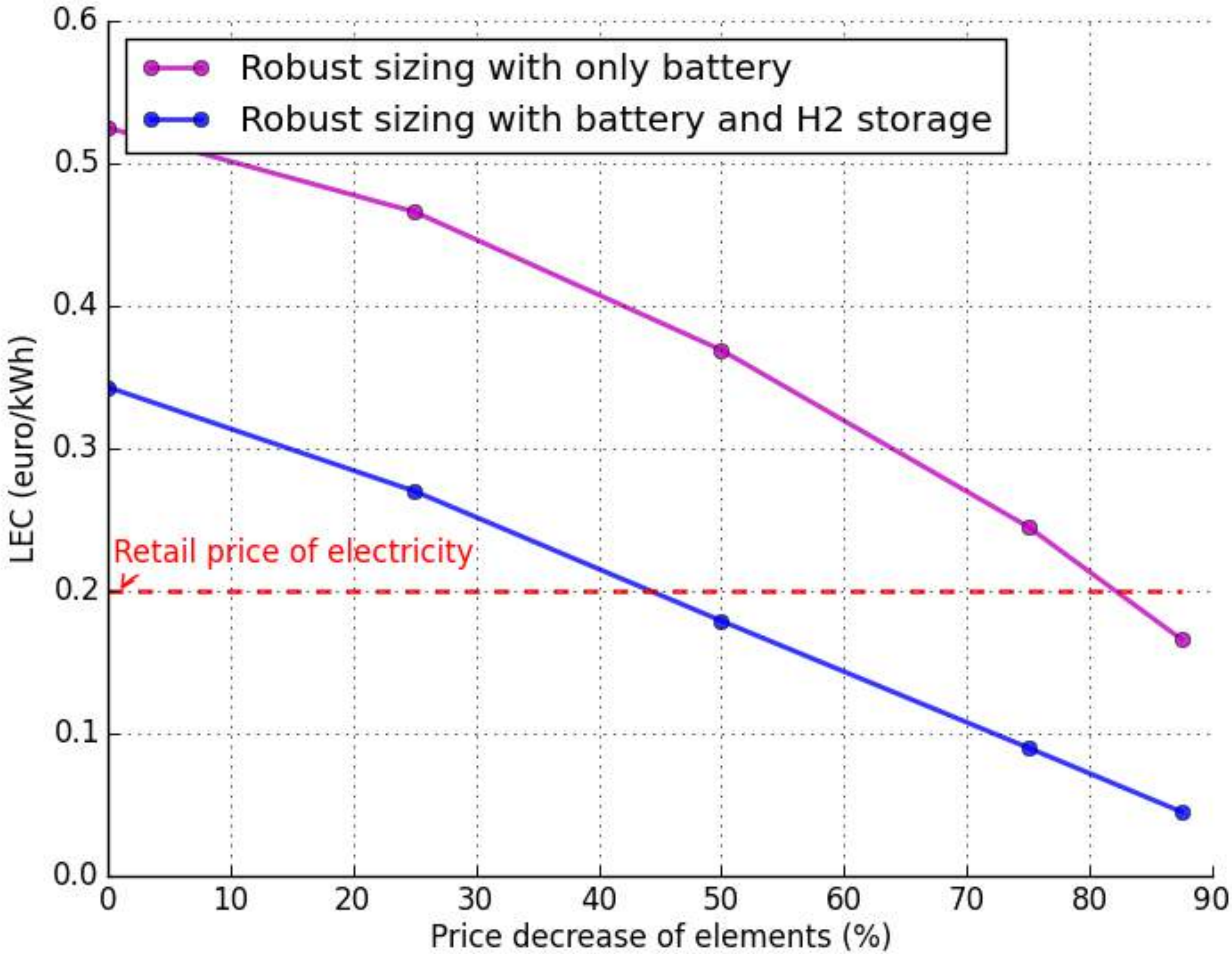


Spain

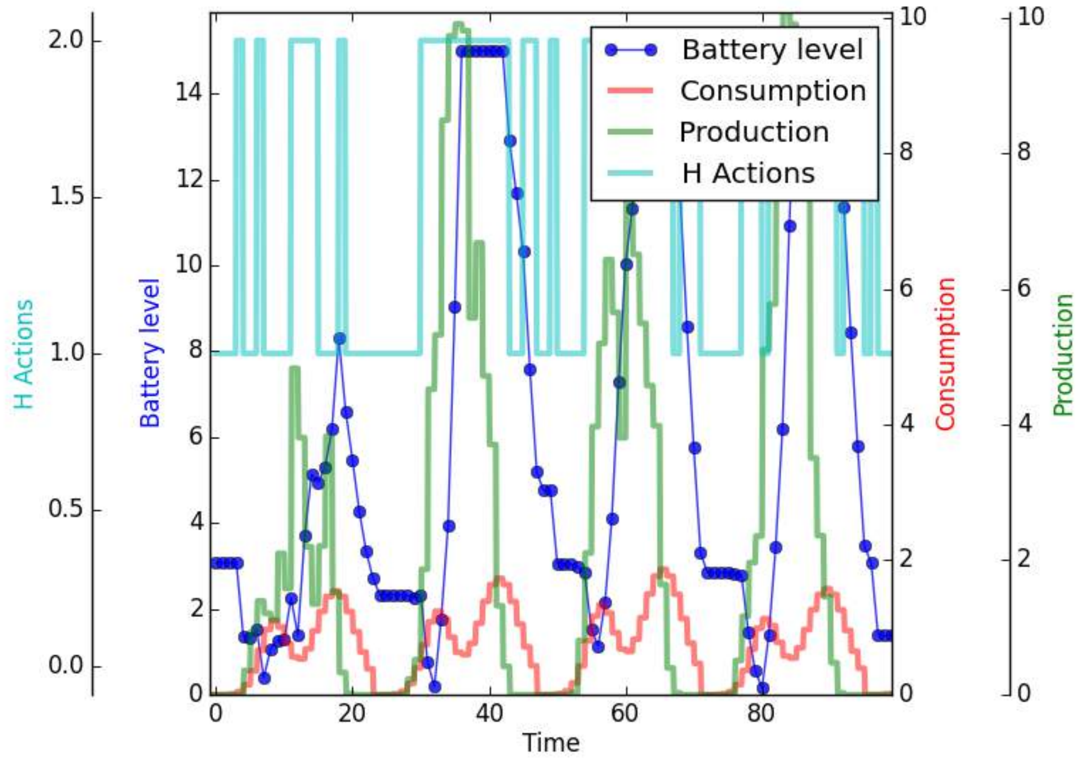


Belgium

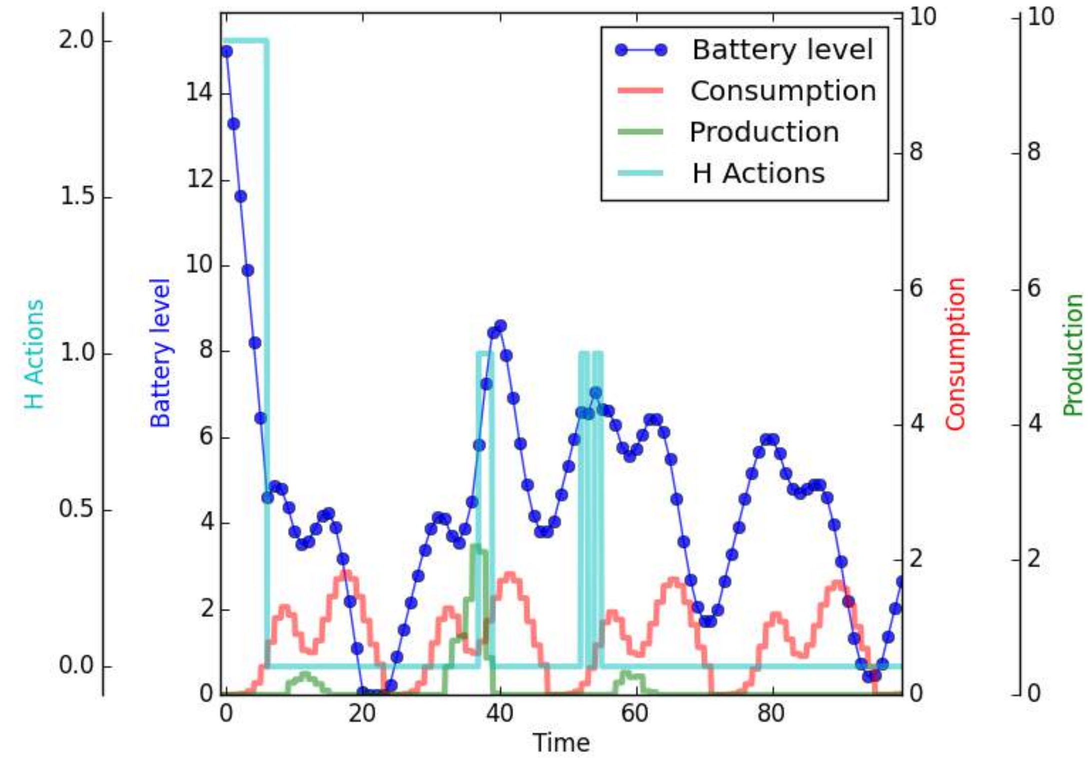
Operating storage devices in microgrids



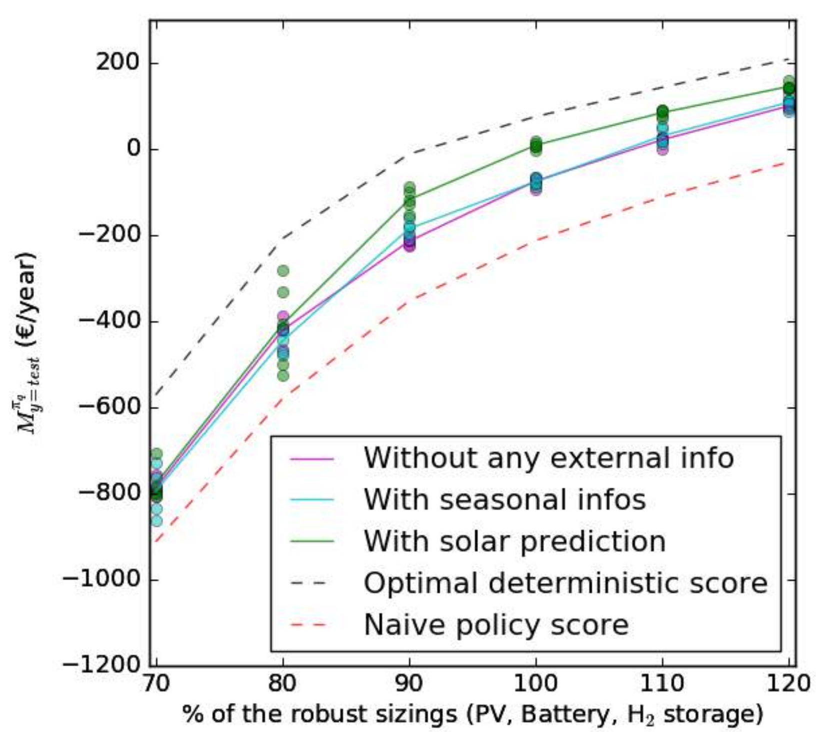
Using Reinforcement Learning…



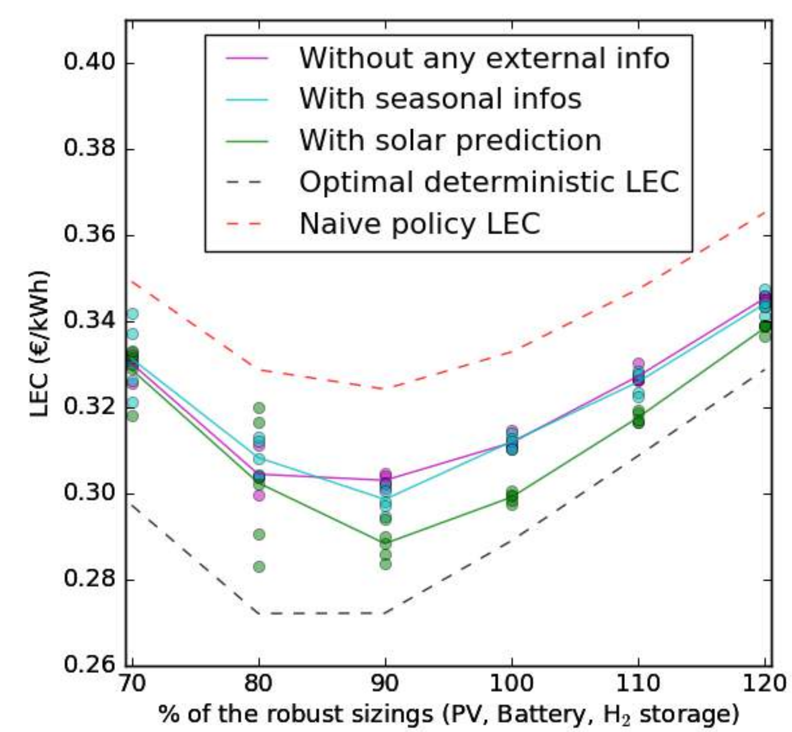
(a) Typical policy during summer



(b) Typical policy during winter



(a) Operational revenue

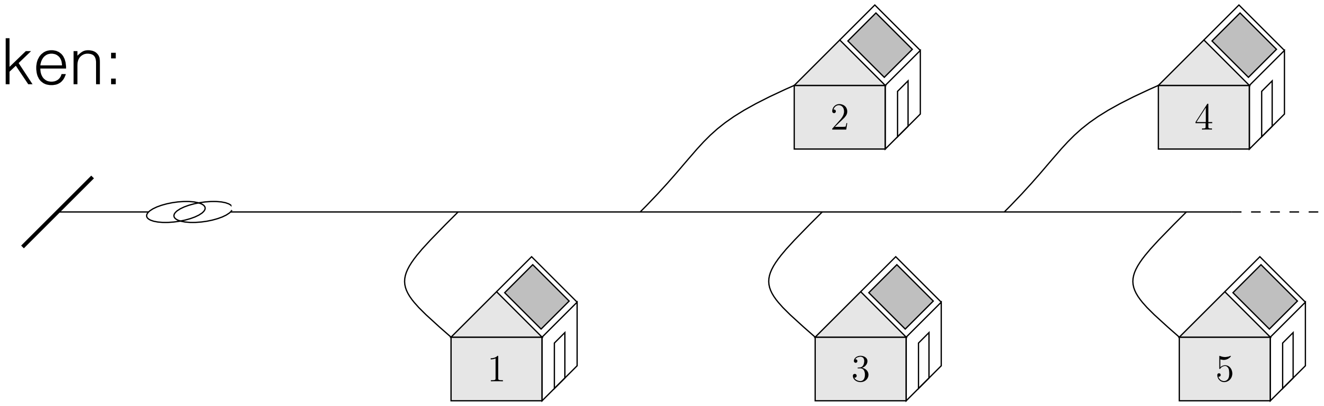


(b) LEC

From microgrids to local energy community

We consider a set of houses with PV panels (+ eventually batteries) sharing their resources in order to attain « community objectives »

At every time-step, decisions can be taken:
Curtailing the PV production
Charging / discharging the battery
Managing the demand

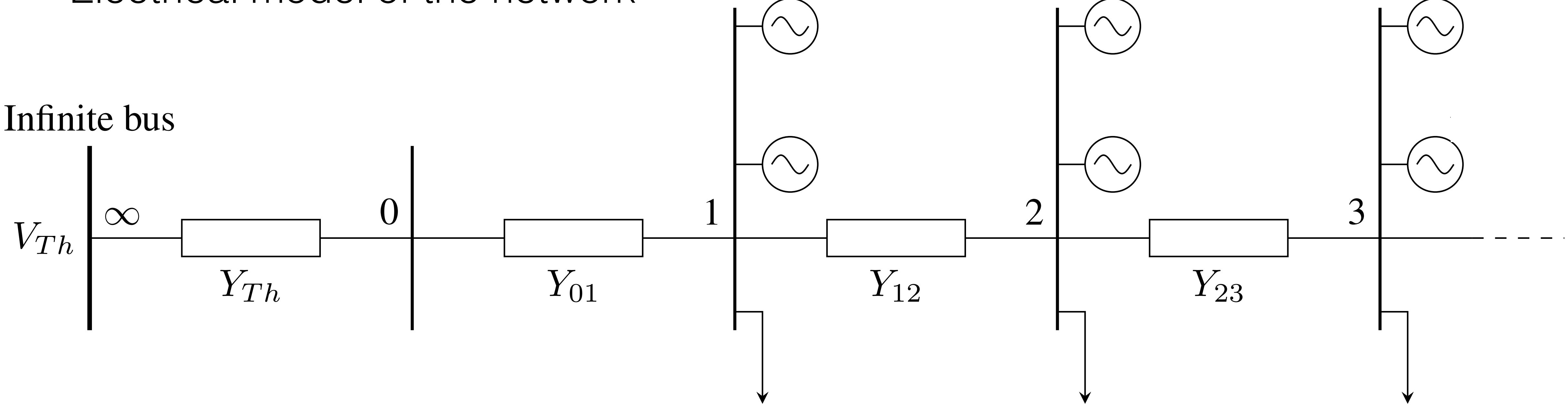


The community needs to defined a **community objective**:
Maximising the PV production,
Minimising the cost of electricity,
Minimising losses…

A community should also discuss how benefits should be shared, and also propose incentives to attract new members

Modelling a local energy community

Electrical model of the network



Modelling a local energy community

N prosumers dynamically interacting with each other over a time horizon T

$$\forall (i,j) \in \{1,\dots,N\}^2, \forall t \in \{0,\dots,T-1\},$$
$$\theta_t^{(i \rightarrow j)} = \theta_t^{(j \leftarrow i)}$$

$$\text{with the convention that } \theta_t^{(i \rightarrow i)} = 0, \theta_t^{(i \leftarrow i)} = 0 \ \forall i, t.$$

$$\forall t, i, \ \ P_{P,t}^{(i)} = L_{P,t}^{(i)} + D_{P,t}^{(i)} + S_{P,t}^{(i)}$$

$$\forall t, i, \ \ D_{P,t}^{(i)} = \sum_{j=1}^{N} \left(\theta_t^{(i \rightarrow j)} - \theta_t^{(i \leftarrow j)} \right) + \delta D_{P,t}^{(i)}$$

Modelling a local energy community

Conservation of reactive power at the prosumer's location

$$\forall t, i,\ \ P_{Q,t}^{(i)} = L_{Q,t}^{(i)} + D_{Q,t}^{(i)}$$

Other power-related constraints:

$$\forall t, i\ P_{P,t}^{(i)} \leq P_{P,t}^{(i),\max}$$

$$\forall t, i\ \ \left| P_{Q,t}^{(i)} \right| \leq P_Q^{(i),\max}\left(P_{P,t}^{(i)} \right)$$

$$\forall t, i,\ \ \left| S_t^{(i)} \right| \leq S^{(i),\max}\left(\lambda_t^{(i)} \right)$$

$$\forall t, i\quad 0 \leq \lambda_t^{(i)} \leq \lambda^{(i),\max}$$

Modelling a local energy community

Network constraints:

$$\forall t, i, \quad \left|D_{P,t}^{(i)}\right| \leq D_{P}^{(i),\max}\left(P_{P,t}^{(i)}, P_{Q,t}^{(i)}, L_{P,t}^{(i)}, L_{Q,t}^{(i)}, S_{t}^{(i)}, D_{P,t}^{(j\neq i)}, D_{Q,t}^{(j\neq i)}\right)$$

$$\forall t, i, \quad \left|D_{Q,t}^{(i)}\right| \leq D_{Q}^{(i),\max}\left(P_{P,t}^{(i)}, P_{Q,t}^{(i)}, L_{P,t}^{(i)}, L_{Q,t}^{(i)}, S_{t}^{(i)}, D_{P,t}^{(j\neq i)}, D_{Q,t}^{(j\neq i)}\right)$$

At the root of the community:

$$\forall t \quad \Lambda_{P,t}^{(c)} = D_{P,t}^{(c)} - \sum_{i=1}^{N} D_{P,t}^{(i)}$$

$$\forall t \quad \Lambda_{Q,t}^{(c)} = D_{Q,t}^{(c)} - \sum_{i=1}^{N} D_{Q,t}^{(i)}$$

Modelling a local energy community

Costs and revenues

$$c_t^{(i)} = \Delta\Bigg(\max\left(-\delta D_t^{(i)}, 0\right) Pr_t^{(D\rightarrow i)} + \sum_{j=1}^{N} \max\left(\theta_t^{(i\leftarrow j)}, 0\right) Pr_t^{(j\rightarrow i)} \Bigg)$$

$$r_t^{(i)} = \Delta\Bigg(\max\left(\delta D_t^{(i)}, 0\right) Pr_t^{(i\rightarrow D)} + \sum_{j=1}^{N} \max\left(\theta_t^{(j\leftarrow i)}, 0\right) Pr_t^{(j\rightarrow i)} \Bigg)$$

Modelling a local energy community

State and prices vector

$$\Theta_t^{\rightarrow} = \left(\theta_t^{(i\rightarrow j)}\right)_{i,j}, \qquad \Theta_t^{\leftarrow} = \left(\theta_t^{(i\leftarrow j)}\right)_{i,j}$$

$$\Xi_t = \begin{pmatrix} P_{P,t}^{(1)} & P_{Q,t}^{(1)} \\ P_{P,t}^{(1),\max} & P_{Q,t}^{(1),\max} \\ \vdots & \vdots \\ P_{P,t}^{(N)} & P_{Q,t}^{(N)} \\ P_{P,t}^{(N),\max} & P_{Q,t}^{(N),\max} \\ S_t^{(1)} & \lambda_t^{(1)} \\ \vdots & \vdots \\ S_t^{(N)} & \lambda_t^{(N)} \\ L_{P,t}^{(1)} & L_{Q,t}^{(1)} \\ \vdots & \vdots \\ L_{P,t}^{(N)} & L_{Q,t}^{(N)} \\ D_{P,t}^{(1)} & D_{Q,t}^{(1)} \\ \vdots & \vdots \\ D_{P,t}^{(N)} & D_{Q,t}^{(N)} \end{pmatrix}, \quad \Phi_t = \begin{pmatrix} Pr_t^{(D\rightarrow 1)} \\ Pr_t^{(1\rightarrow D)} \\ \vdots \\ Pr_t^{(D\rightarrow N)} \\ Pr_t^{(N\rightarrow D)} \\ Pr_t^{(1\rightarrow 2)} \\ Pr_t^{(2\rightarrow 1)} \\ \vdots \\ Pr_t^{(1\rightarrow N)} \\ Pr_t^{(N\rightarrow 1)} \\ \vdots \\ Pr_t^{(N-1\rightarrow N)} \\ Pr_t^{(N\rightarrow N-1)} \end{pmatrix}$$

$$\Xi_{t+1} = F(\Xi_t, \Phi_t, \Theta_t^{\rightarrow}, \Theta_t^{\leftarrow} \ldots, \Xi_0, \Phi_0, \Theta_0^{\rightarrow}, \Theta_0^{\leftarrow}, \omega_t) \qquad \omega_t \sim P_t(\cdot)$$

Modelling a local energy community

Need for an optimisation criterion:

Maximising **production**

$$\max_{\substack{P^{(i)}_{P,t}, P^{(i)}_{Q,t}, L^{(i)}_{P,t}, L^{(i)}_{Q,t}, S^{(i)}_t, \Theta^{\rightarrow}_t, \Theta^{\leftarrow}_t \\ t \in \{0,\dots,T-1\} \\ i \in \{1,\dots,N\}}} \mathbb{E}\left[\sum_{t=0}^{T-1}\sum_{i=1}^{N} P^{(i)}_{P,t}\right]$$

Taking **losses** into account

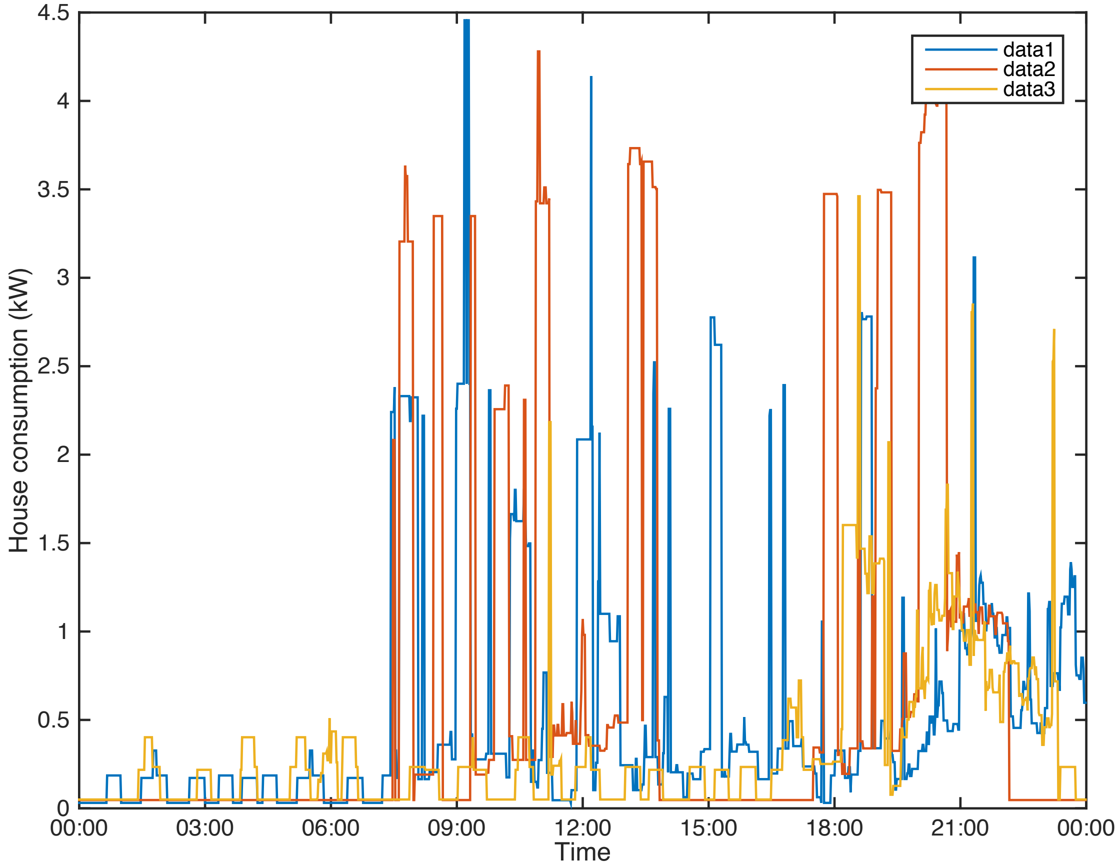
$$\max_{\substack{P^{(i)}_{P,t}, P^{(i)}_{Q,t}, L^{(i)}_{P,t}, L^{(i)}_{Q,t}, S^{(i)}_t, \\ \Theta^{\rightarrow}_t, \Theta^{\leftarrow}_t \\ t \in \{0,\dots,T-1\} \\ i \in \{1,\dots,N\}}} \mathbb{E}\left[\sum_{t=0}^{T-1}\sum_{i=1}^{N} P^{(i)}_{P,t} - \Lambda^{(c)}_{P,t}\right]$$

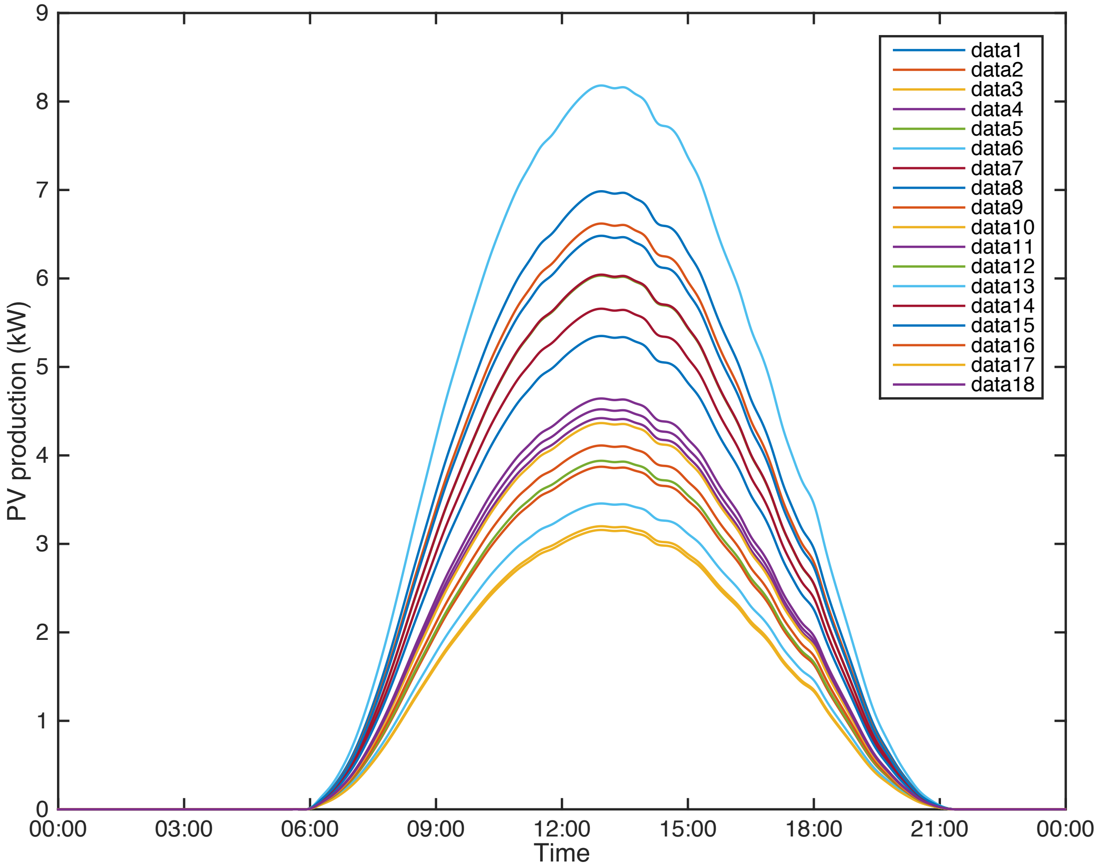
Maximising **revenues-costs**

$$\max_{\substack{P^{(i)}_{P,t}, P^{(i)}_{Q,t}, L^{(i)}_{P,t}, L^{(i)}_{Q,t}, S^{(i)}_t, \Theta^{\rightarrow}_t, \Theta^{\leftarrow}_t \\ t \in \{0,\dots,T-1\} \\ i \in \{1,\dots,N\}}} \mathbb{E}\left[\sum_{t=0}^{T-1}\sum_{i=1}^{N} r^{(i)}_t - c^{(i)}_t\right]$$

Maximising PV production

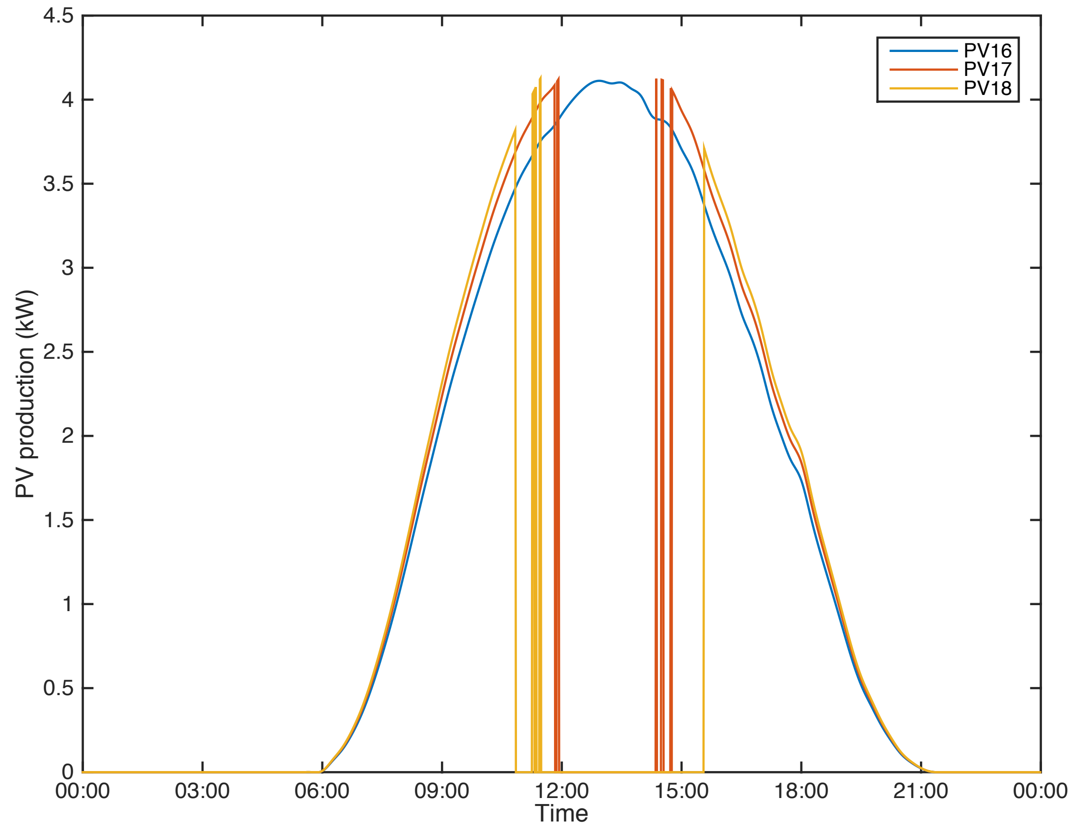
Setting load profiles and PV production patterns

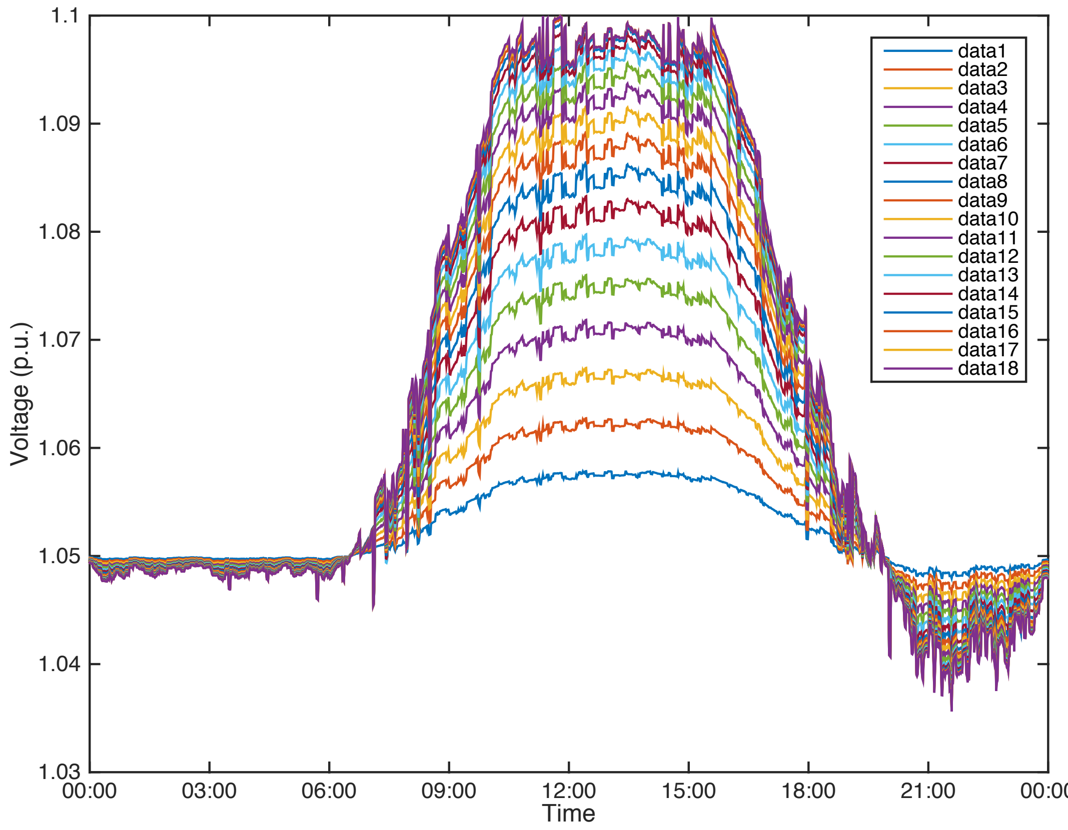




Maximising PV production

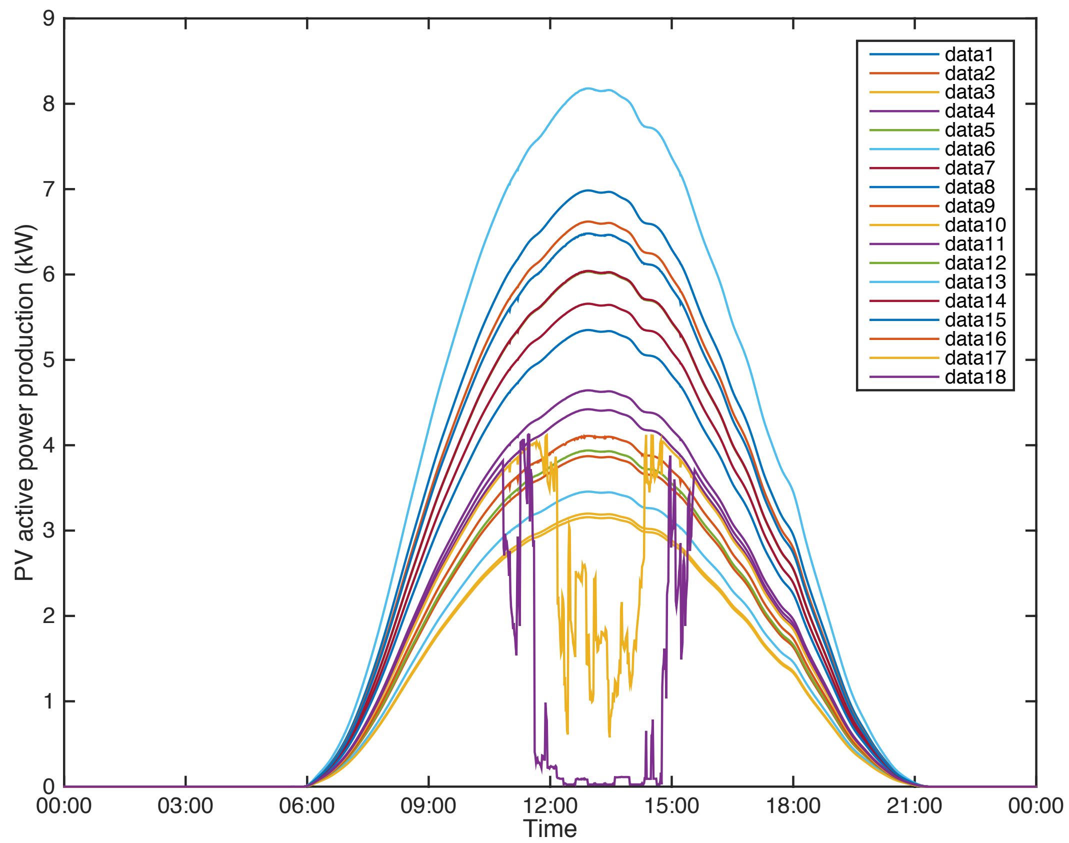
The basic approach: as soon as an over voltage is observed, the PV production is 100% curtailed for a few seconds.

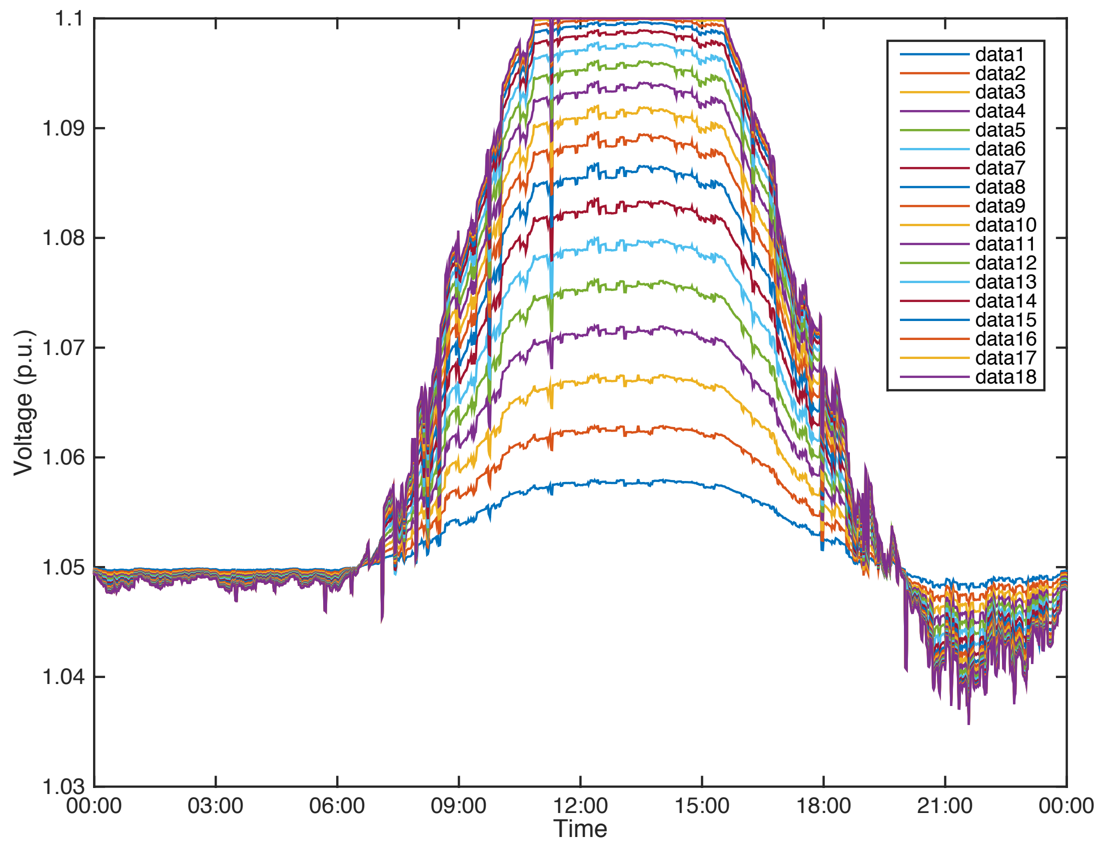




Maximising PV production

The centralised controlled approach: optimise the production over the whole feeder in a centralised way. A home-made OPF solution has been specifically designed for this network.





Basic approach, PV production loss over one day: **31.63 kWh**
Centralised community approach, PV production loss over one day: **21.38 kWh**

Including batteries into the story: from centralised to decentralised solutions

A centralised strategy

> We use the forward backward sweep optimal power flow strategy proposed in [Fortenbacher et al.]

> We obtain both a sizing and centralised planning strategy, for a given load and solar irradiance scenario

Optimal Sizing and Placement of Distributed Storage in Low Voltage Networks. Philipp Fortenbacher Martin Zellner Göran Andersson. IEEE Power Systems Computation Conference (PSCC), 2016.

Including batteries into the story: from centralised to decentralised solutions

Technical challenges for building centralised strategies

- Information gathering
- Need for a centralised controller for processing information
- Concretising computational results into applied actions

Including batteries into the story: from centralised to decentralised solutions

We propose a data-driven, « learning approach »:

1. Built a set of centralised solutions

2. Generate learning (input, output) samples, where the input is made from local indicators, and the output is a decision that should be applied locally

3. Learn a strategy from the samples

    - Imitative learning

Building a set of data

First, generate scenarios: a solar irradiance scenarios, a set of load scenarios (for each prosumer).

Then, solve the pairs {solar irradiance, load profiles} (using, for instance, a forward backward sweep power flow approach)

$$\left[\Xi_0^*, \ldots, \Xi_{T-1}^*\right]$$

From this time series of data, on can extract a series of local data, i.e. relative to one single prosumer (i) :

$$\left[\Xi_0^{(i),*}, \ldots, \Xi_{T-1}^{(i),*}\right] \qquad \Xi_t^{(i),*} = \begin{pmatrix} P_{P,t}^{(i),*} & P_{Q,t}^{(i),*} \\ P_{P,t}^{(i),\max} & P_{Q,t}^{(i),\max} \\ S_t^{(i),*} & \lambda_t^{(i),*} \\ L_{P,t}^{(i)} & L_{Q,t}^{(i)} \\ D_{P,t}^{(i),*} & D_{Q,t}^{(i),*} \\ \left|V_t^{(i)}\right| & arg\left(V_t^{(i)}\right) \end{pmatrix}$$

Learning from data - Imitative learning

We propose to use a machine learning approach

Machine learning is about extracting pattern from data

From the sample of data $L = (s^{(i)}, a^{(i)})_{i=1}^{N}$
we learning a mapping state -> action

Here, we adopt a slightly indirect approach by learning 4 different regressors:

Active power

Reactive power

Charging battery

Discharging the battery

Building 4 regressors from data (Active & reactive power, charge & discharge)

Data set:

$$\mathcal{L}^P = \left\{ \left(in_P^{i,t}, out_P^{i,t} \right) \right\}_{i=1,t=0}^{i=N,t=T-1}$$

$$\mathcal{L}^Q = \left\{ \left(in_Q^{i,t}, out_Q^{i,t} \right) \right\}_{i=1,t=0}^{i=N,t=T-1}$$

$$\mathcal{L}^C = \left\{ \left(in_C^{i,t}, out_C^{i,t} \right) \right\}_{i=1,t=0}^{i=N,t=T-1}$$

$$\mathcal{L}^D = \left\{ \left(in_D^{i,t}, out_D^{i,t} \right) \right\}_{i=1,t=0}^{i=N,t=T-1}$$

- i : id number of the bus
- $|\overline{\mathbf{v}}_t^{(i)}|$: magnitude of the voltage at bus i at time step t
- $arg(\overline{\mathbf{v}}_t^{(i)})$: phase of the voltage at bus i at time step t
- ϕ_t : electricity price at time step t, considered as being unique in the whole feeder
- $\lambda_t^{(i)}$: level of charge of the storage of bus i at time step t
- $L_{P,t}^{(i)}$: load consumption at bus i at time step t
- $P_{P,t}^{(i),max}$: maximal production potential at bus i at time step t

$$in_P^{i,t} = in_Q^{i,t} = in_C^{i,t} = in_D^{i,t} = \left(i,\ |\overline{\mathbf{v}}_t^{(i)}|,\ arg(\overline{\mathbf{v}}_t^{(i),*}),\ \phi_t,\ \lambda_t^{(i),*},\ L_{P,t}^{(i)},\ P_{P,t}^{(i),max} \right)$$

$$out_P^{i,t} = P_{P,t}^{(i),*} \qquad out_C^{i,t} = \max\left(S_t^{(i),*}, 0 \right)$$

$$out_Q^{i,t} = P_{Q,t}^{(i),*} \qquad out_D^{i,t} = \max\left(-S_t^{(i),*}, 0 \right)$$

Post processing solutions & and testing solutions

Post-processing solutions

-> Ensure physical constraints are satisfied

For the active and reactive power production levels, ensure that the production levels are compatible with production bounds, for each prosumer i

For the power injected into / drawn from the battery, ensure that both maximal charging/discharging powers and of the level of charge evolution are feasible

Generating other scenarios to try the learned strategy

-> Evaluate the performance of learned policies in other environments

Test case

The number of buses is 15

The number of prosumers is 14

The number of branches is 14

Δt is 1h

The time horizon T is 8760

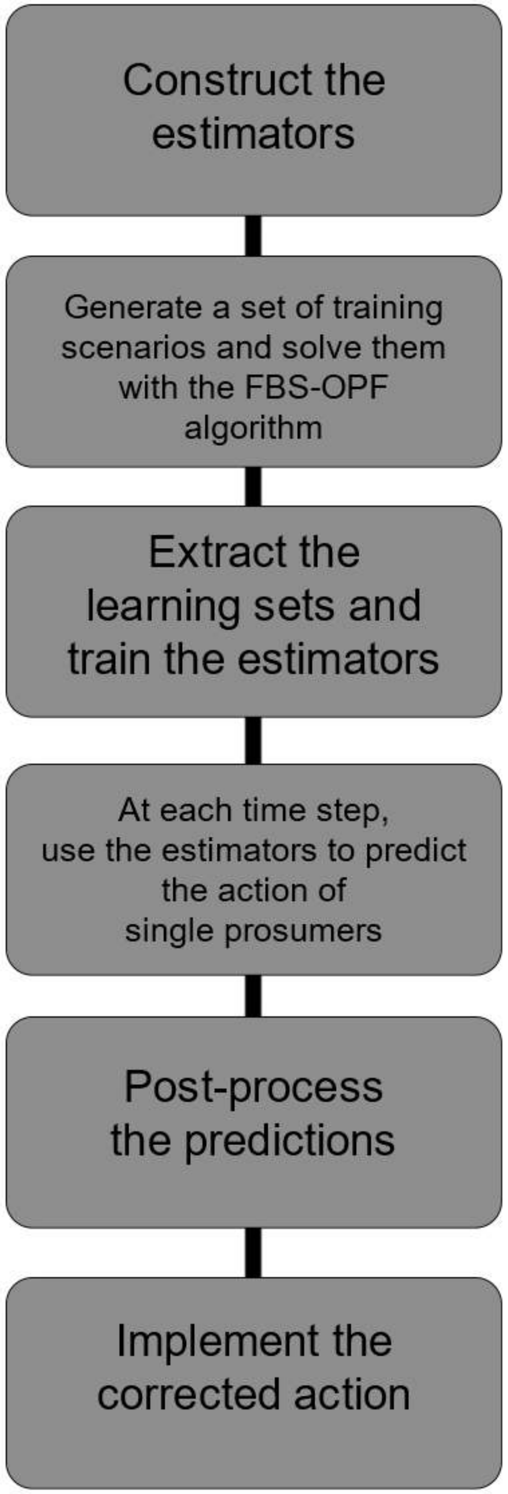
The line resistance $R_{d1} = R_{d2} = \ldots = R_{dL}$ is 0.025 Ω

The line reactance $X_{d1} = X_{d2} = \ldots = X_{dL}$ is 0.005 Ω

The nominal voltage of the network is 400 V

The maximum admissible voltage v^{max} is 1.10 *pu*

The minimum admissible voltage v^{min} is 0.90 *pu*



Test case: prosumers characteristics

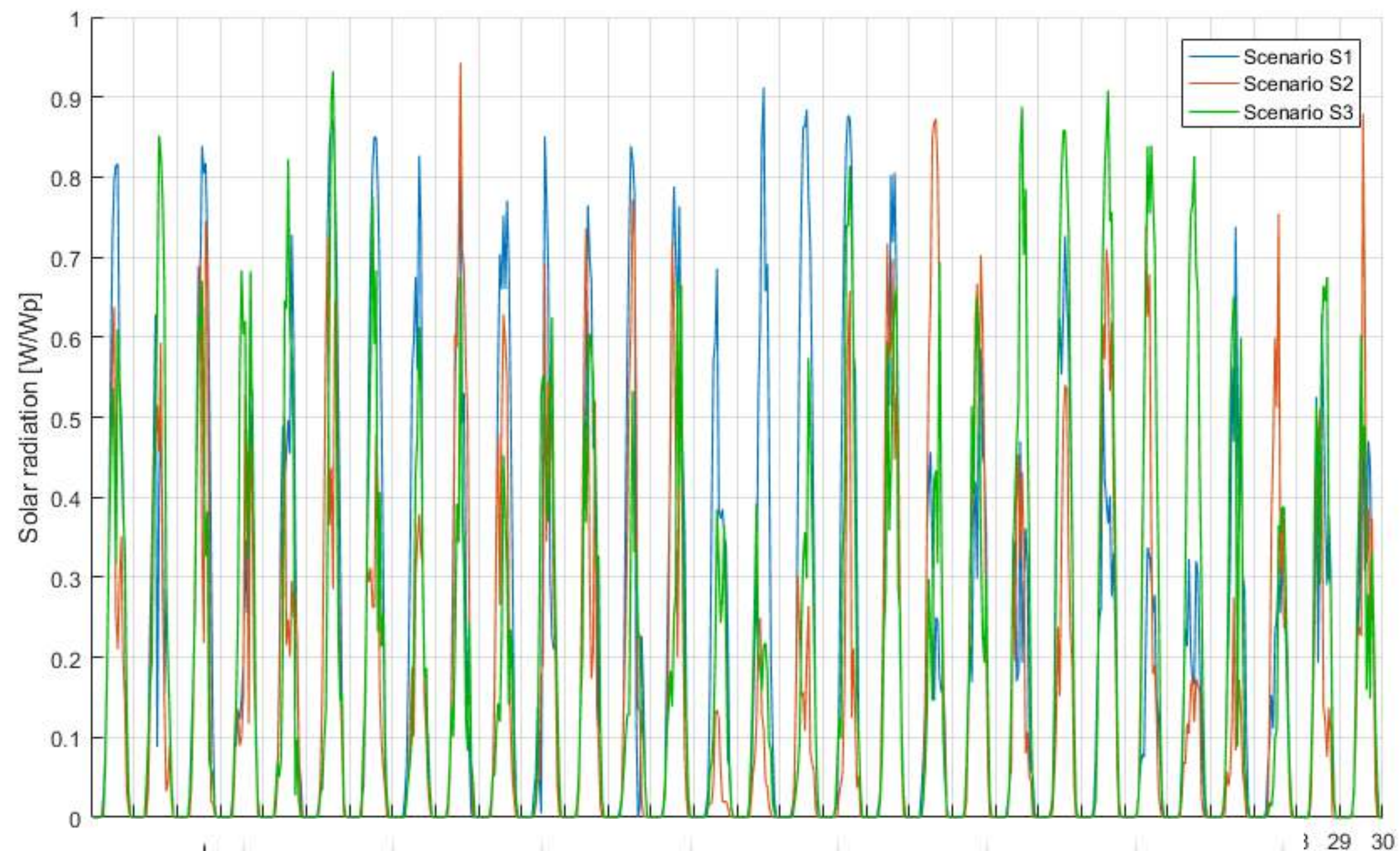
Id	Number of occupants	PV installed capacity kW_p	Storage installed capacity kWh
1	1	2	2
2	1	2	2
3	2	3	2
4	2	3	2
5	2	3	2
6	3	3.5	5
7	3	3.5	5
8	3	3.5	5
9	4	5	6
10	4	5	6
11	4	5	6
12	4	5	6
13	5	7	8
14	5	7	8

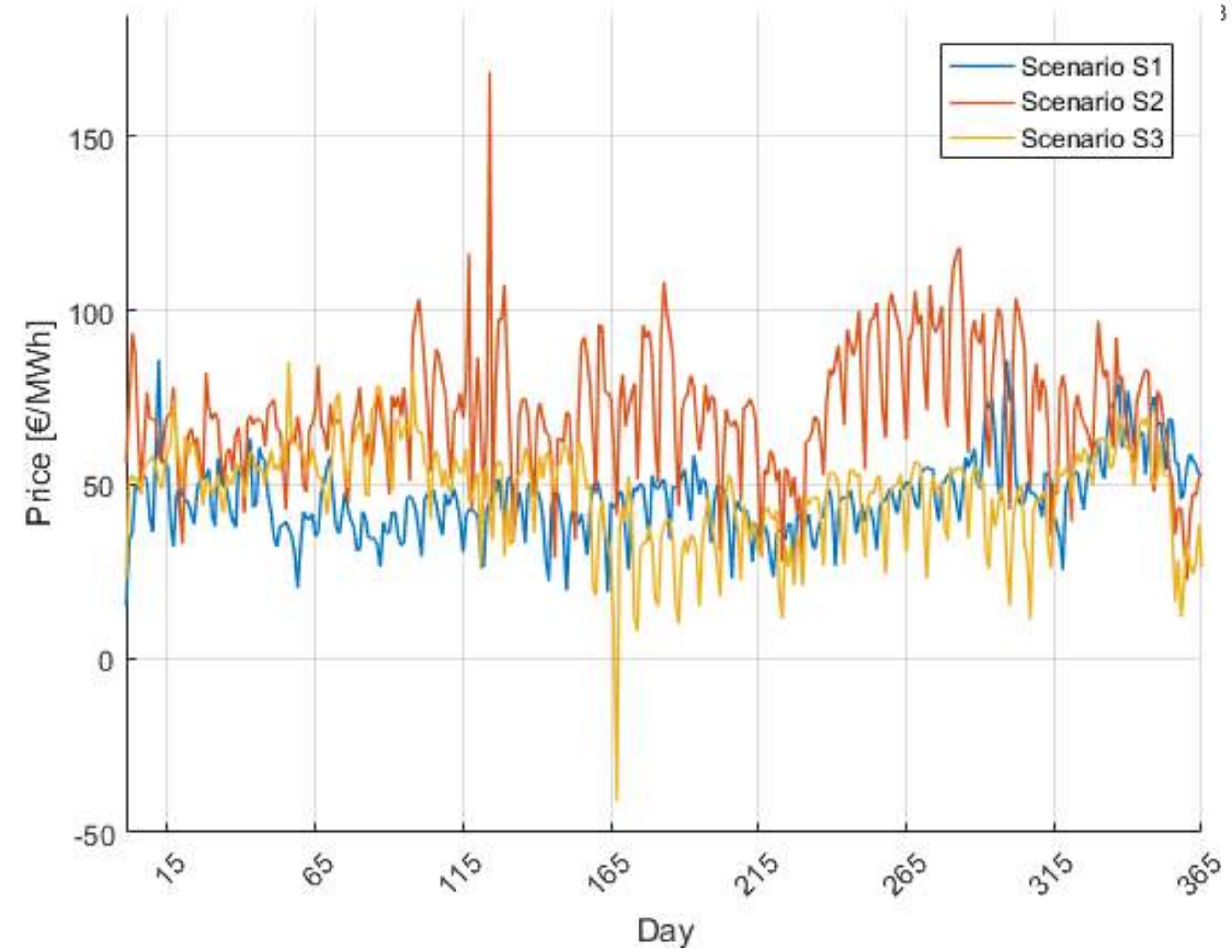
Test scenarios

Load profiles are generated using the model provided in:

Richardson, I., Thomson, M., Infield, D., & Clifford, C. (2010). Domestic electricity use: A high-resolution energy demand model. *Energy and buildings*, *42*(10), 1878-1887.

3 scenarios solar production + electricity prices



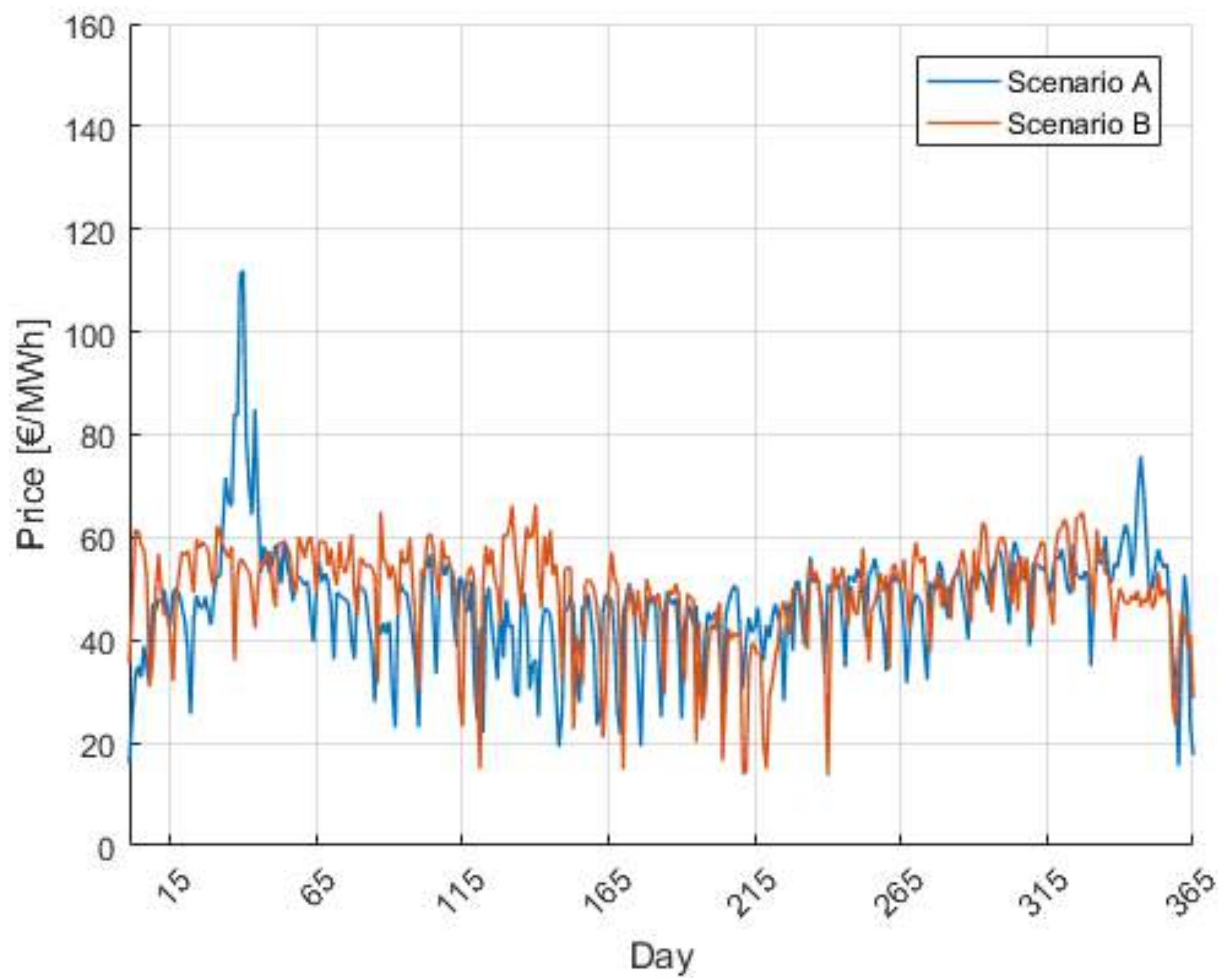


Learning scenarios

We generate two additional price scenarios, S4 and S5.

The FBS-OPF algorithm is run on these two scenarios.

The resulting outputs of the FBS-OPF are used to generate learning sets for the regressors.



Results

Overall costs (objective function)

Overall costs			
Scenario	S1	S2	S3
FBS-OPF algorithm	1105.54 €	2121.16 €	1837.80 €
SL algorithm	2711.44 €	7832.43 €	5123.09 €
RT algorithm	5143.32 €	6501.94 €	5807.77 €

Energy outlook:

Curtailments over the year			
Scenario	S1	S2	S3
FBS-OPF algorithm	7.01%	11.20%	9.69%
SL algorithm	11.13%	32.78%	14.80%
RT algorithm	11.91%	13.46%	15.12%

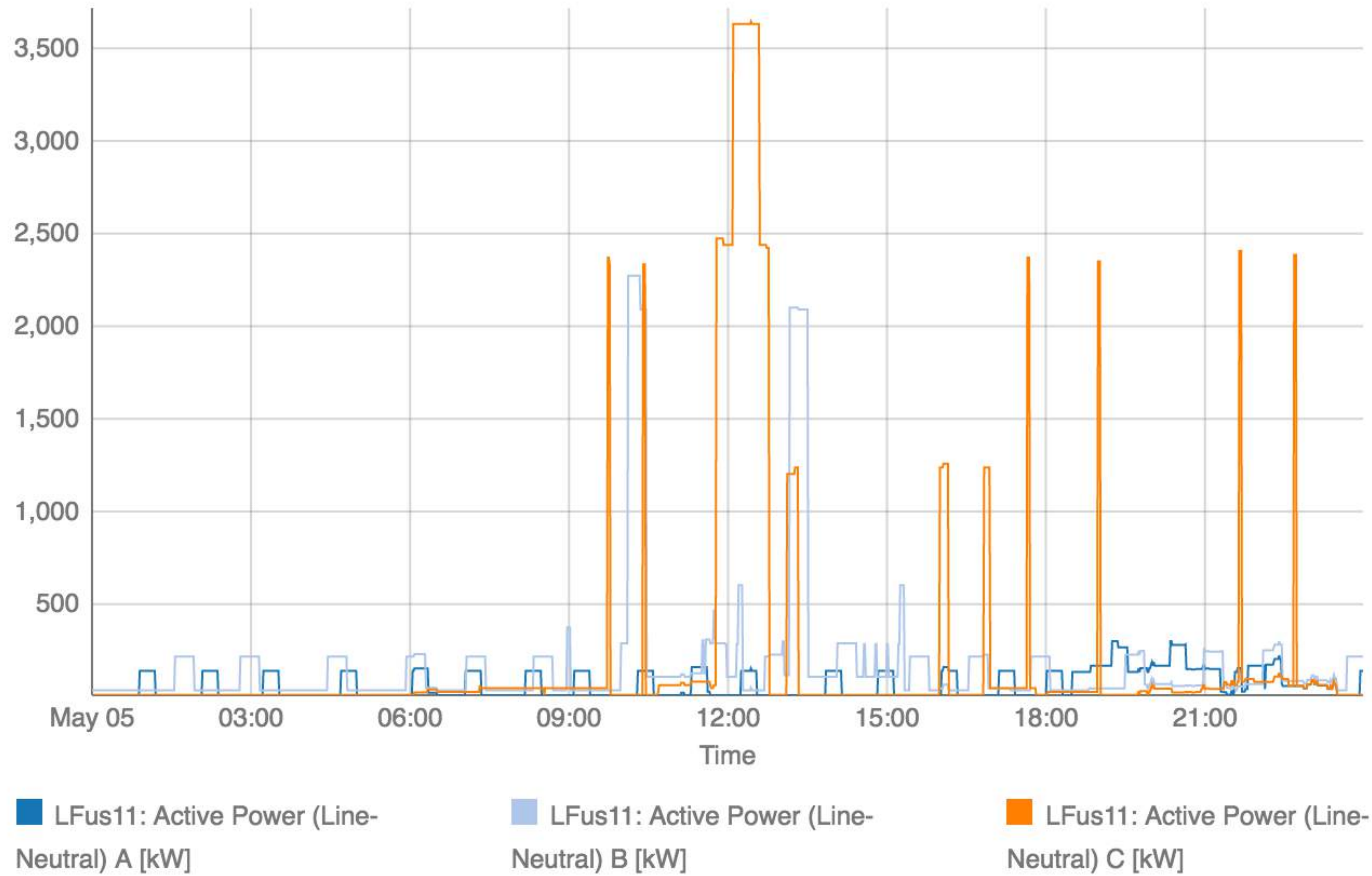
Simulating a 3-phase unbalanced network

Generate a set of SLPs

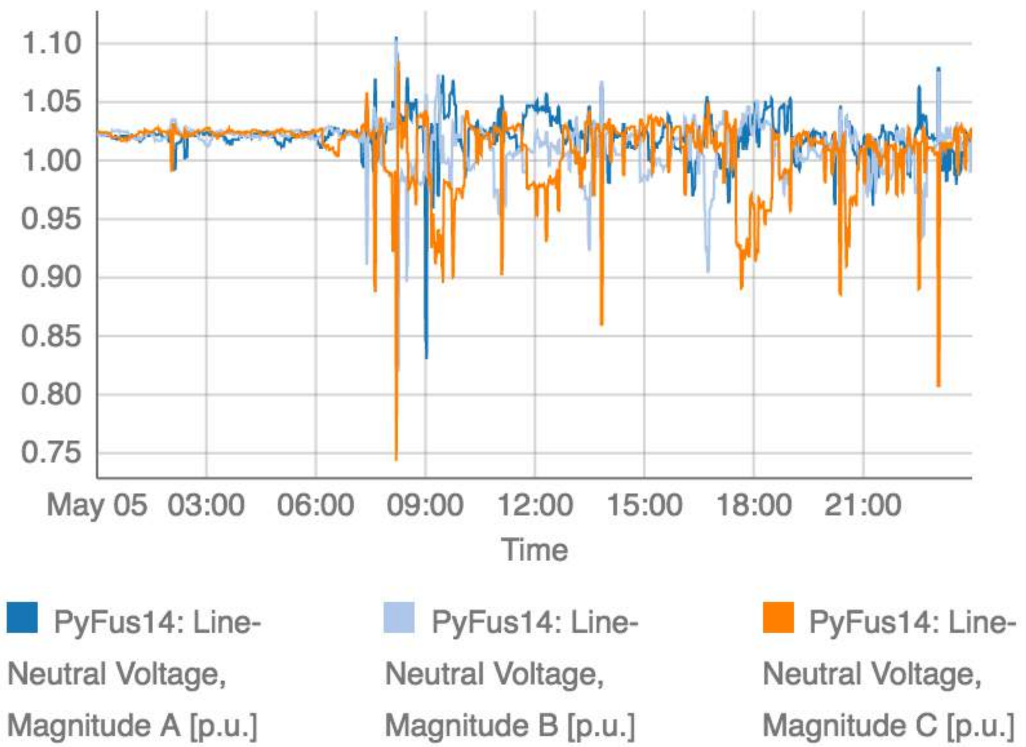
Dispatch SLPs over the 3 phases by « approximating the job of an electrician »

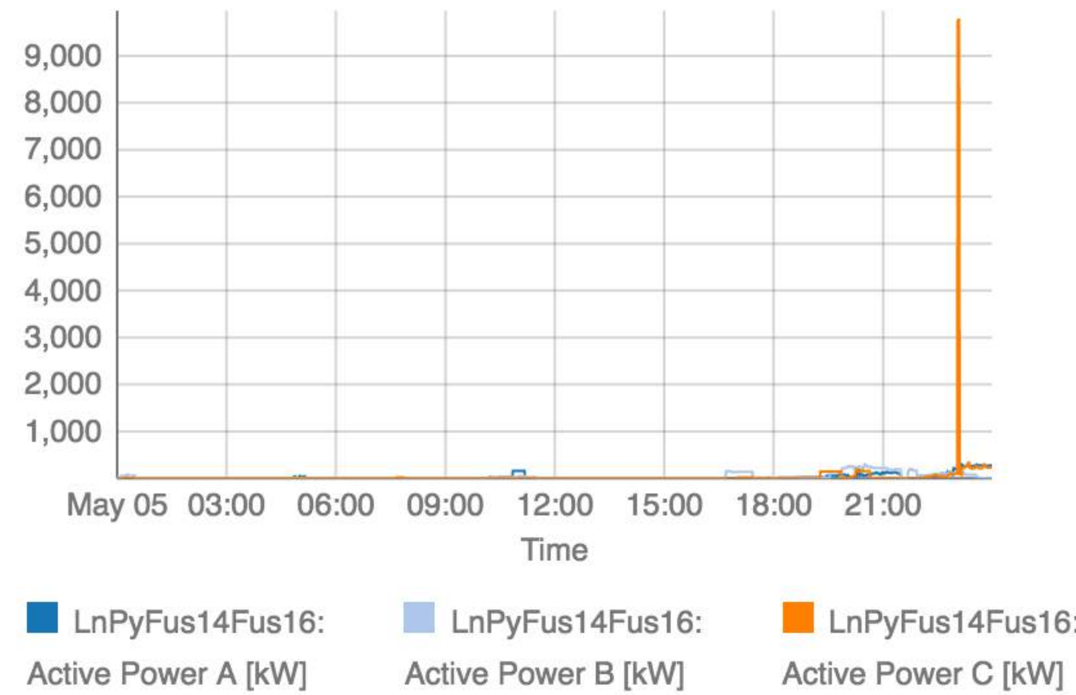
Propose scenarii (PV, EVs).

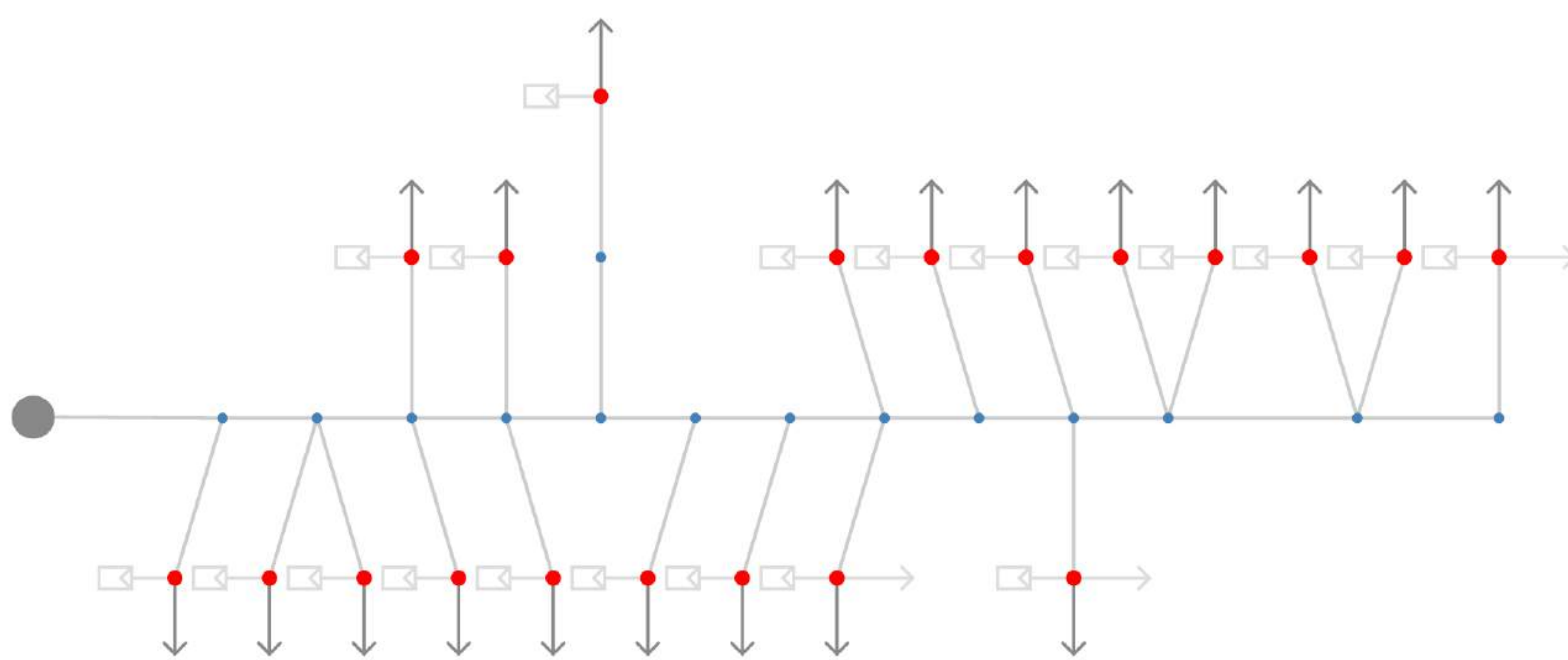
Simulating a 3-phase unbalanced network (load sample)



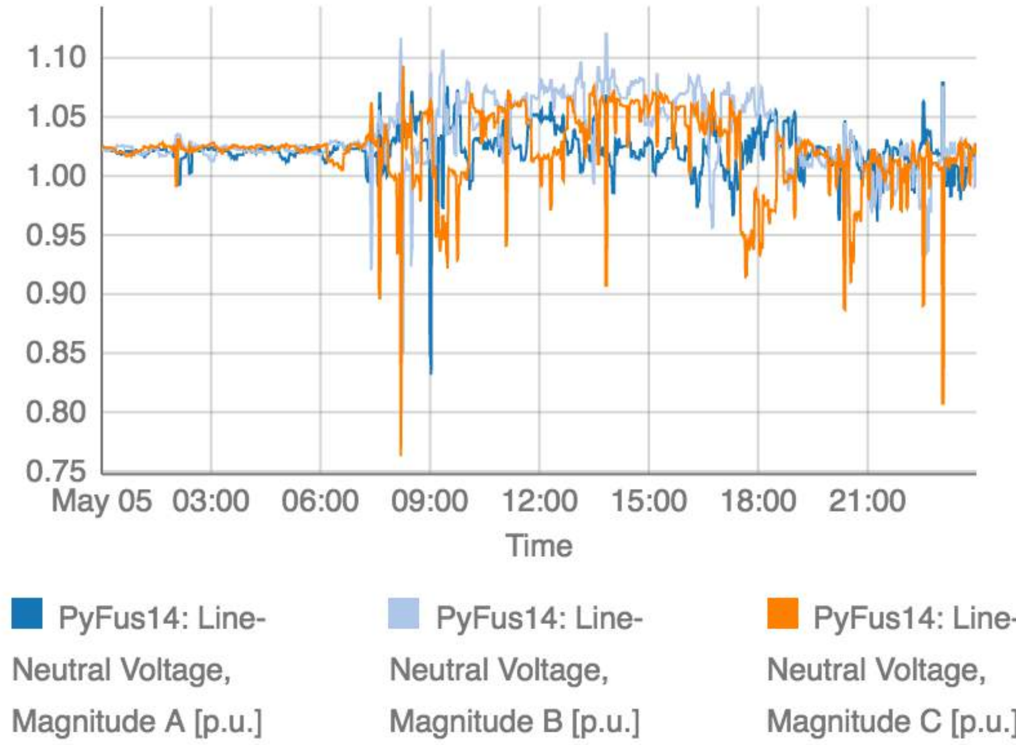
Simulating a 3-phase unbalanced network (load only)

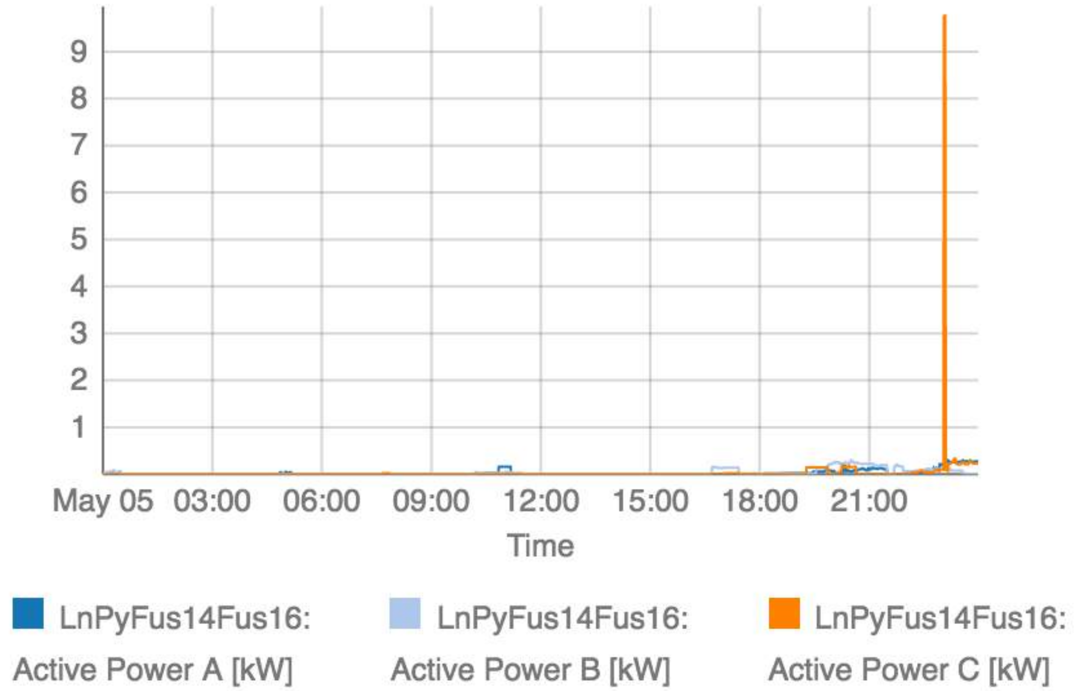


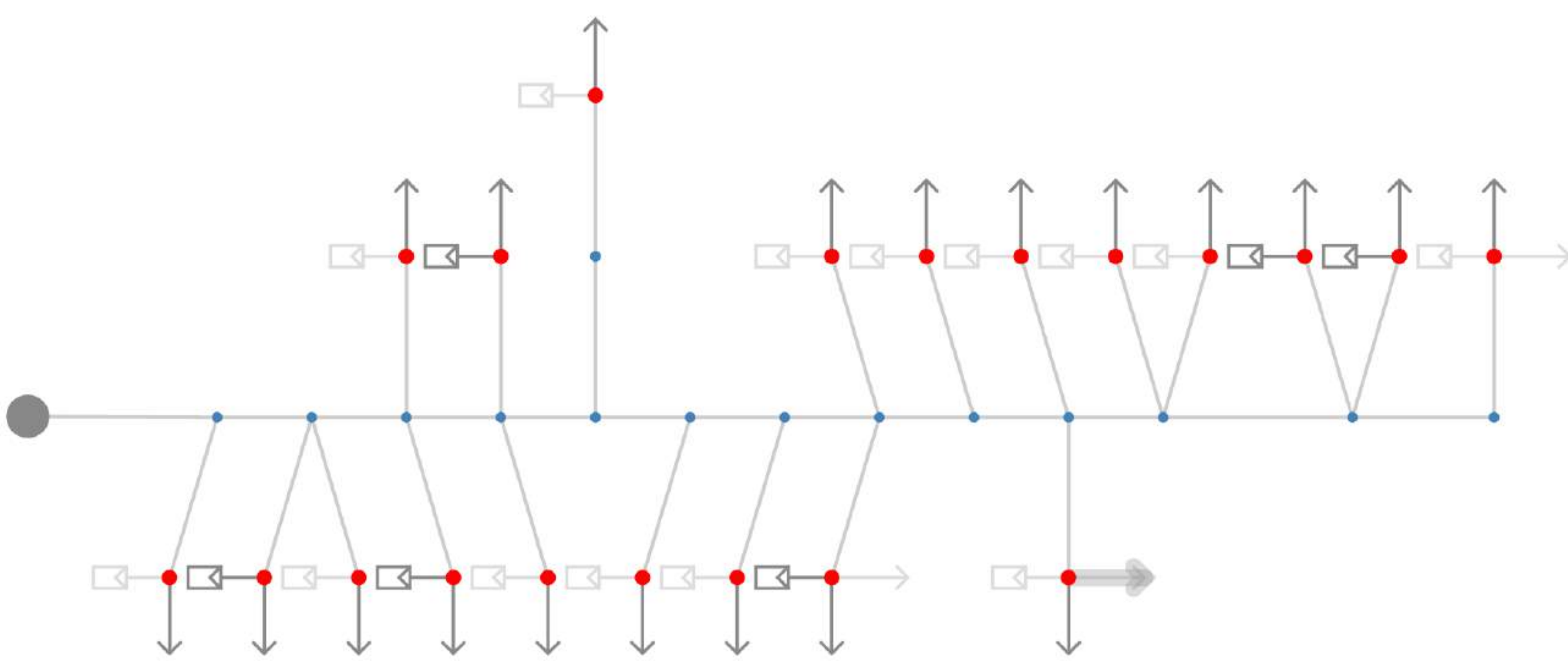




Simulating a 3-phase unbalanced network (a few PVs)

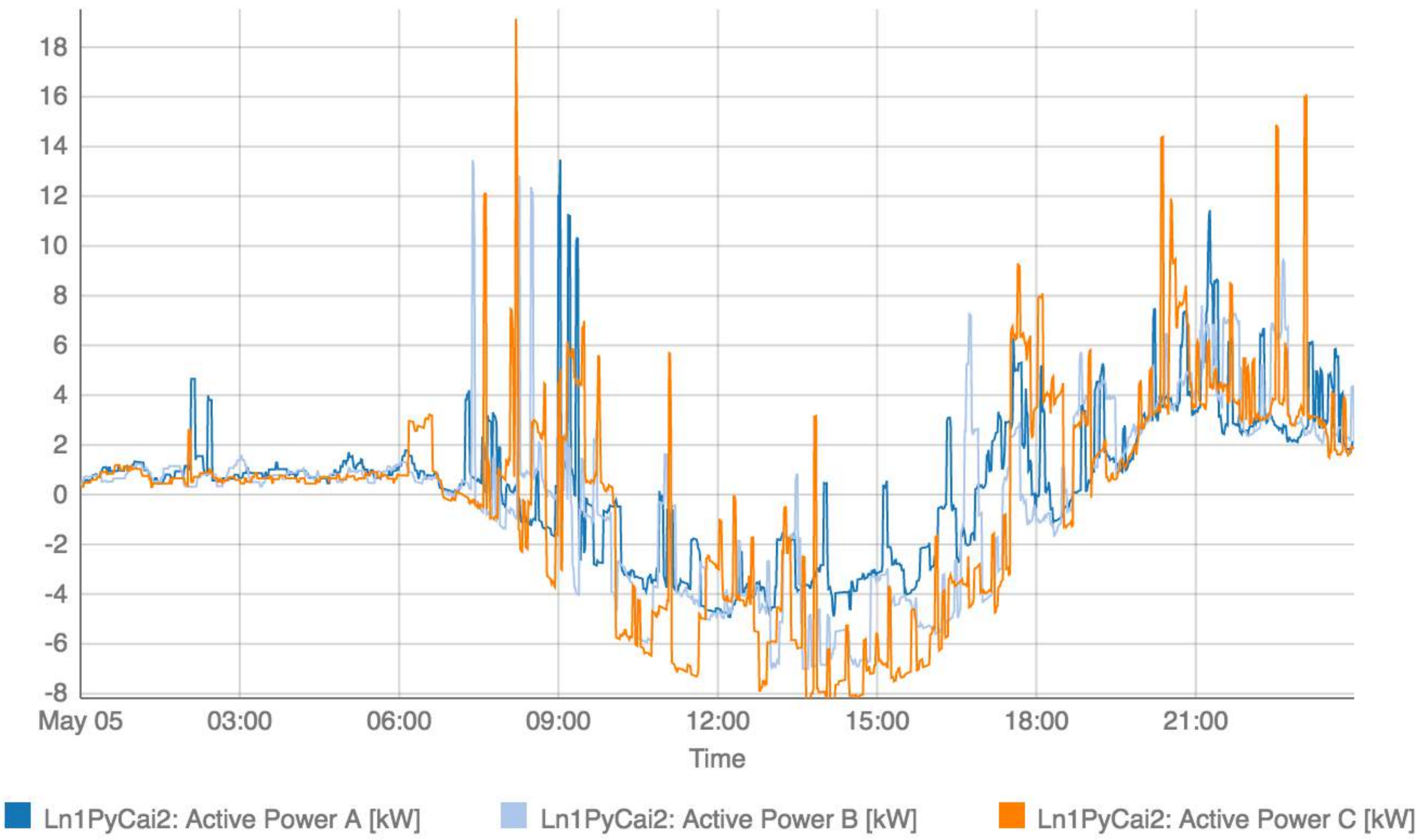




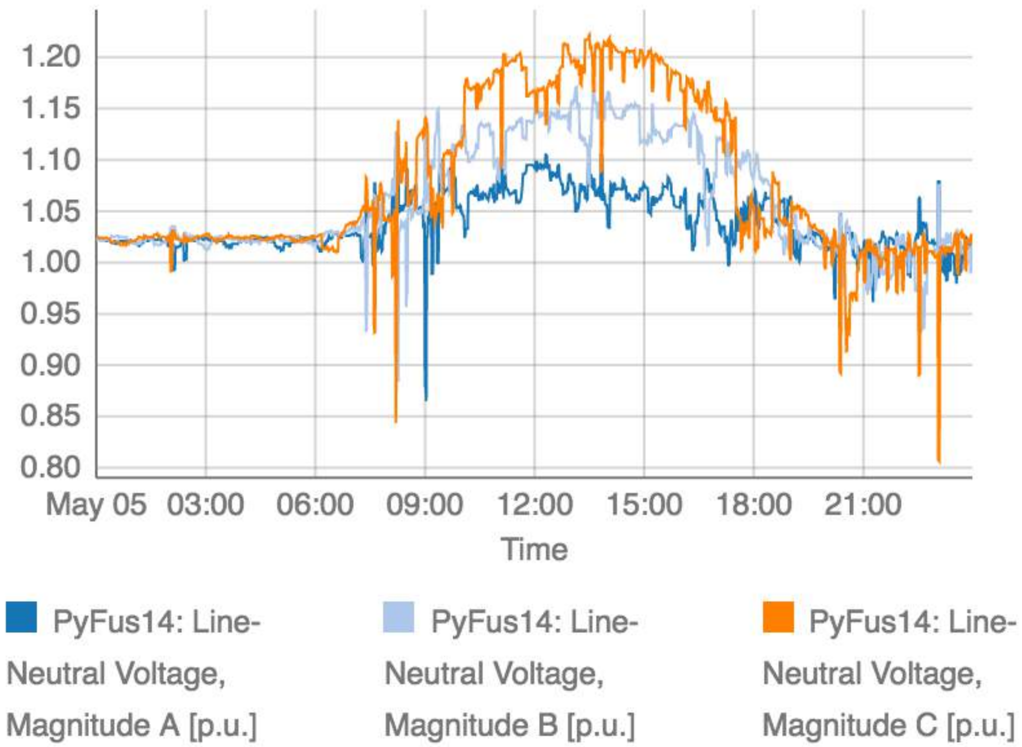


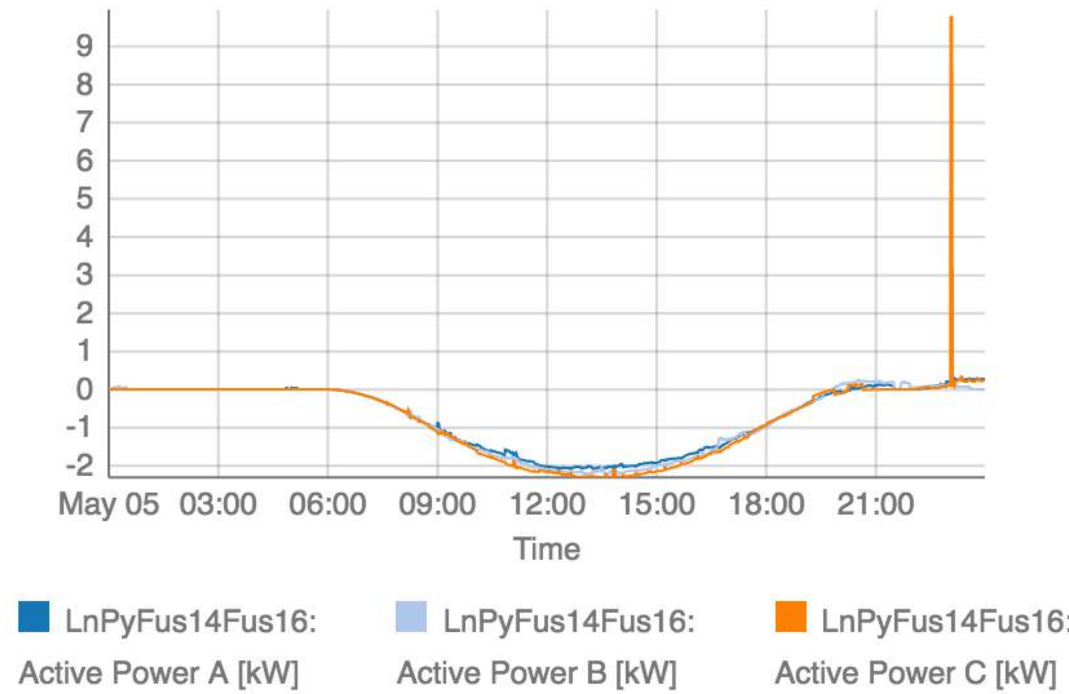
Simulating a 3-phase unbalanced network (a few PVs)

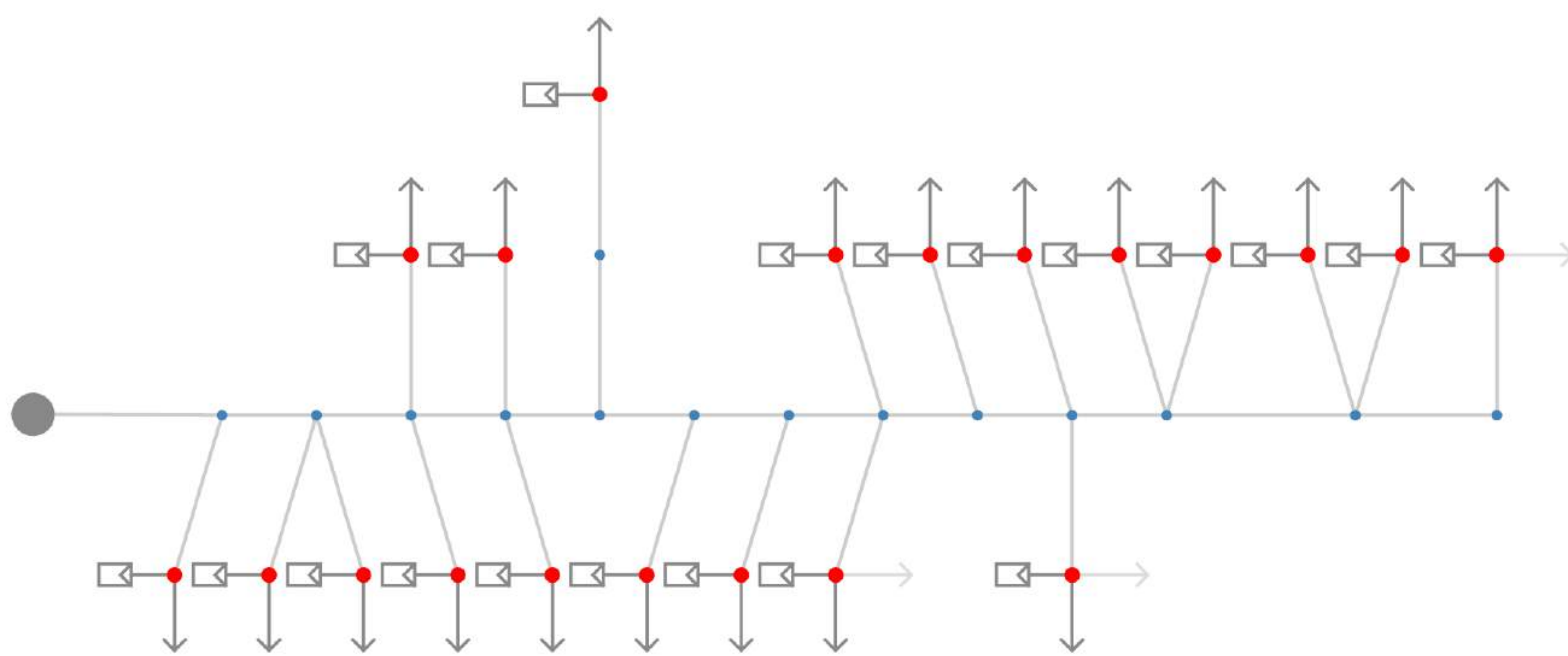
Power flow at the transformer



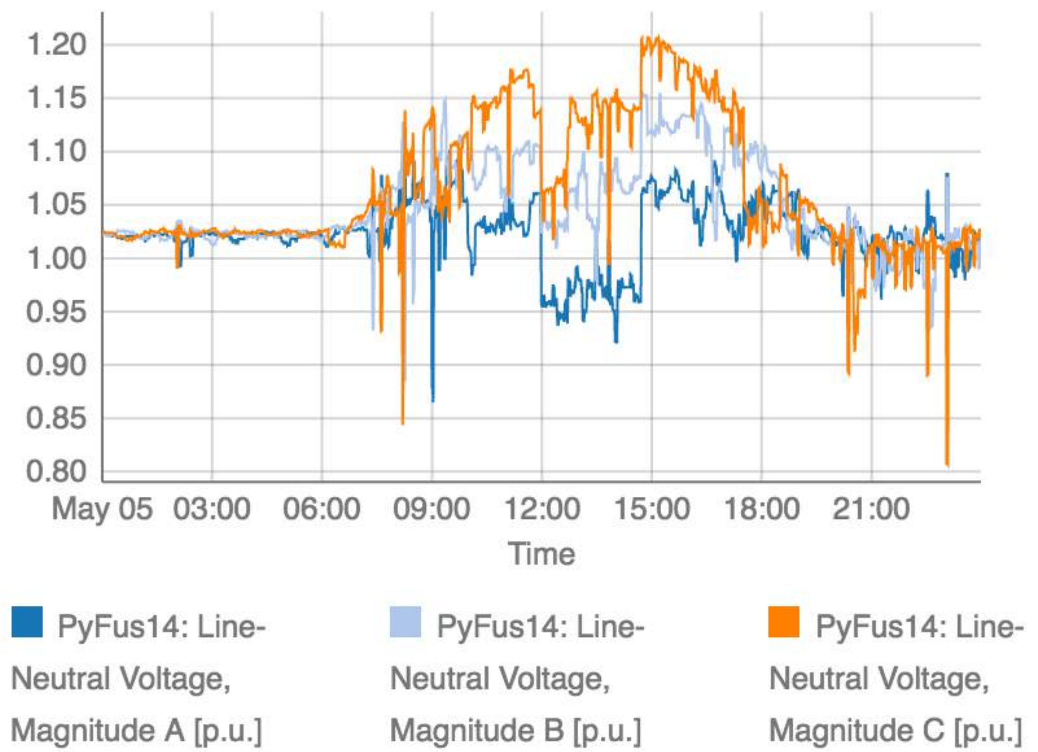
Simulating a 3-phase unbalanced network (PVs everywhere)

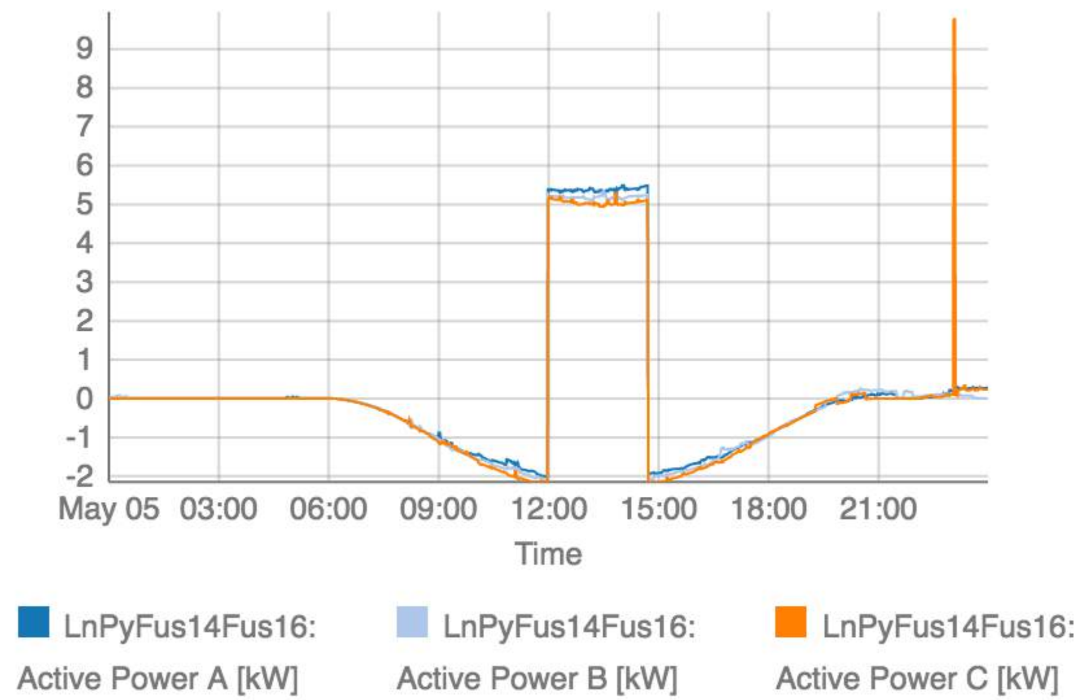


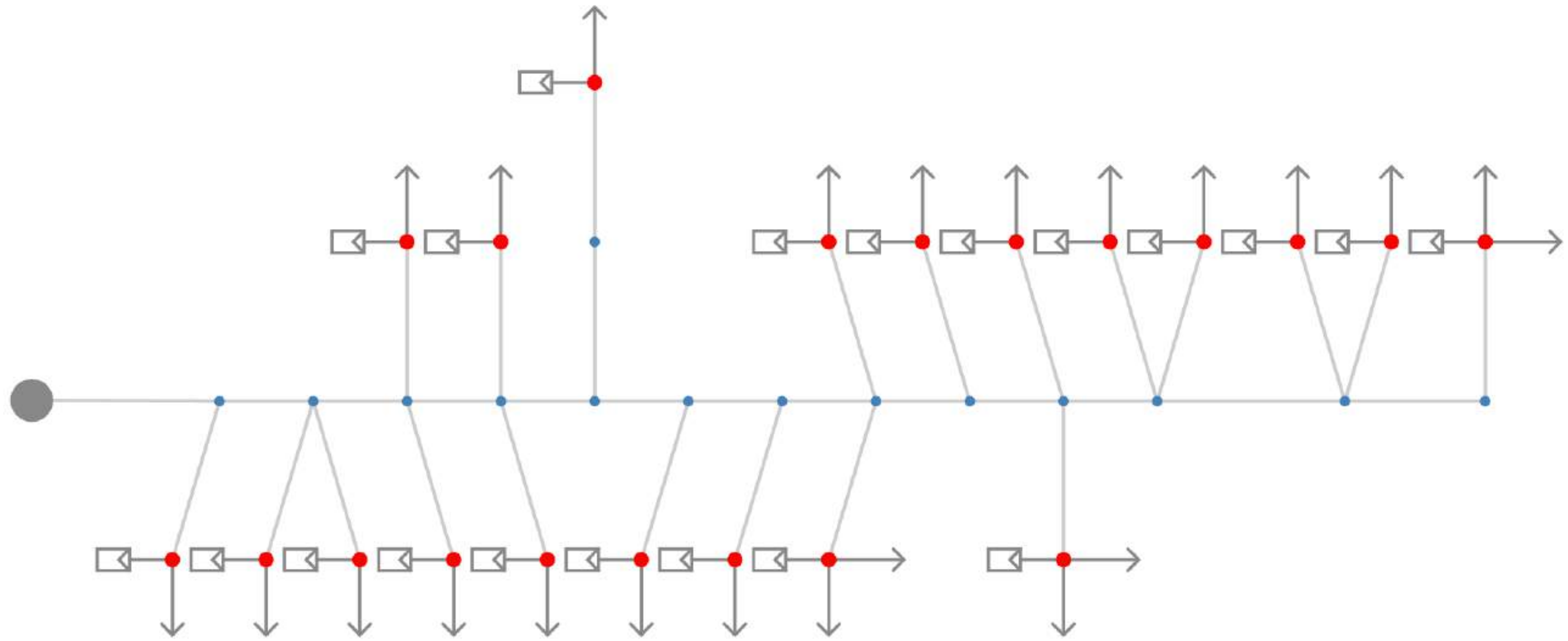




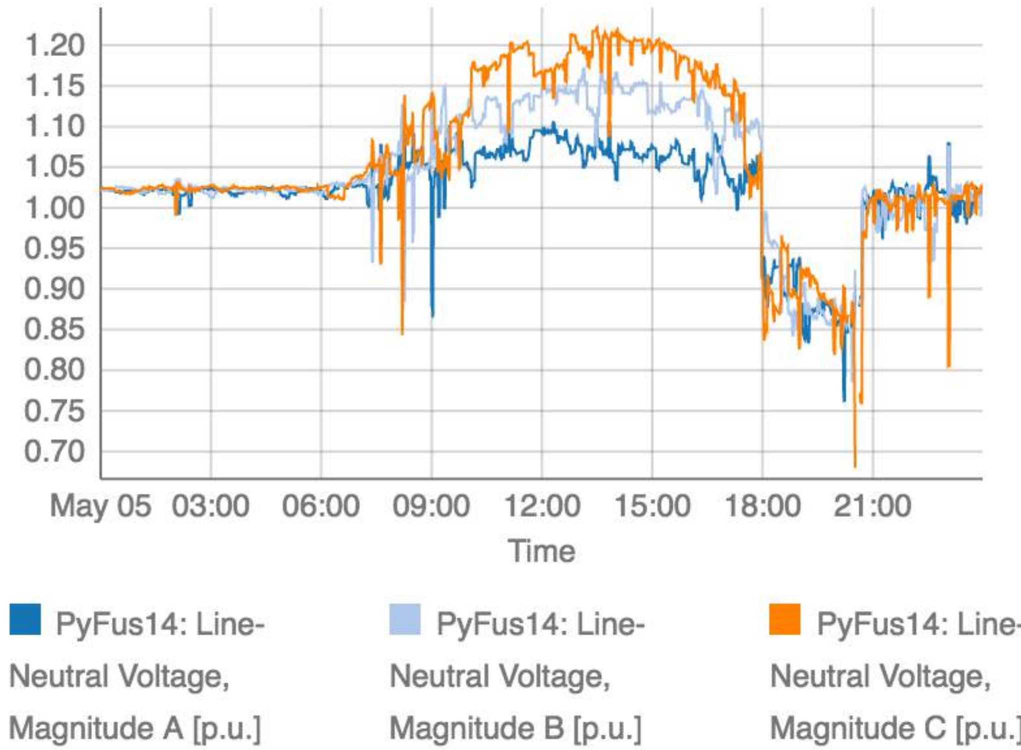
Simulating a 3-phase unbalanced network (EVs 10h-12h)

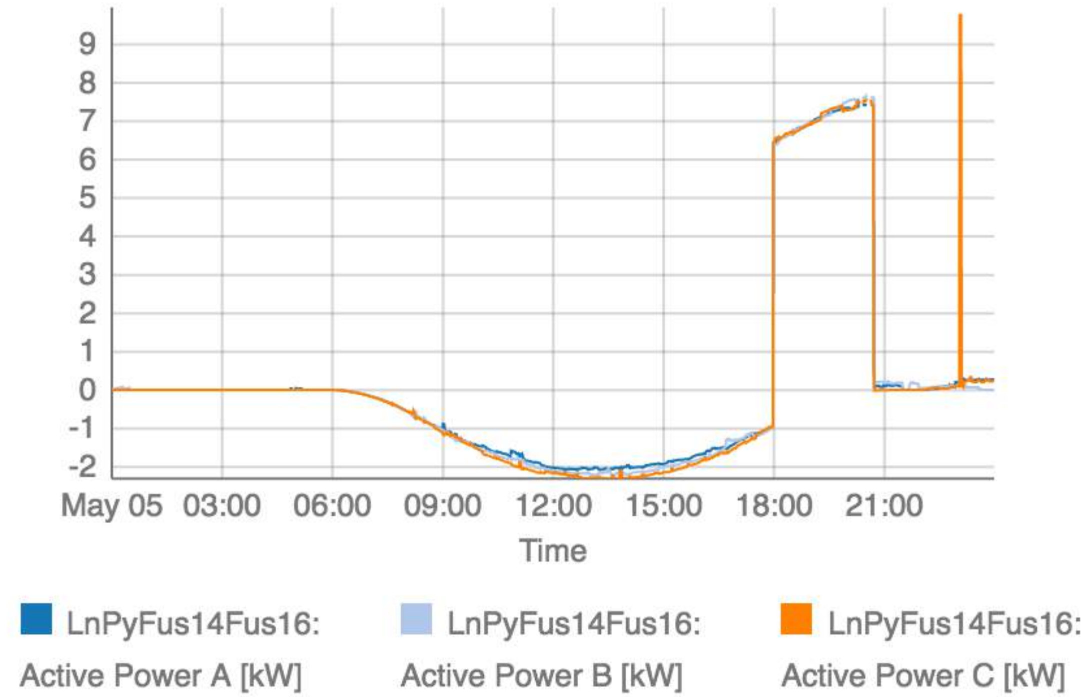


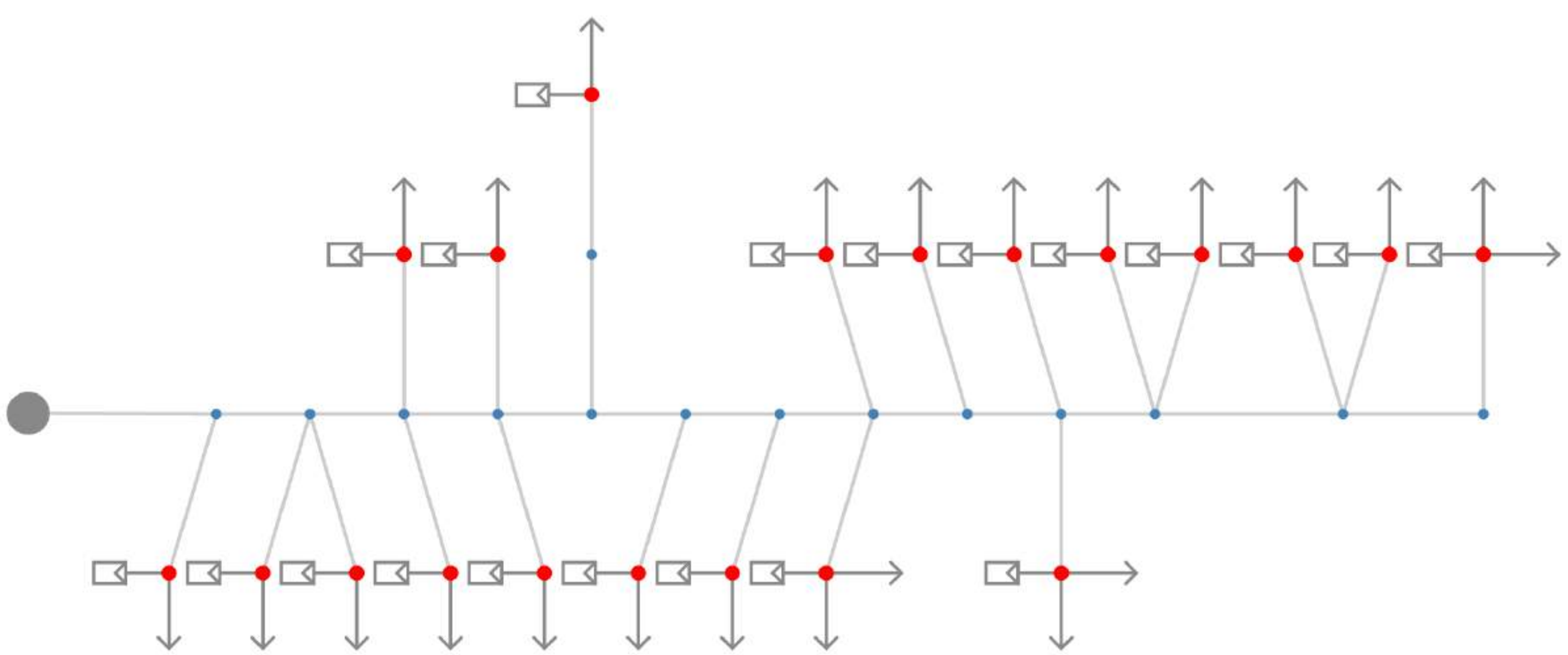




Simulating a 3-phase unbalanced network (EVs 18h)







II.
The mobile community

The mobile community

We assume that the community is made of:

A set of electricity consumers using EVs

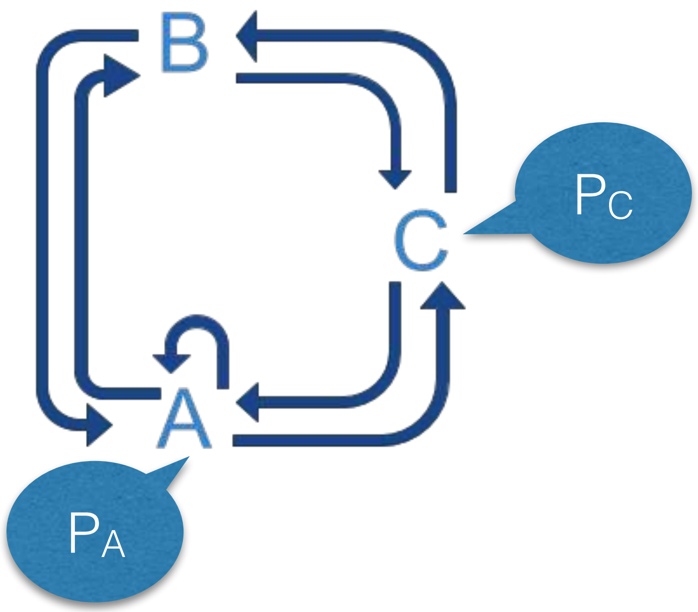
A set of location pairs (starting point, destination) corresponding to EVs travels

A set of electricity producers using renewable energy production capacities

The goal is to:

Maximise the consumption of local electricity, while avoiding electricity shortages of EVs

The atomic case



An EV starts from A and wants to join B
(A: home, B: office)

You can charge your EV at home in A at a price P_A

There exists a source of electricity at C at a price P_C

P_C may be lower than P_A, but it has a cost to be reached (detour)

The question is: how to compute decision making strategies to minimise the electricity budget, given the knowledge of:

- Prices, distances, time horizon
- Battery level

The atomic case

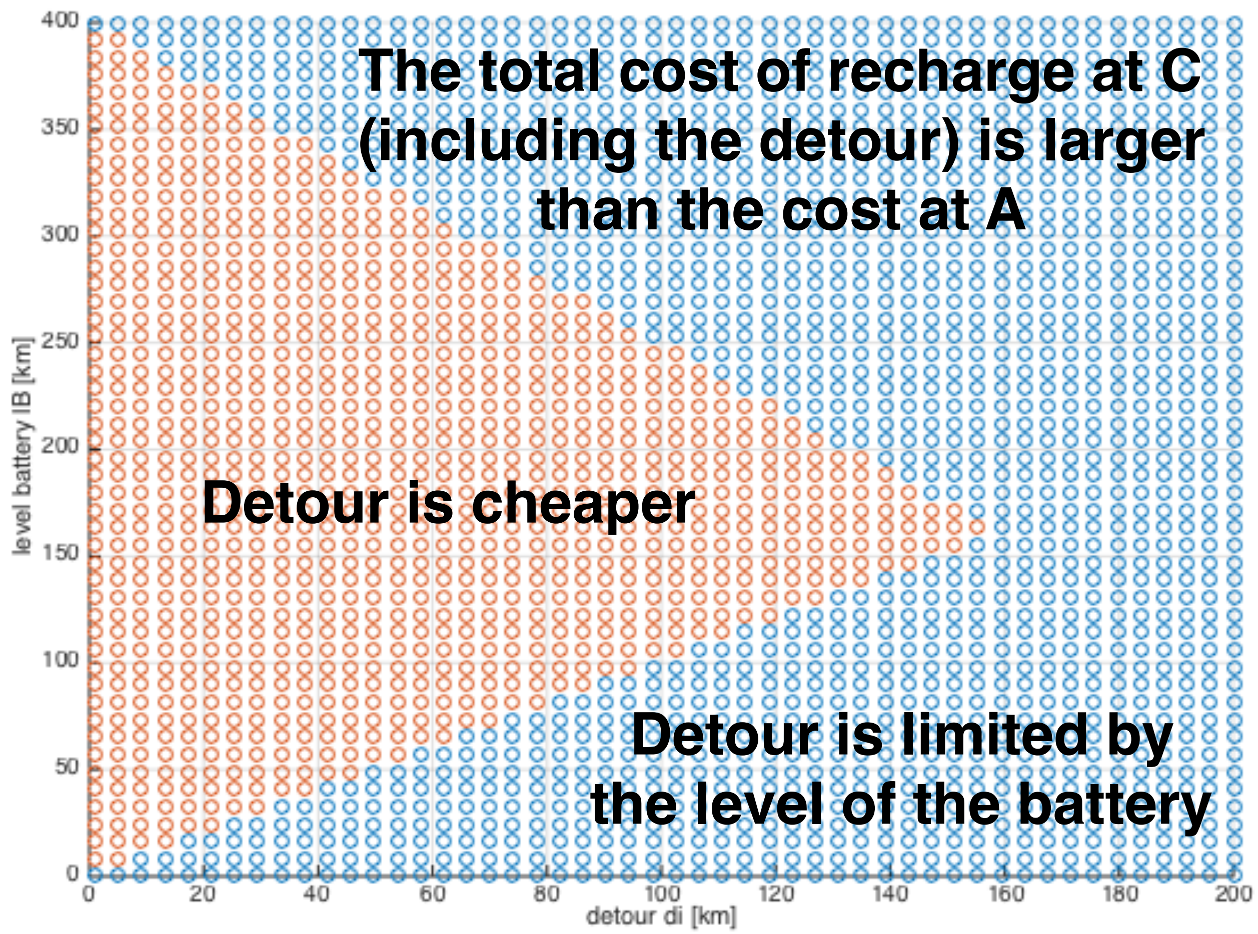
Start in A with a certain battery charge level

Consider different values of detour to reach C

Prices are constant:

A (at the network price) : 0.25€/kWh

C (from a PV installation) : 0.15€/kWh



Beyond the atomic case

We have identified three different configurations:

1. **Charge all-day long (eventually on a low power charging station)**

   Residential PVs

   Small wind turbines

2. **Charge during lunch time with a fast-charger (with a parameter fixing the maximal distance that may be travelled)**

   Fast chargers

   Wind turbines

3. **Make a detour**

   Fast chargers

Beyond the atomic case

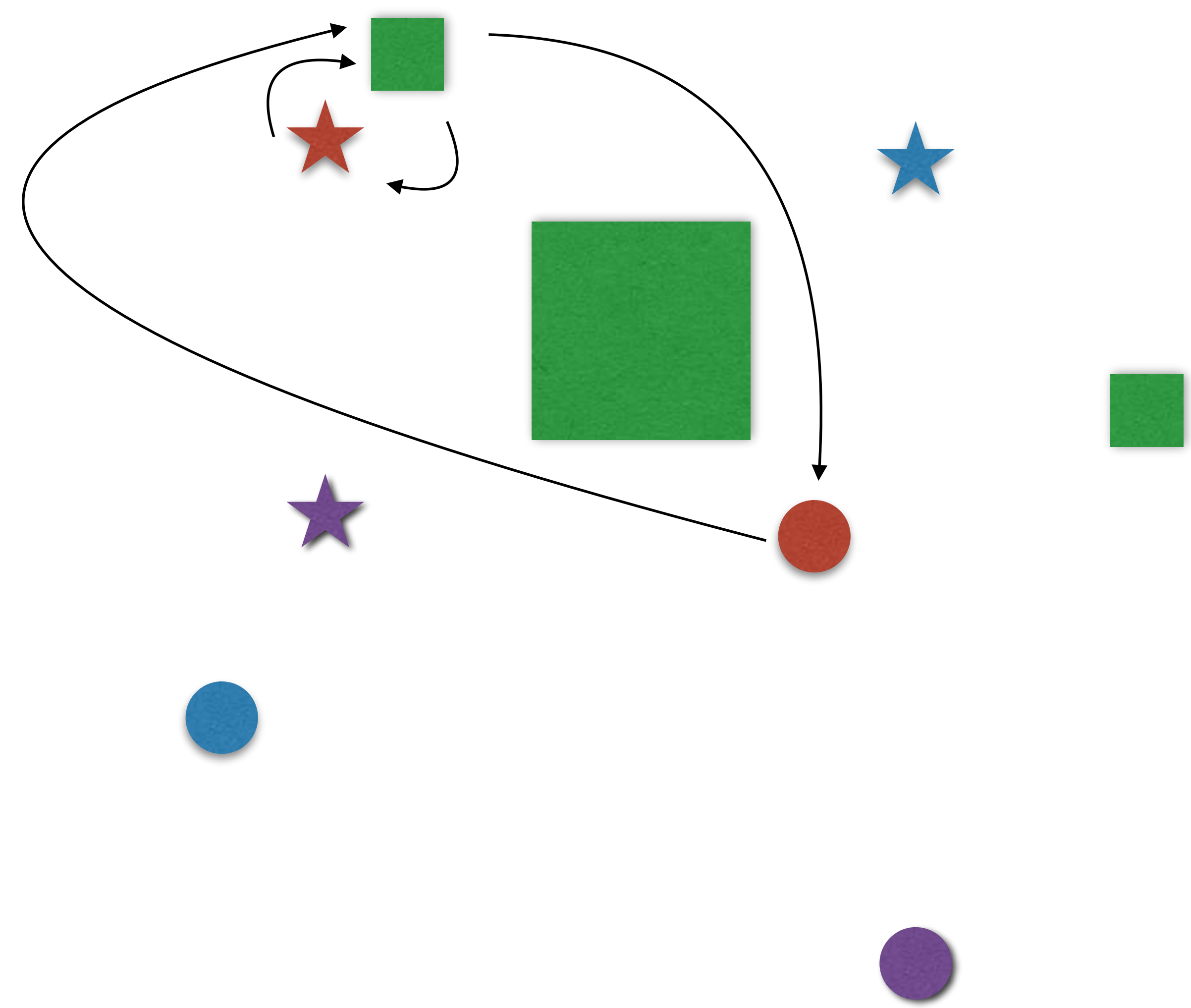
1st case

'Fast' charger

'Slow' charger

Starting point

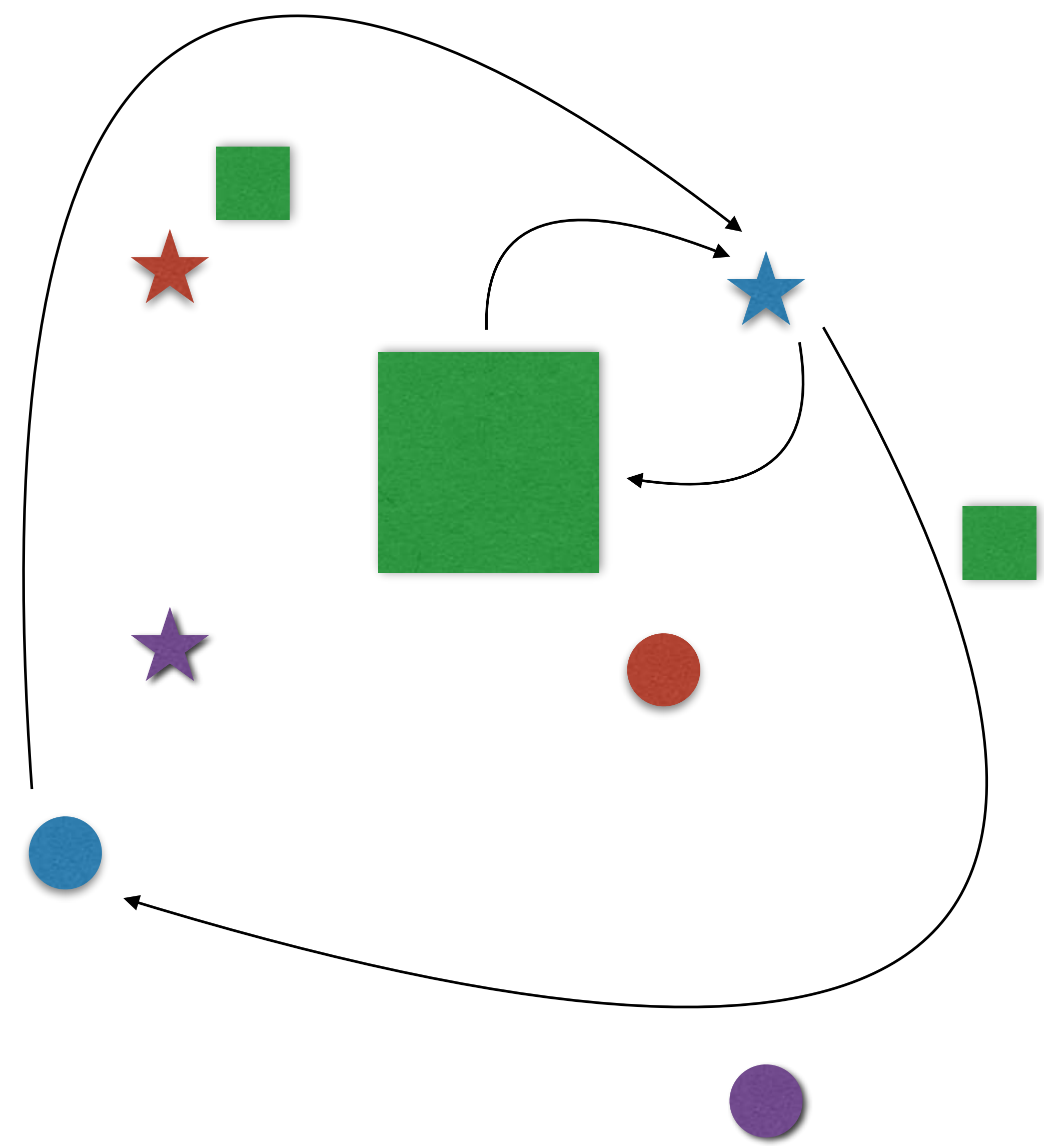
Destination



Beyond the atomic case

2nd case

- ‘Fast’ charger
- ‘Slow’ charger
- Starting point
- Destination



Beyond the atomic case

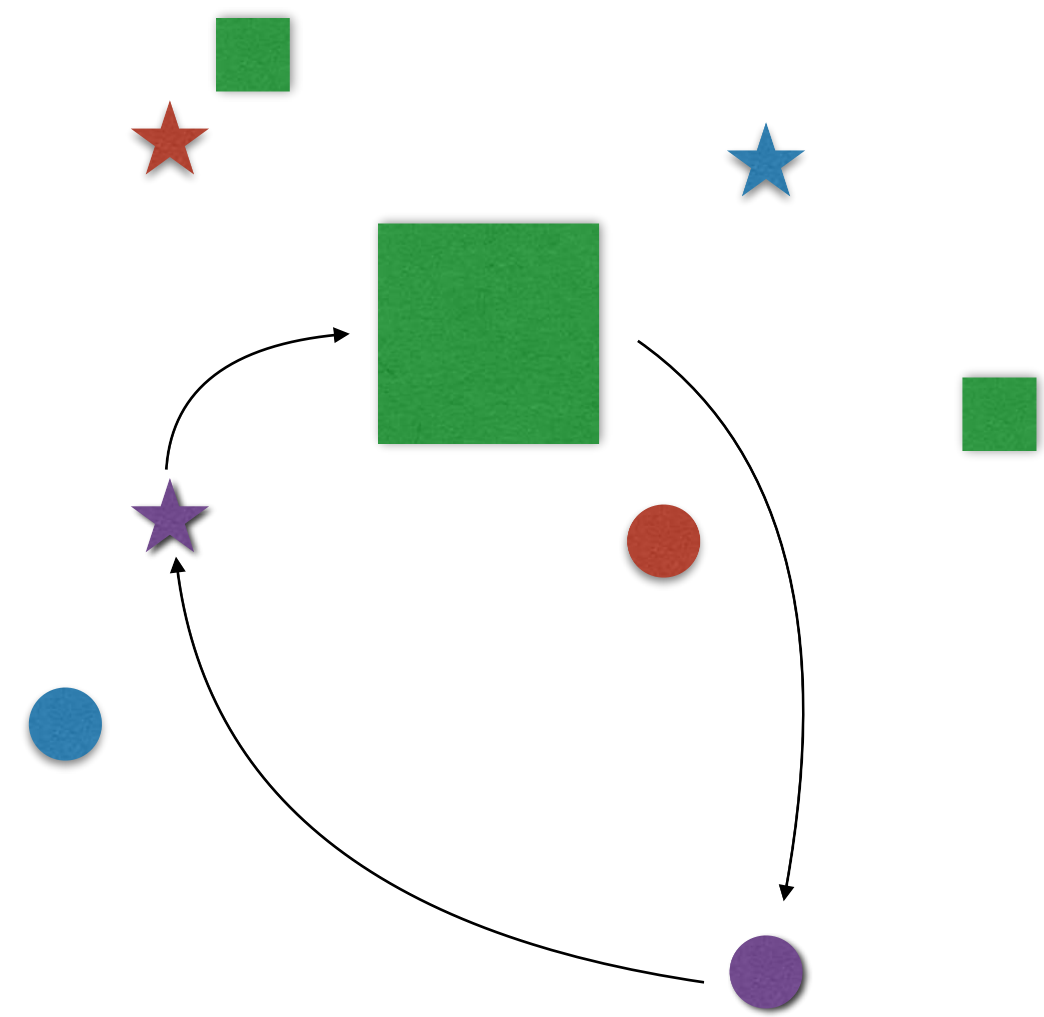
3rd case

‘Fast’ charger

‘Slow’ charger

Starting point

Destination



Beyond the atomic case

Finding a place to charge can be seen as a dispatching problem:

$$d : EV \to Station$$

We have first developed a intuitive heuristics to dispatch the fleet of EVS

This strategy is founded on a few parameters defining the maximal distances that are admissible (detour, lunch time round-trip, one-day charge)

This strategy aims at maximising the amount of energy that is gathered « locally »

This strategy will be the reference strategy.

Beyond the atomic case

$$EV_i(A_i, B_i)$$
$$\forall i \in \{1, 2, ..., nbEV\}$$

$$C_j$$
$$\forall j \in \{1, 2, ..., nbStation\}$$

Long
recharging time

Short
recharging time

Charge all-day long
$dist(B_i, C_j) \leq dist_{ADL}$

Charge during lunch time
$dist(B_i, C_j) \leq dist_{LT}$

Make a detour
$dist(A_i, C_j) + dist(B_i, C_j) \leq dist_{detour}$

Slow charger:
Residential PV installation

Fast charger:
Windturbine - PV farm

Beyond the atomic case

Next-step: optimising the dispatch strategy

$$d^* \in \arg\max_{d \in \Sigma} Q(d)$$

Necessity to have access to a value function Q (*quality function*) that would assess the quality of a dispatch strategy, including constraints satisfaction

No convexity neither differentiability ; use of Derivative-Free Optimisation techniques

Also looking for decentralised dispatch strategies

Getting closer to reality

Charging stations

Domestic PV installation (5 kWc)

Industrial PV system (100 kWc)

PV farm (100 MWc)

Single wind turbine (1 MW)

Wind farm (10 MW)

Chargers

22 kW, 50 kW and 120 kW

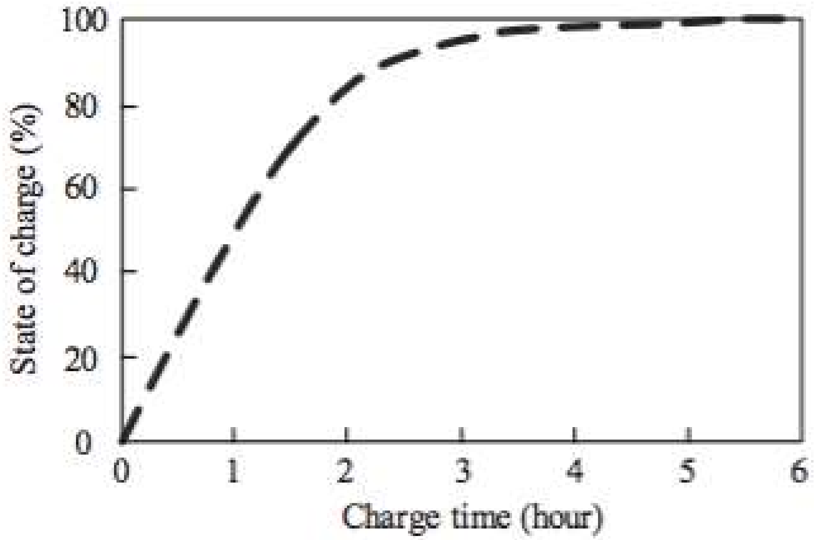
EVs capacity & charging curve

Capacity: 60 kWh, consumption: 20 kWh/100km, range: 300 km.

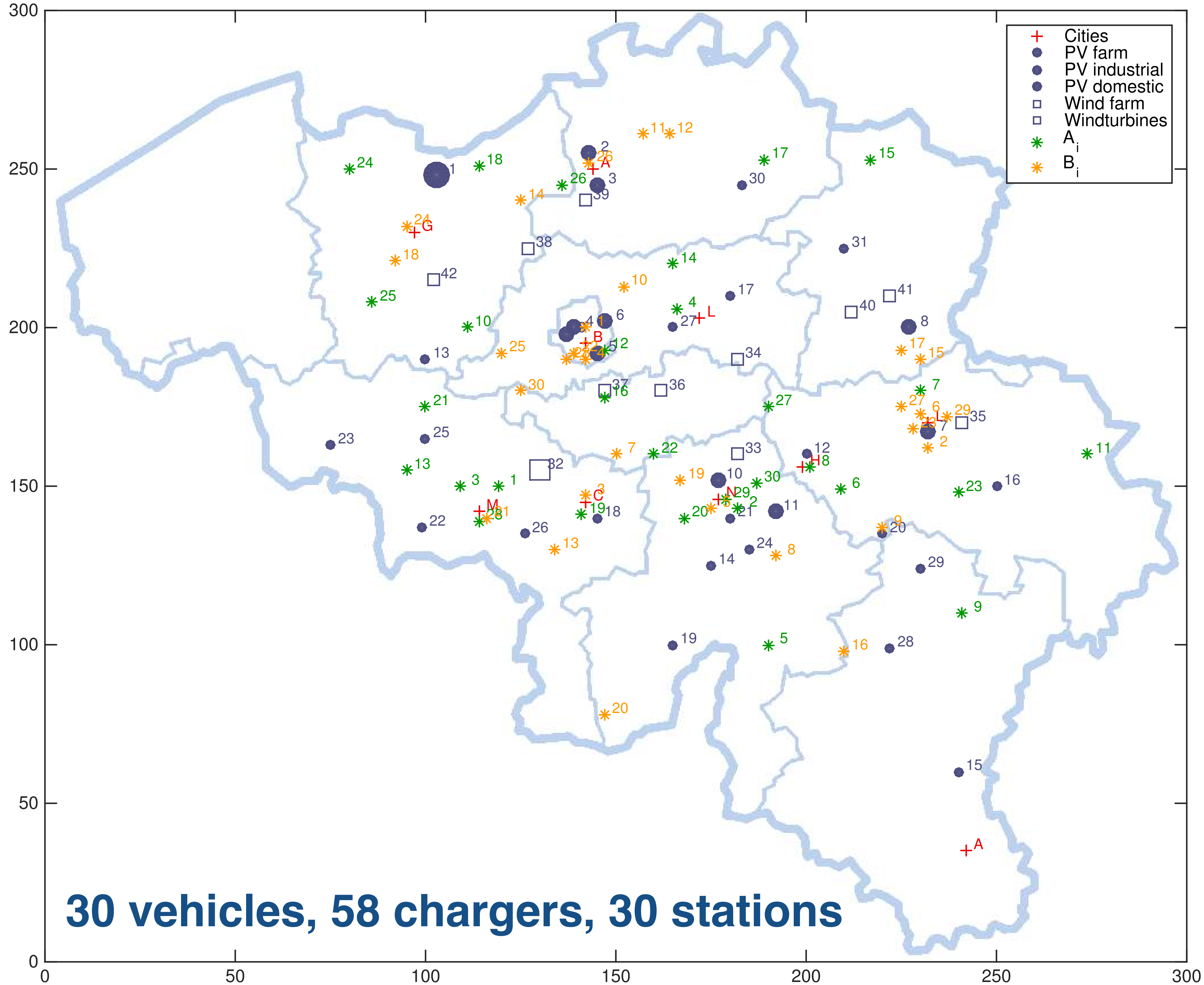
Charging curve taken from Gao, S., Chau, K.T., Chan, C.C., Liu, C., Wu, D., 2011. ***Optimal control framework and scheme for integrating plug-in hybrid electric vehicles into grid***. Journal of Asian Electric Vehicles

PV farm of Toul-Rosières, 115 MWc

Wind farm of Estinnes, 81 MW



Getting closer to reality



30 vehicles, 58 chargers, 30 stations

The dispatching optimisation problem

Problem structure

There is no natural structure in the problem

No continuity, convexity, or ‘proximity’ notion may be easily (at this stage) deductible from the position of locations on the map

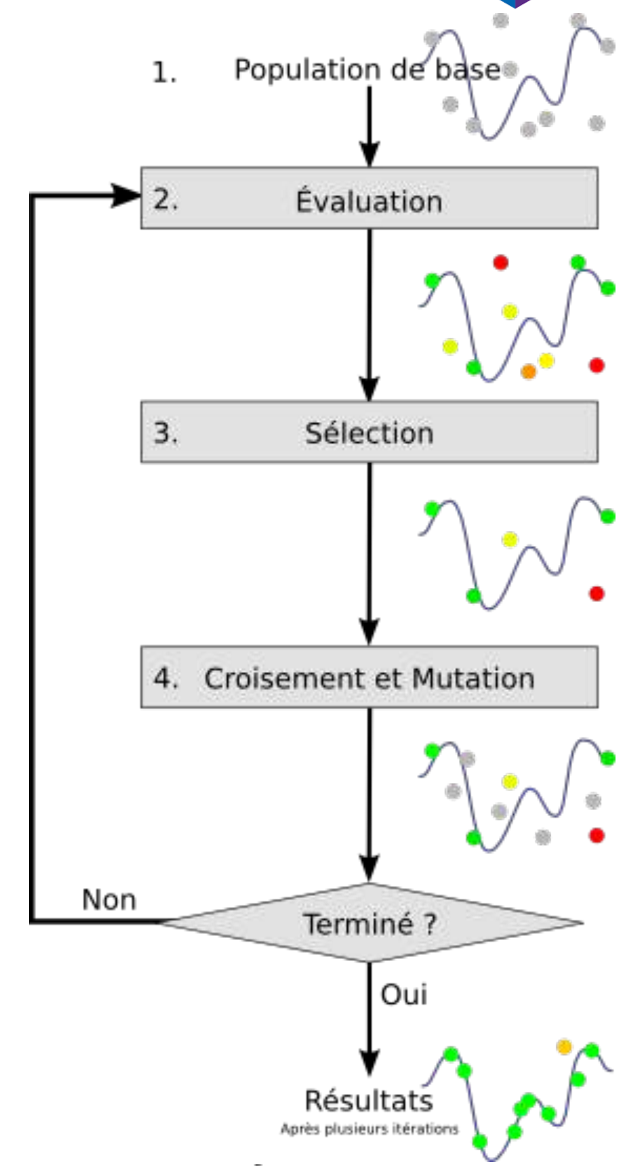
We propose to develop a genetic algorithm approach to optimise the dispatching between vehicles and charging

A gene represents a dispatch strategy, i.e. a set of associations between a EVs and charging stations:

1	3	7	4	2	6	8	9	5	10

Genes are evaluated using a ‘fitness function’

Genetic optimisation



More concretely

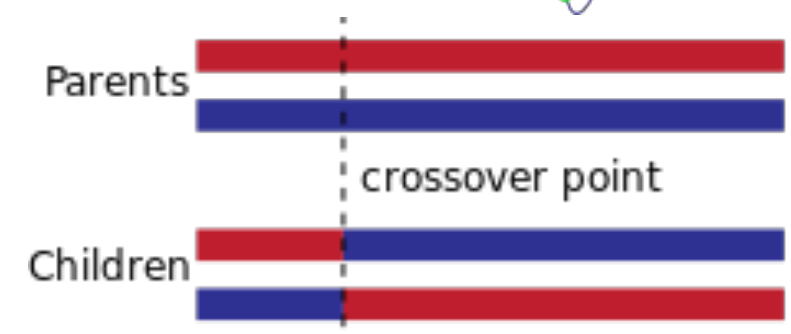
Start with an initial population of genes

Using the fitness function, form a subpopulation with the best genes

Generate a new population using genetic operators (e.g. crossing-over, mutations)

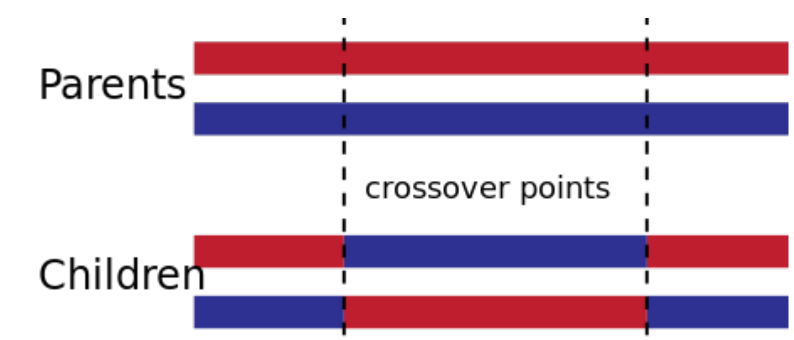
Iterate the process until a stopping condition is reached

Genetic operators



Crossing-over & recombination

Mutations (uniform, non-uniform, Gaussian…)



Note that in our specific context, we also need to avoid ‘collisions’, i.e. the fact that two vehicles are dispatched to the same charger

Genetic optimisation

The fitness function

The fitness function summarises how ‘good’ a given solution (encoded using a gene)

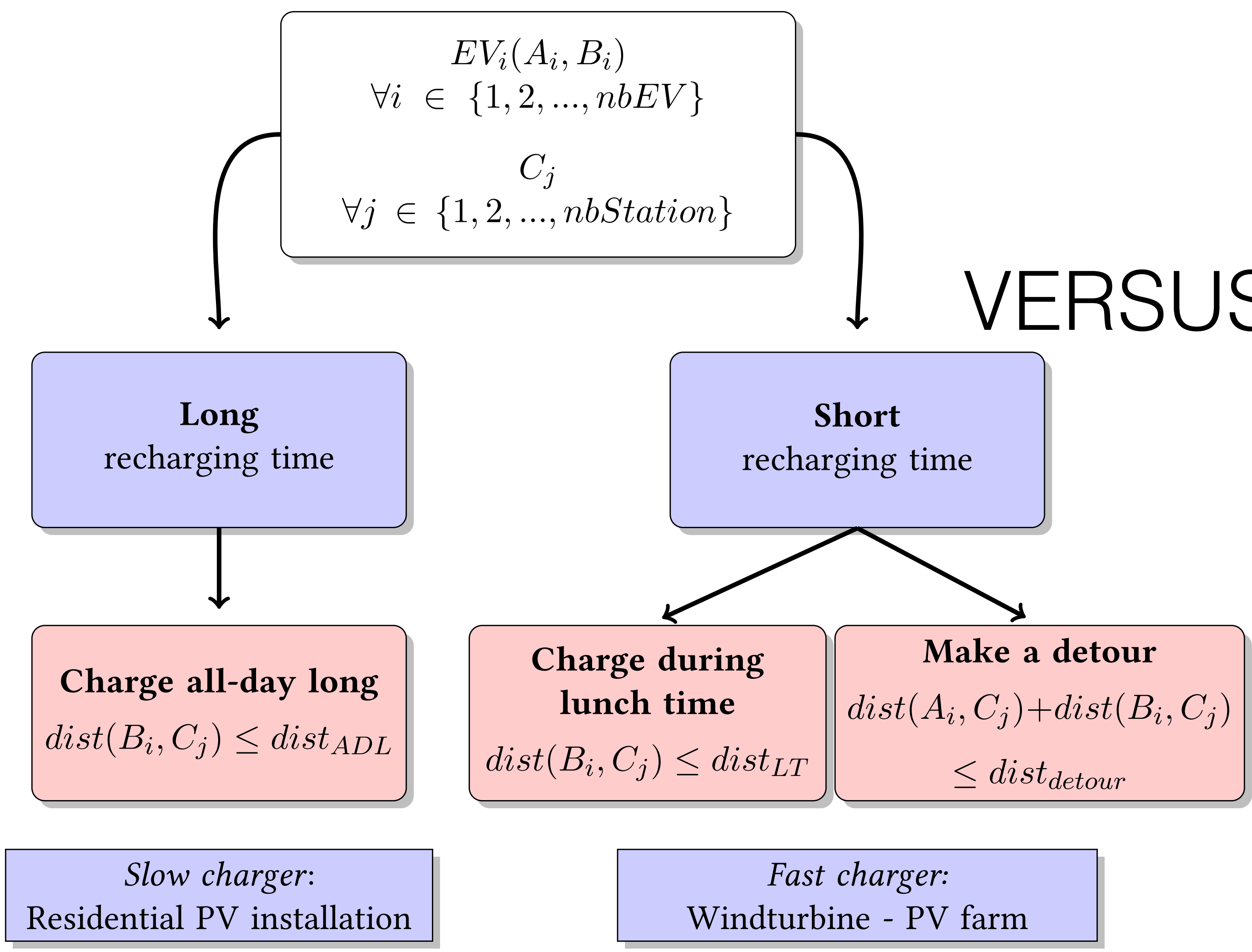
Several fitness functions may be chosen; here we focus on:

- Maximising the average (on the whole fleet of EVs) level of charge at the end of the day

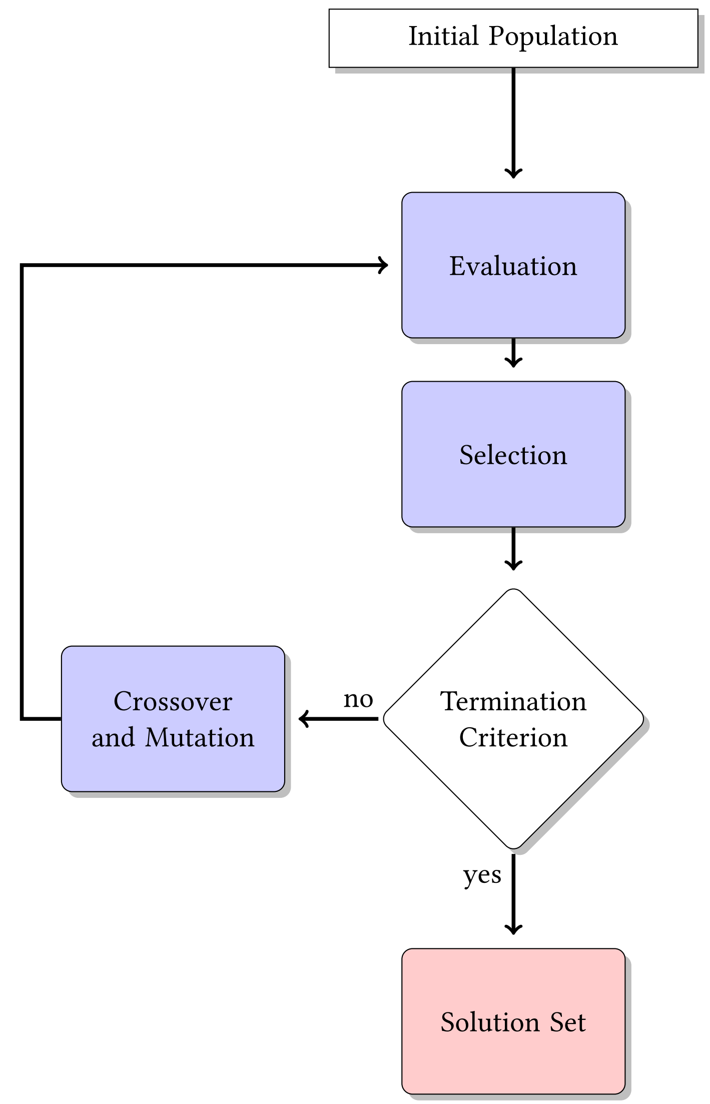
$$fitness(gene) = \sum_{i=1}^{N} level_{i,T}$$

Why « at the end of the day » ? In order to minimise the quantity of energy taken from the grid (EVs start everyday with a full battery)

The match

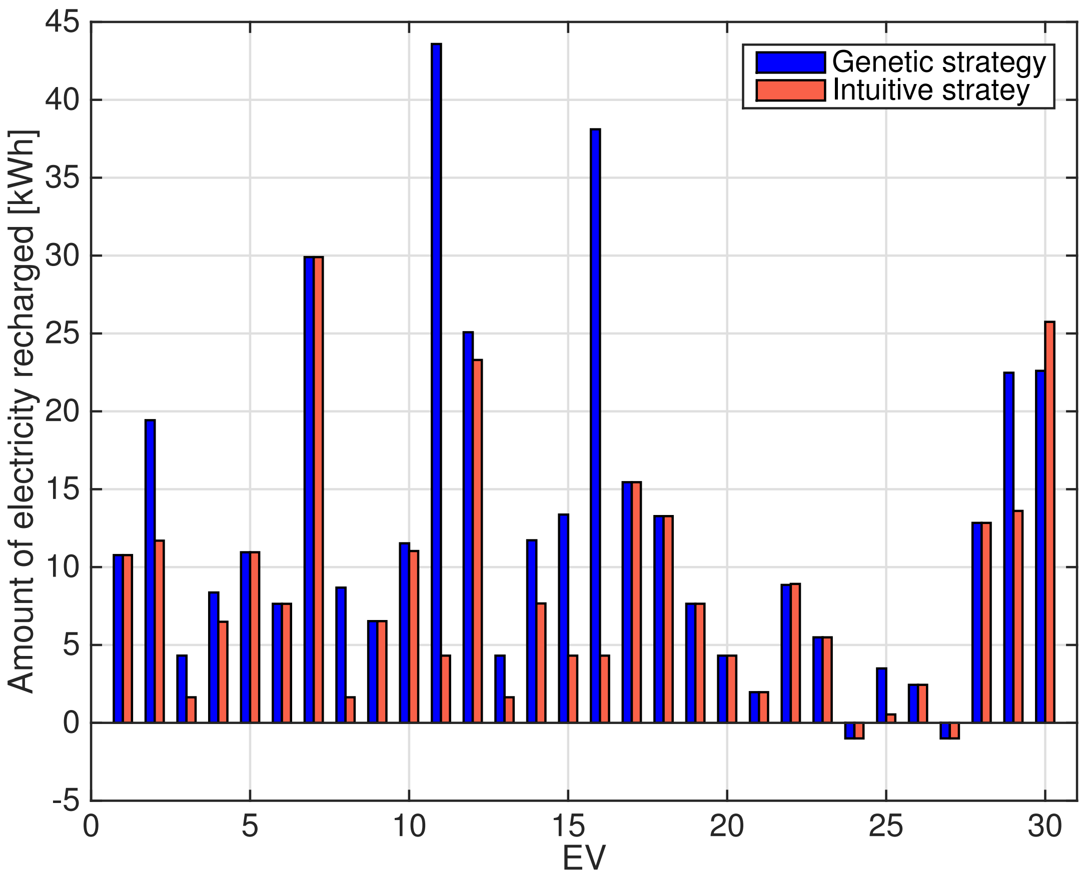


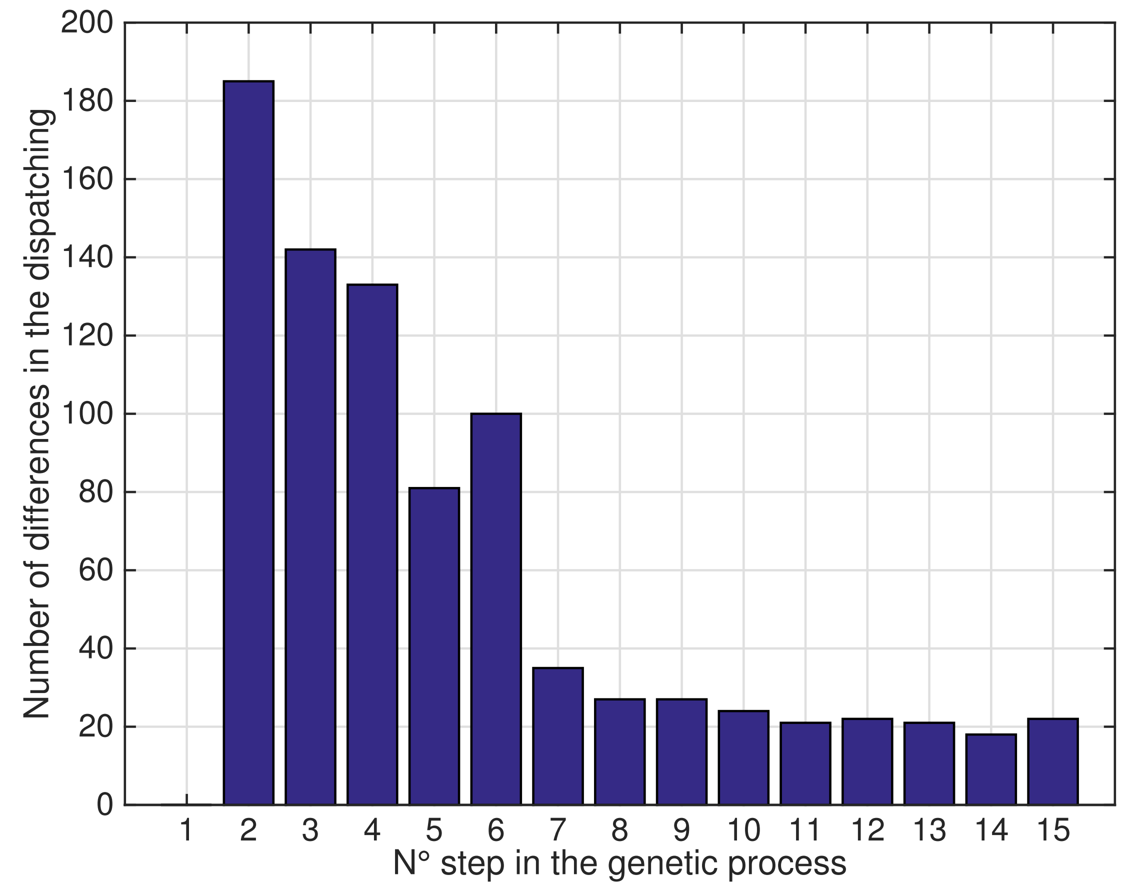
VERSUS



$$\text{fitness(gene)} = \sum_{i=1}^{nbEV} SoC_{i,T}$$

The results





Run 1	Run 2	Run 3	Run 4	Run 5
286.86	278.77	286.65	270.87	279.79

- Priority-base strategy 211 kWh
- Genetic strategy 279 kWh

Scaling-up

Next steps: bigger, faster

±4000 green power stations(based on real data)

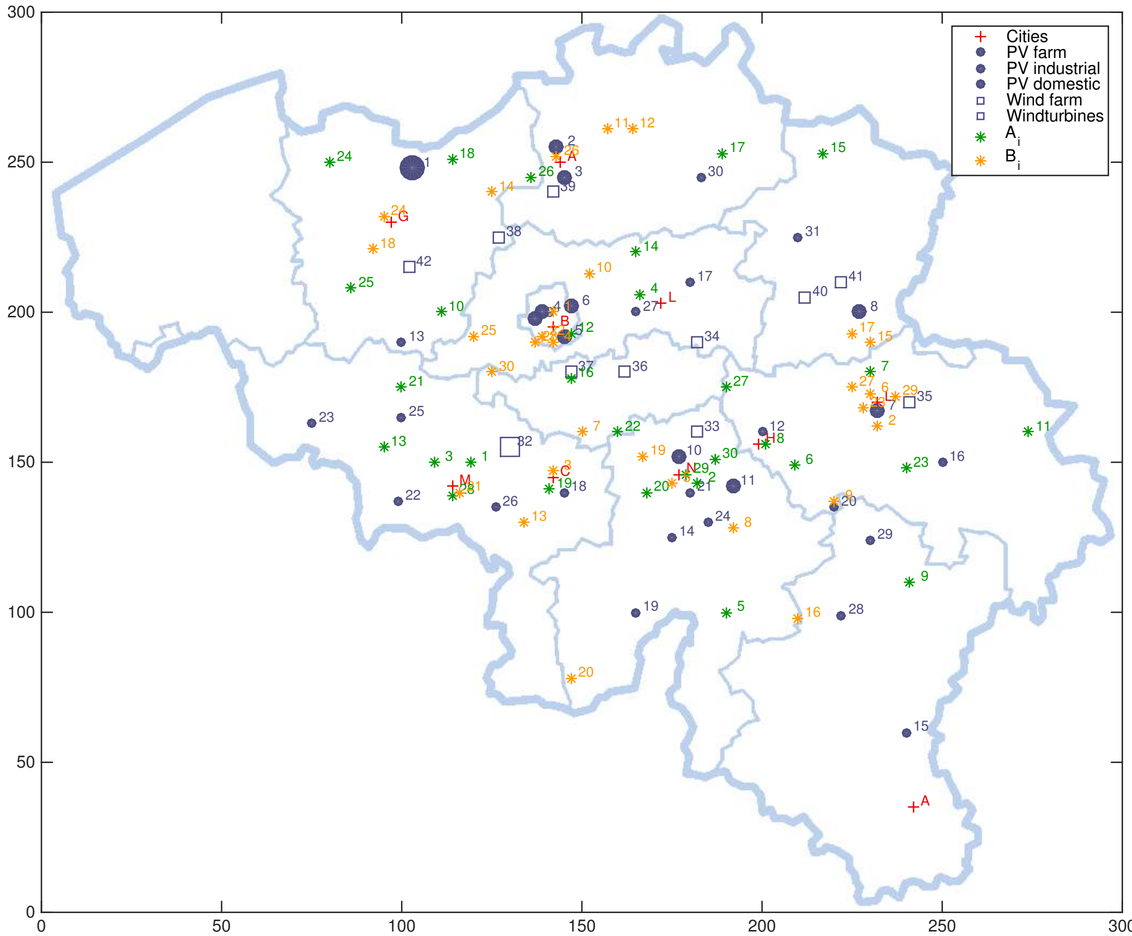
±3800 EVs(with different journey configurations)

Bing/Google map API for realistic distances and result visualisation tool

More time-slots

New dispatching algorithms

Scaling-up


Cities
PV farm
PV industrial
PV domestic
Wind farm
Windturbines
A_i
B_i
0
50
100
150
200
250
300


Middelbourg
Berg-op-Zoom
Eindhoven
Anvers
Dunkerque
Calais
Lille
Maastricht
Aix-la-Chapelle
Mönchengladbach
Cologne
Bonn
Lens
Arras
Maubeuge
Amiens
Saint-Quentin
Charleville-Mézières
Sedan
Laon
Beauvais
Compiègne
Soissons
Luxembourg
Thionville
Bastogne
Rochefort
Trèves


Dordrecht
Bois-le-Duc
Tilbourg
Nimègue
Eindhoven
Duisbourg
Essen
Düsseldorf
Mönchengladbach
Cologne
Bonn
Dunkerque
Calais
Lille
Lens
Arras
Maubeuge
Amiens
Saint-Quentin
Charleville-Mézières
Sedan
Laon
Beauvais
Compiègne
Luxembourg
Bastogne
Rochefort
Trèves

Upgrading the dispatching algorithm for A-B-C rides

1. **Compute**, for each point B, the **150 nearest power stations** in a radius of maximum 10km (the EV owner will have to select a station within this range)

2. **Build a graph** where each point B is linked to power stations with interest in the 150 closest ones, i.e power stations with sufficient power compared to the energy needed in the time wasted at B.

   - To construct this graph, we need to choose a metric for edges. Two metrics are proposed:
     (i) the physical distance between the station and B
     (ii) the mathematical distance between the power of the station and the optimal power needed by the car to recharge the correct amount of energy.

3. From the graph, **compute a minimal spanning tree**: the resulting tree gives to each point B at least one “near-optimal” charging station.

Results

Random(in a 10km radius) allocation			
data \ size	500	1000	3765
number of vehicle with a station	3430,4	3407,2	3383,4
average detour(m)	7741,7	7767,9	7732,0
standard deviation of detour(m)	4470,9	4481,1	4452,2
average recharge(%)	56,3	55,9	55,9
standard deviation of recharge(%)	44,0	44,0	43,9
Average total energy recharged(kWh)	57 939,5	57 138,7	56 756,4

Minimizing distance			
data \ size	500	1000	3765 [7]
number of vehicle with a station	3232,2	3163,2	2864
average detour(m)	4271,6	4072,4	3647,5
standard deviation of detour(m)	3862,0	4481,1	3859,7
average recharge(%)	69,0	68,5	65,7
standard deviation of recharge(%)	39,6	39,9	41,1
Average total energy recharged(kWh)	66 906,5	65 003,8	56 449,4

Maximizing energy recharged			
data \ size	500	1000	3765 [7]
number of vehicle with a station	3375,0	3295,2	2824
average detour(m)	7515,9	7406,6	7305,2
standard deviation of detour(m)	4858,5	4481,1	4992,3
average recharge(%)	72,6	70,9	67,8
standard deviation of recharge(%)	39,1	39,9	42,0
Average total energy recharged(kWh)	73 507,5	70 088,9	57 440,2

Egoist minimizing distance			
data \ size	500	1000	3765 [7]
number of vehicle with a station	3368,0	3350,2	3313
average detour(m)	3571,7	3520,5	3493,1
standard deviation of detour(m)	3947,3	3883,8	3906,1
average recharge(%)	56,4	56,2	56,1
standard deviation of recharge(%)	43,8	43,7	43,7
Average total energy recharged(kWh)	59 986,6	56 484,4	55 757,8

Egoist maximizing power			
data \ size	500	1000	3765 [7]
number of vehicle with a station	3455,8	3439,2	3432
average detour(m)	6561,1	6536,6	6485,14
standard deviation of detour(m)	4897,0	4891,0	4862,5
average recharge(%)	66,6	66,7	66,7
standard deviation of recharge(%)	41,0	40,9	40,9
Average total energy recharged(kWh)	69 046,9	68 818,4	68 674,32

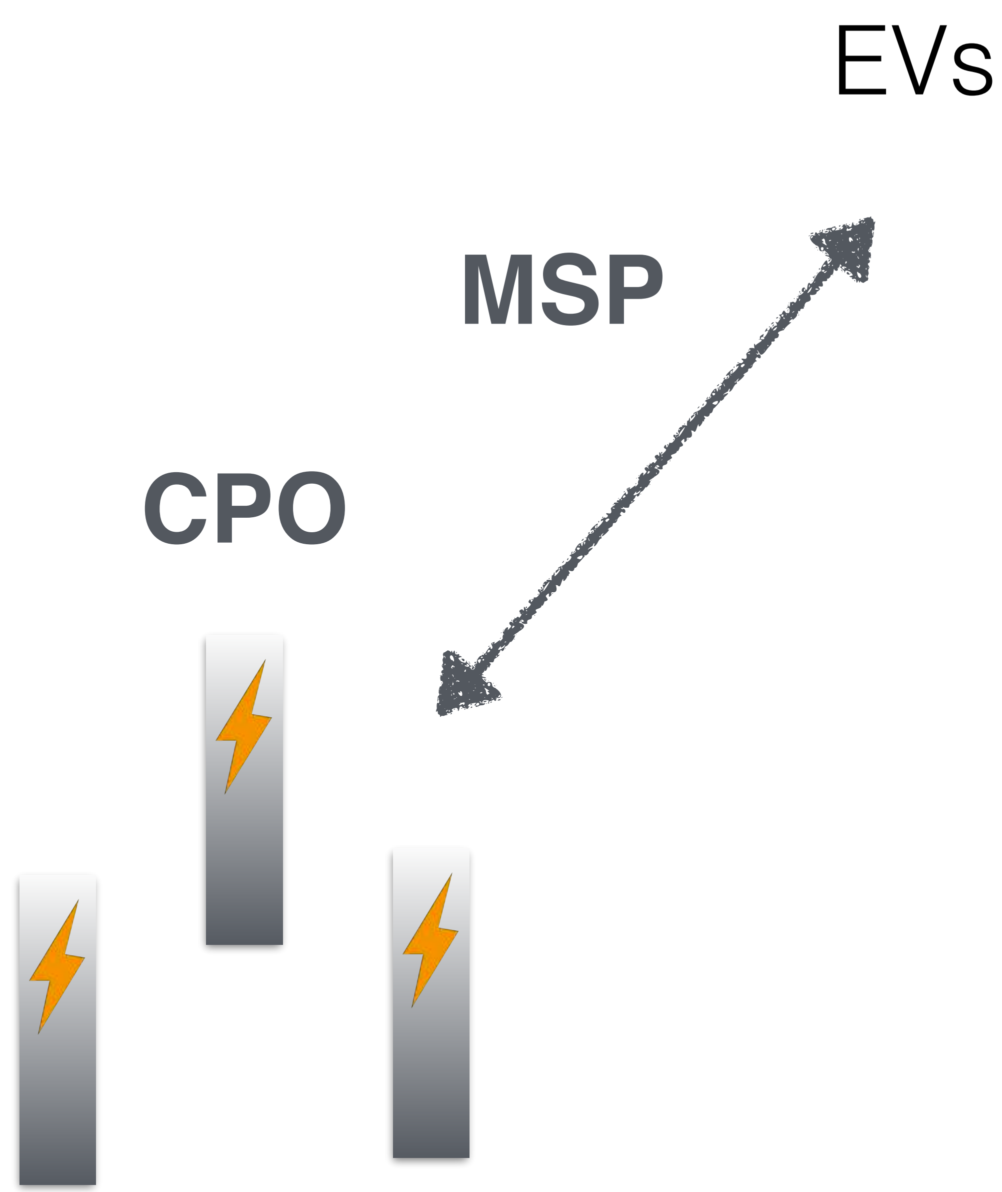
III.
Integrating communities

A viewpoint on the energy landscape

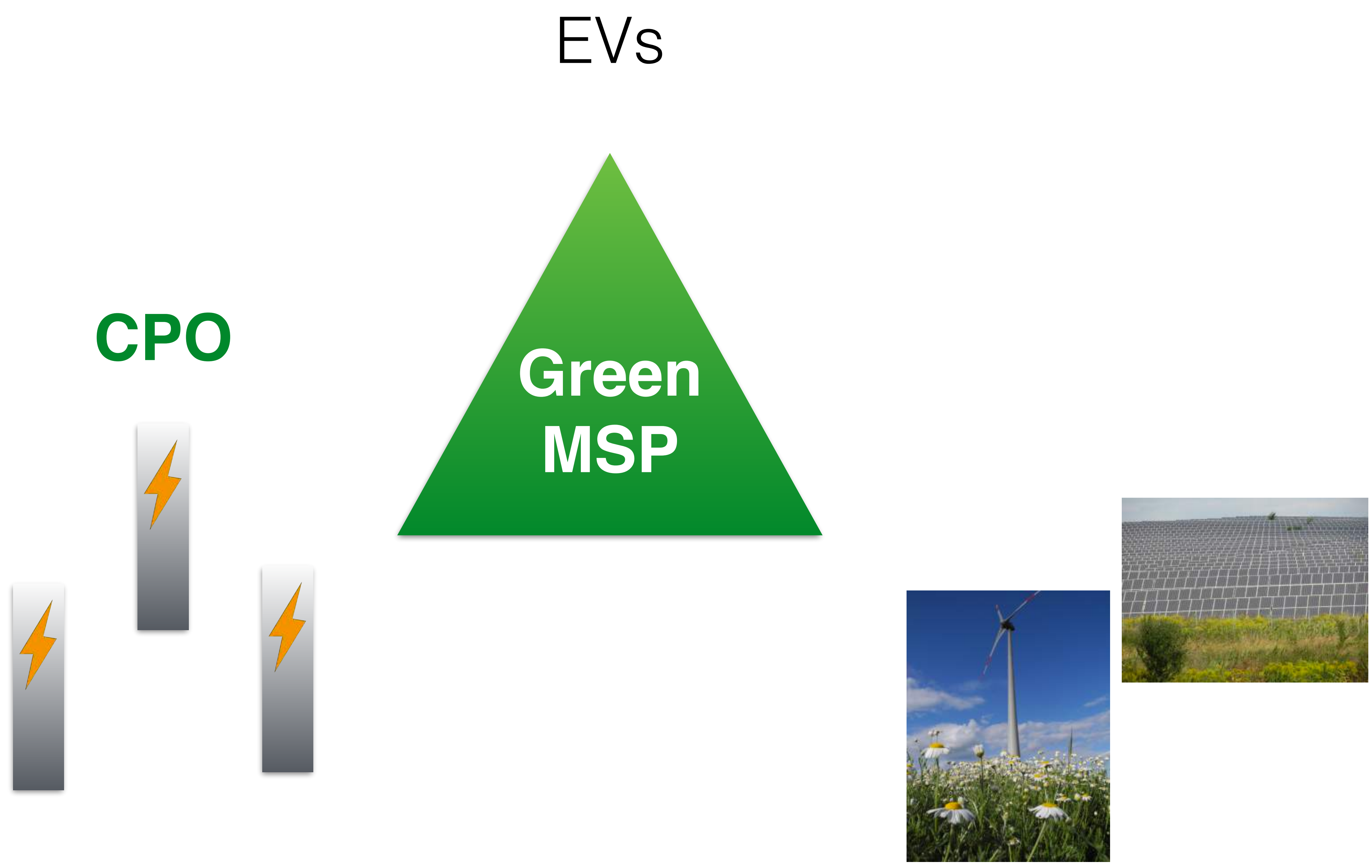
Renewable production
needs storage and/or
flexibility

Electric vehicles
need renewable energy
(CO_2-free)

Existing relationships in the EVs content



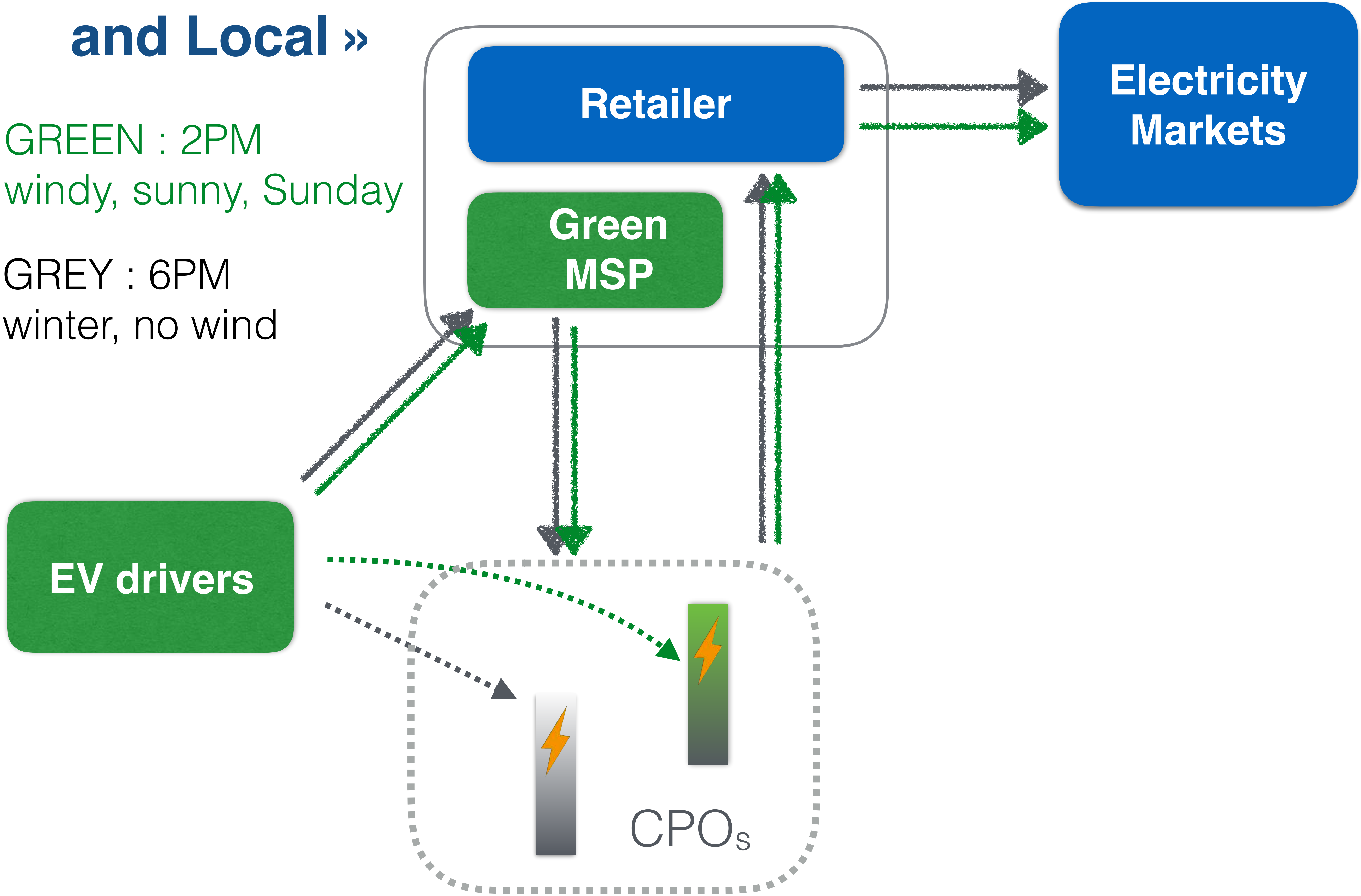
Adding a new dimension



« Drive Green and Local »

GREEN : 2PM
windy, sunny, Sunday

GREY : 6PM
winter, no wind



« Drive Green and Local »

GREEN : 2PM
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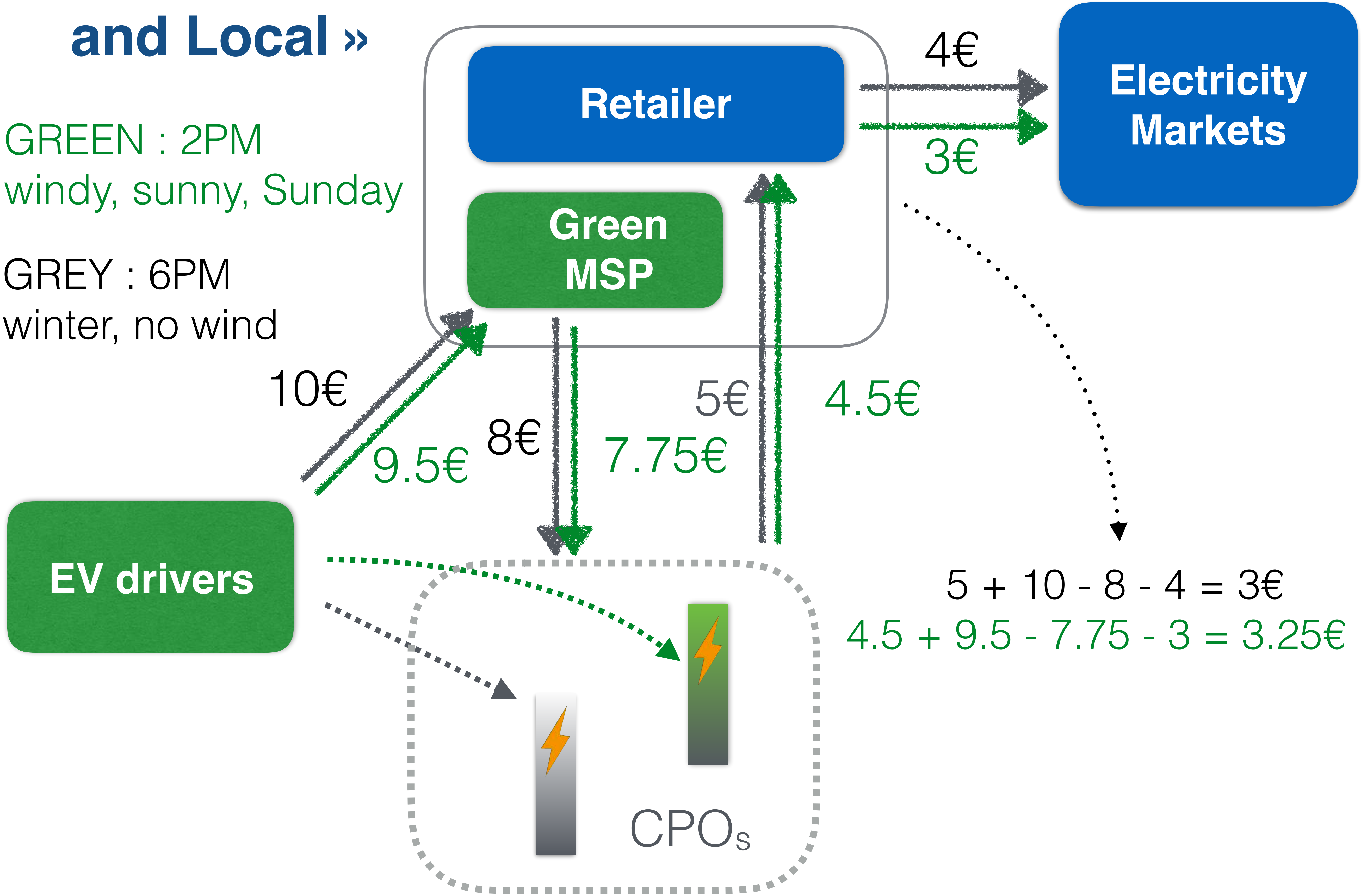


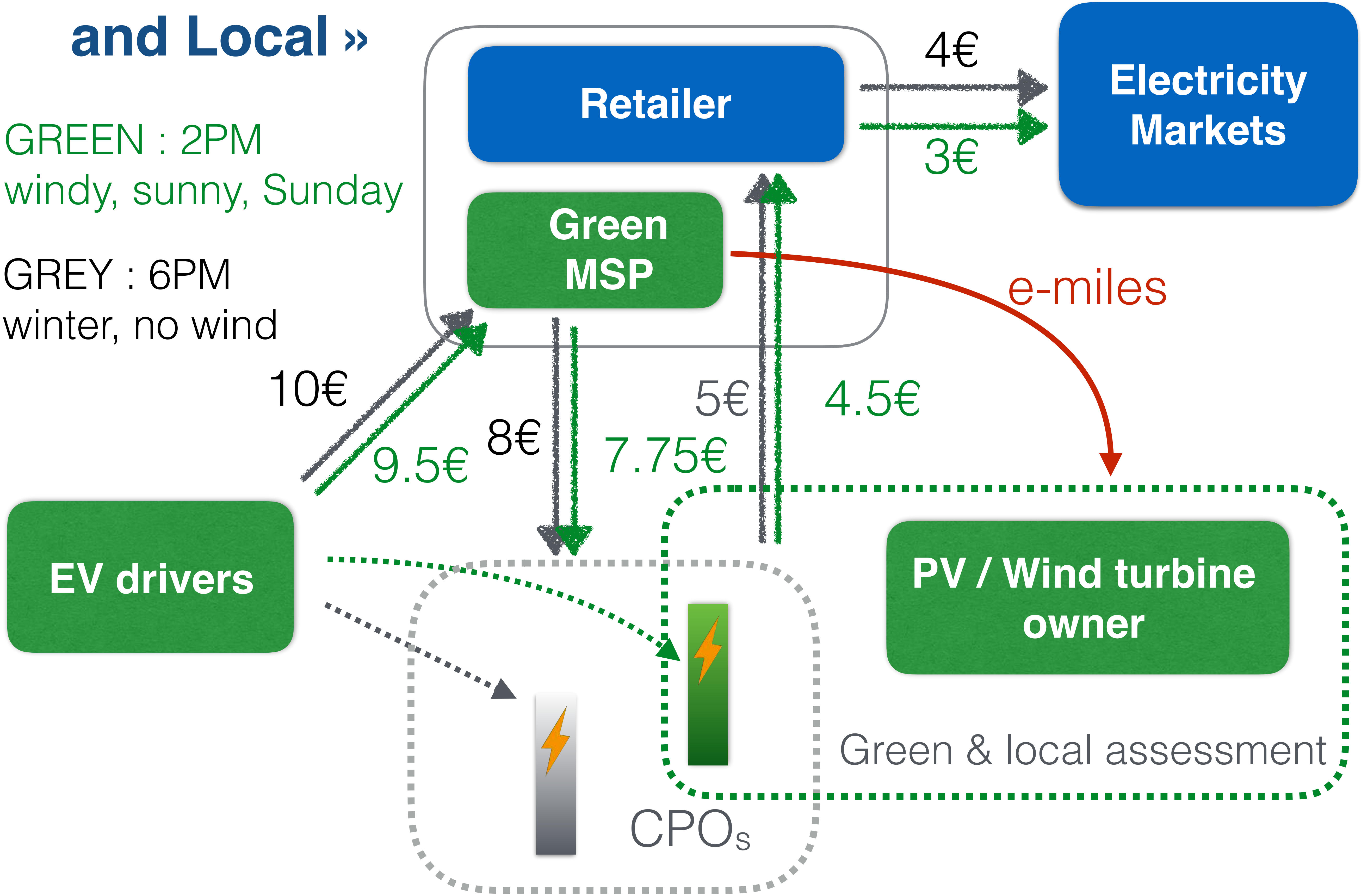
$5 + 10 - 8 - 4 = 3€$

$4.5 + 9.5 - 7.75 - 3 = 3.25€$

« Drive Green and Local »

GREEN : 2PM
windy, sunny, Sunday

GREY : 6PM
winter, no wind



The « Drive Green and Local » Concept

Incentives for EV drivers and RE producers

Drive green, pay less

Play a serious game, become even greener, eventually get access to premium services, get free e-miles

Be part of a community

Incentives for CPOs

Green labelling of charging starting

To the CPO, the Green MSP plays the role of a « classical » MSP able to practice dynamic pricing

A Green MSP may offer to increase the use rate of its charging stations

IV.
Décret “Communautés d’Energie Renouvelable”

Contexte

Actuellement, un cadre légal existe déjà pour le prosumer qui est le client résidentiel qui autoconsomme son électricité (photovoltaïque). Pour rappel, la déclaration de politique régionale du 25 juillet 2017 énonce que : « En s'appuyant sur l'expertise du régulateur, le décret et les arrêtés seront modifiés en vue d'établir un cadre de développement approprié des réseaux alternatifs et micro-réseaux, y compris citoyens, sous leurs différentes formes. L'émergence de ces réseaux se réalisera en étant attentif à une contribution équitable de l'ensemble des utilisateurs du réseau public ».

La nouvelle réforme, portée par le projet de décret, favorise donc la création de communautés d'énergie renouvelable autorisant l'autoconsommation collective d'électricité, ce qui permet de s'affranchir de la dimension physique du réseau. Ainsi, tout en mobilisant le réseau public, plusieurs entités (personnes physiques ou morales), au sein d'un périmètre, pourront s'entendre pour mutualiser et synchroniser leur production et consommation électrique.

Source : https://gouvernement.wallonie.be/home/presse/publications/les-communautes-denergie-renouvelable-pour-une-meilleure-consommation-de-lenergie-1.publicationfull.html

Possibilités

Ce nouveau modèle permettra différentes combinaisons :

- *Soit un ménage produit plus qu'il n'en a besoin et s'associe avec d'autres ménages qui ne produisent pas afin de mutualiser leurs besoins énergétiques ;*

- *Soit un immeuble résidentiel installe de manière commune des panneaux sur son toit afin de répartir la production avec les habitants de l'immeuble ;*

- *Soit plusieurs entreprises s'associent afin de répartir leur production/consommation sur la journée afin de consommer au maximum lors des pics de production d'énergie et moins le reste du temps ;*

- *Soit une autorité locale (ex.: CPAS) installe des panneaux sur un immeuble de logements sociaux afin de faire bénéficier les locataires d'une énergie verte à moindre coût.*

- *Et bien d'autres combinaisons sont encore possibles.*

Source : https://gouvernement.wallonie.be/home/presse/publications/les-communautes-denergie-renouvelable-pour-une-meilleure-consommation-de-lenergie-1.publicationfull.html

Objectifs

L'autoconsommation collective d'électricité :

- *Permettra, à terme, de faire des économies dans le développement et le renforcement du réseau de distribution et aura de manière générale un impact positif sur la facture des participants à ces communautés.*

- *Permettra une meilleure intégration des énergies renouvelables. En effet, les énergies renouvelables sont des énergies dites intermittentes. La synchronisation de la production et de la consommation à une échelle locale permettra effectivement de mobiliser le réseau dans une moindre mesure, ce qui facilite en fin de compte son intégration à ce dernier.*

- *Favorisera également la smartisation du réseau. Posséder un compteur intelligent sera essentiel pour pouvoir participer à une communauté d'énergie renouvelable (meilleur calibrage de la consommation), ce qui permettra in fine d'éveiller la société à une adaptation de son mode de consommation d'électricité et de rebooster la compétitivité énergétique wallonne.*

Source : https://gouvernement.wallonie.be/home/presse/publications/les-communautes-denergie-renouvelable-pour-une-meilleure-consommation-de-lenergie-1.publicationfull.html

Prospective conclusions

The current landscape

Directly selling and buying to other prosumers : ~~currently not really~~ almost possible

(i) Physical problem: need to go through the distribution network ; difficulties to monitor who buys, who produces : there is a potential accounting problem,
(ii) A regulation problem,
(iii) Also, a « contracting problem »: prosumers may not want to spend time to manage transactions with other prosumers.
… but wait… Décret CERs !

Less dependency on centralised structures

(i) EVs may offer such an eventuality…
(ii) But the actual distribution network was clearly not designed for this.

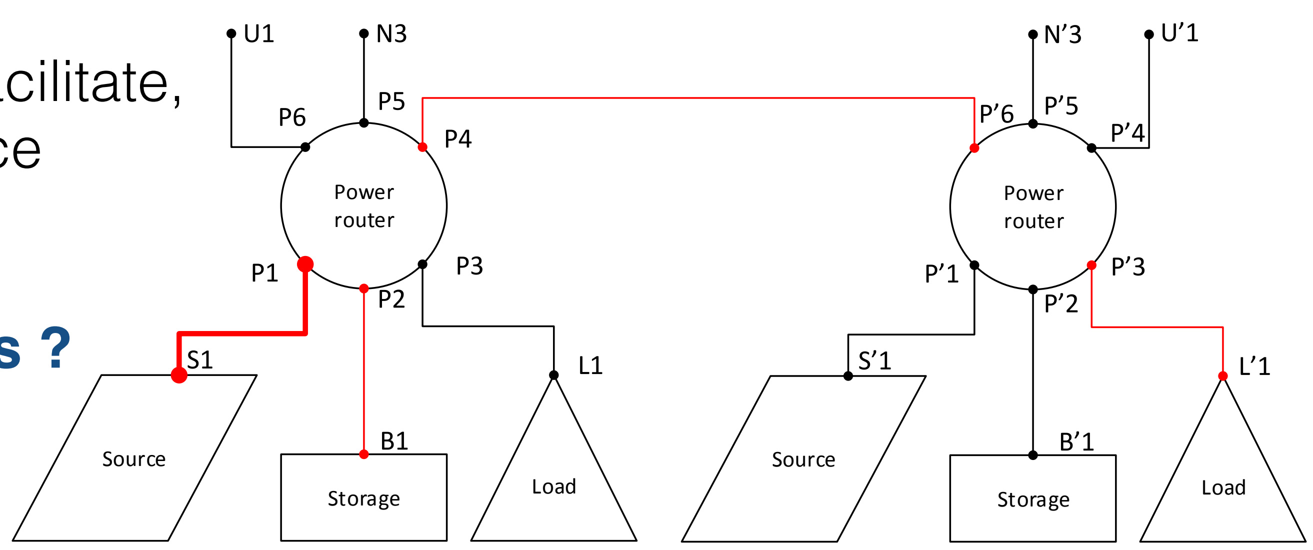
Decentralisation (& digitalisation)

What is a « distributed ledger » ?
A distributed ledger is a consensus of replicated, shared, and synchronised digital data geographically spread across multiple sites, countries, or institutions. There is no central administrator or centralised data storage
However, a peer-to-peer network is required as well as consensus algorithms to ensure replication across nodes is undertaken
Ex: Blockchain

Why a distributed ledger ?
Transparency, reliability and low operational costs for managing transaction between prosumers

And what about smart contracts ?
Smart contracts are computer protocols that facilitate, verify, or enforce the negotiation or performance of a contract

Towards 'peer-to-peer' distribution networks ?



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