

Integration of renewable energy sources and demand-side management into distribution networks

by

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Outline

Active network management

Rethinking the whole decision chain - the GREDOR project

GREDOR as an optimization problem

Finding m^* , the optimal interaction model

Finding i^* , the optimal investment strategy

Finding o^* , the optimal operation strategy

Finding r^* , the optimal real-time control strategy

Conclusion

Microgrid: an essential element for integrating renewable energy



Active network management

Distribution networks traditionally operated according to the **fit and forget doctrine**.

Fit and forget.

Network planning is made with respect to a set of critical scenarios to ensure that sufficient operational margins are always guaranteed (i.e., no over/under voltage problems, overloads) without any control over the loads or the generation sources.

Shortcomings.

With rapid growth of distributed generation resources, maintaining such conservative margins comes at continuously increasing network reinforcement costs.



The buzzwords for avoiding prohibitively reinforcement costs:
active network management.

Active network management.

Smart modulation of generation sources, loads and storages so as to safely operate the electrical network without having to rely on significant investments in infrastructure.



A first example: How to maximize the PV production within a low voltage feeder without suffering over-voltages?

What is currently done:

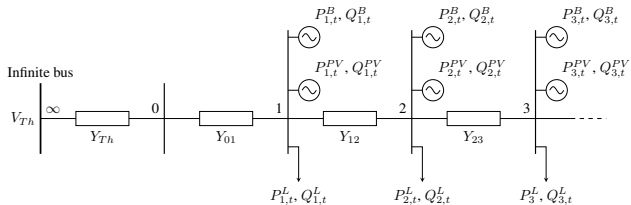
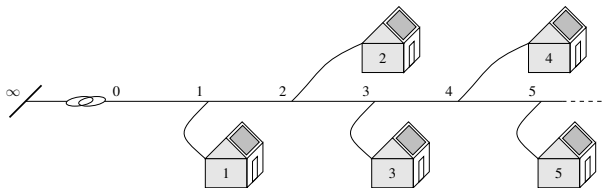
The active power produced by PV panels is 100% curtailed as soon as over-voltage is observed. The curtailment is done automatically by the inverter.

Objective:

Why not investigate better control schemes for minimizing the curtailment?



The low-voltage feeder example:



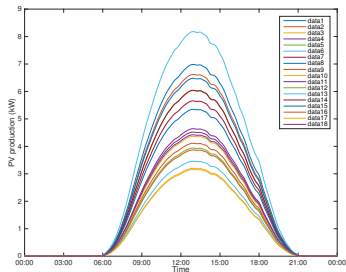
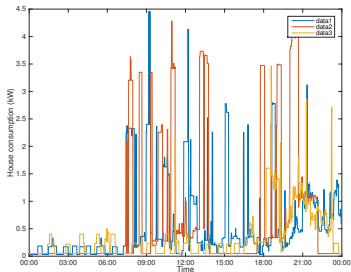
Control actions:

At every time-step, for such a problem, various decisions can typically be taken regarding the feeder:

- ▶ Curtailing the PV active power / activating reactive power
- ▶ Charging or discharging batteries
- ▶ Managing the demand



Modeling the load (SLP) and PV production (from Belgian data)



The current (and basic) approach

Principle:

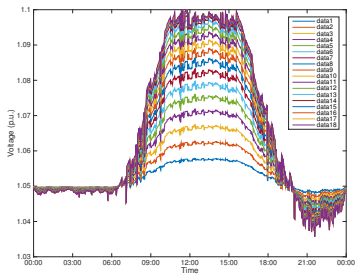
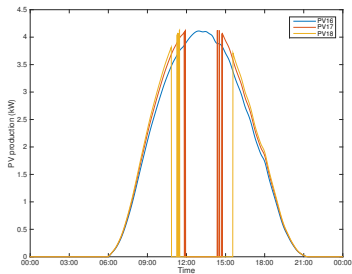
As soon as an over-voltage is observed at a bus, the corresponding inverter disconnects the PV panels from the feeder during a pre-determined period of time.

$$\forall j \in \{1, \dots, N\}, \forall t \in \{0, \dots, T - 1\}, P_{j,t}^{PV} = \begin{cases} 0 & \text{if } V_{j,t} > V_{max}, \\ P_{j,t}^{PV,max} & \text{otherwise.} \end{cases}$$

This control scheme, which is currently the one that is applied in practice, will be considered as the reference strategy.



Effects of the current (and basic) control scheme on the load and the PV production



The centralized optimization approach

Principle:

Solve an optimization problem over the set of all inverters:

$$(P_{1,t}^{PV*}, Q_{1,t}^{PV*}, \dots, P_{N,t}^{PV*}, Q_{N,t}^{PV*}) \in \arg \min_{P_{1,t}^{PV}, Q_{1,t}^{PV}, \dots, P_{N,t}^{PV}, Q_{N,t}^{PV}} \sum_{j=1}^N P_{j,t}^{PV, \max} - P_{j,t}^{PV}$$

subject to

$$h(P_{1,t}^{PV}, Q_{1,t}^{PV}, \dots, P_{N,t}^{PV}, Q_{N,t}^{PV}, V_{1,t}, \dots, V_{N,t}, \theta_{1,t}, \dots, \theta_{N,t}) = 0$$

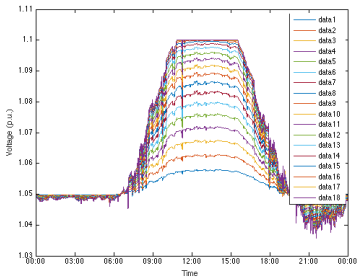
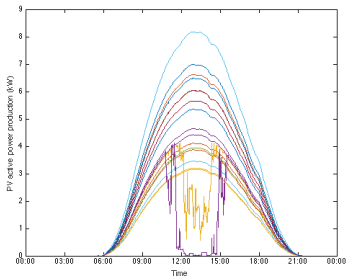
$$V^{\min} \leq |V_{j,t}| \leq V^{\max}, \quad j = 1, \dots, N$$

$$0 \leq P_{j,t}^{PV} \leq P_{j,t}^{PV, \max}, \quad j = 1, \dots, N$$

$$|Q_{j,t}^{PV}| \leq g(P_{j,t}^{PV}), \quad j = 1, \dots, N$$



Effects of the centralized optimization approach on the load and the PV production



Potential gain in this example:

Curtailed energy with the basic approach: 31.63 kWh

Curtailed energy with the centralized approach: 21.38 kWh



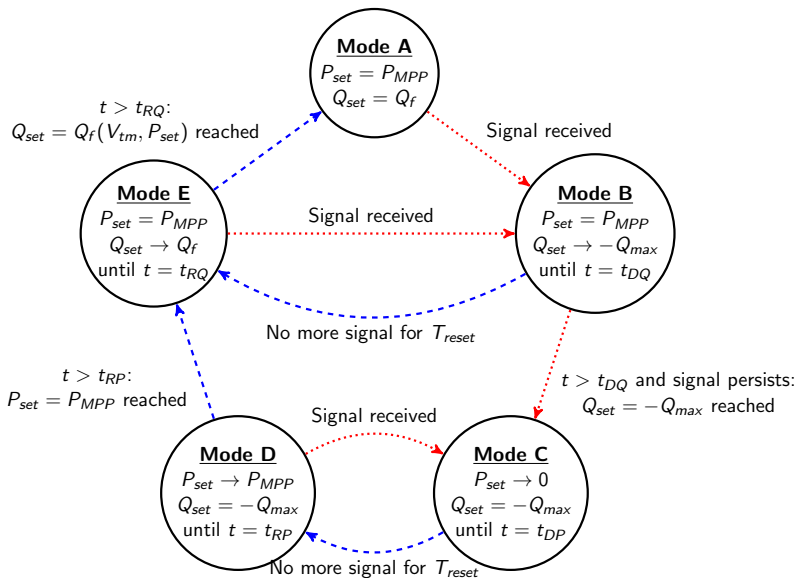
Towards decentralized approaches

Principle:

We are investigating control schemes that would only need local information. These control schemes work by measuring the sensitivity of the voltage (measured locally by the inverter) with respect to the injections of active and reactive power.



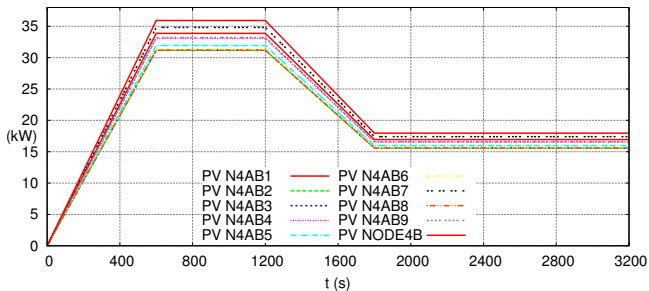
State transition diagram of the distributed control scheme:



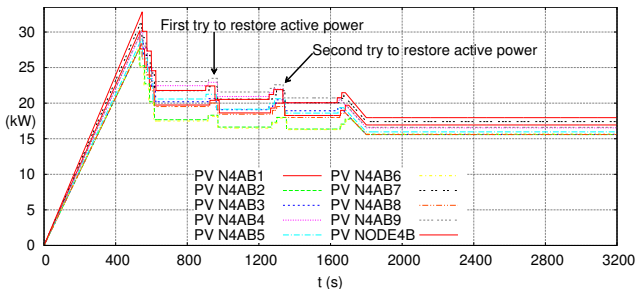
- ▶ The red dotted lines are the emergency control transitions while blue dashed lines are the restoring ones.
- ▶ t_{DQ} (resp. t_{DP}) is the time needed in Mode B (resp. Mode C) to use all available reactive (resp. active) controls.
- ▶ T_{reset} is the elapsed time without emergency signal for the controller to start restoring active/reactive power.
- ▶ t_{RP} (resp. t_{RQ}) is the time needed in Mode D (resp. Mode E) to restore active (resp. reactive) power to the set point values of Mode A.
- ▶ P_{set} and Q_{set} are the active and reactive power set points of the controller.
- ▶ P_{MPP} is the maximum available active power of the PV module and depends on the solar irradiation.
- ▶ Q_{max} is the maximum available reactive power; it varies according to the capability curve as a function of the active power output.



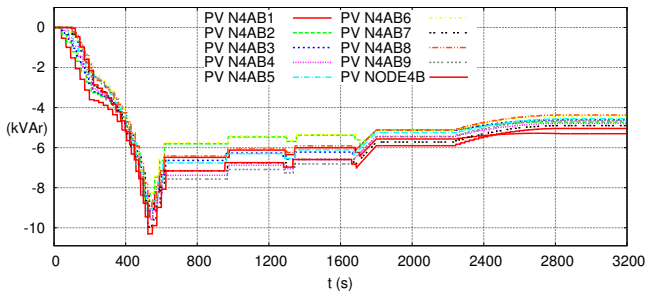
Maximum PV active power that could be produced



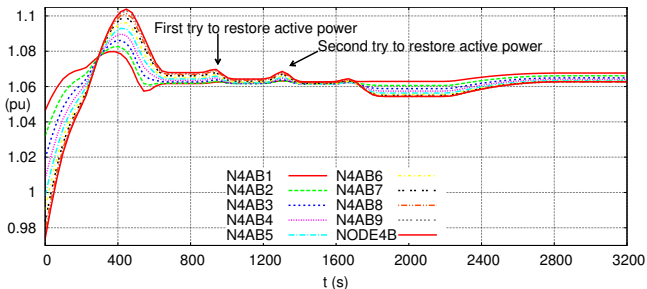
Active power produced by the PV



Reactive power produced by the PV



Resulting voltages



Outline

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Rethinking the whole decision chain - the GREDOR project

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Microgrid: an essential element for integrating renewable energy



The GREDOR project.

Redesigning in an integrated way the **whole decision chain** that is used for managing distribution networks in order to perform active network management optimally (i.e., maximisation of social welfare).



Decision chain

The **four stages of the decision chain** for managing distribution networks:

1. Interaction models
2. Investments
3. Operational planning
4. Real-time control



1. Interaction models

An interaction model defines the **flows of information, services and money** between the different actors. Defined (at least partially) in the regulation.

Example: The Distribution System Operator (DSO) may curtail a wind farm at a regulated activation cost.

2. Investments

Planning of the investments needed to upgrade the network.

Examples: Decisions to build new cables, investing in telemeasurements, etc.



3. Operational planning

Decisions taken a few minutes to a few days before real-time.
Decisions that may interfere with energy markets.

Example: Decision to buy the day-ahead load flexibility to solve overload problems.

4. Real-time control

Virtually real-time decisions. In the normal mode (no emergency situation caused by an “unfortunate event”), these decisions should not modify production/consumption over a market period.

Examples: modifying the reactive power injected by wind farms into the network, changing the tap setting of transformers.



GREDOR as an optimization problem

- \mathcal{M} : Set of possible **m**odels of interaction
- \mathcal{I} : Set of possible **i**nvestment strategies
- \mathcal{O} : Set of possible **o**perational planning strategies
- \mathcal{R} : Set of possible **r**eal-time control strategies

Solve:

$$\arg \max_{(m,i,o,r) \in \mathcal{M} \times \mathcal{I} \times \mathcal{O} \times \mathcal{R}} \text{social_welfare}(m, i, o, r)$$

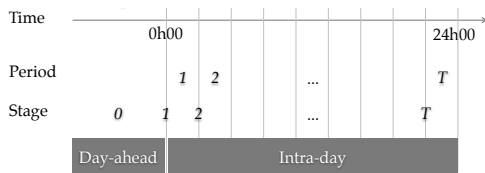


A simple example

\mathcal{M} : Reduced to one single element.

Interaction model mainly defined by these two components:

1. The DSO can buy the day-ahead load flexibility service.
2. Between the beginning of every market period, it can decide to curtail generation for the next market period or activate the load flexibility service. Curtailment decisions have a cost.



\mathcal{I} : Made of two elements. Either to invest in an asset A or not to invest in it.

\mathcal{O} : The set of operational strategies is the set of all algorithms that:

- (i) In the day-ahead process information available to the DSO to decide which flexible loads to buy
- (ii) Process before every market period this information to decide
 - ▶ how to modulate the flexible loads
 - ▶ how to curtail generation.

\mathcal{R} : Empty set. No real-time control implemented.

$social_welfare(m, i, o, r)$: The (expected) costs for the DSO.



The optimal operational strategy

Let o^* be an optimal operational strategy. Such a strategy has the following characteristics:

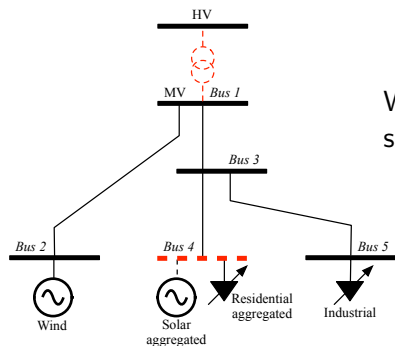
1. For every market period, it leads to a safe operating point of the network (no overloads, no voltage problems).
2. There are no strategies in \mathcal{O} leading to a safe operating point and having a lower (expected) **total cost** than o^* . This cost is defined as the cost of buying flexibility plus the costs for curtailing generation.

It can be shown that the optimal operation strategy can be written as a **stochastic sequential optimization problem**.

Solving this problem is challenging. Getting even a good suboptimal solution may be particularly difficult for large distribution networks and/or when there is strong uncertainty on the power injected/withdrawn day-ahead.



Illustrative problem



When Distributed Generation (DG) sources produce a lot of power:

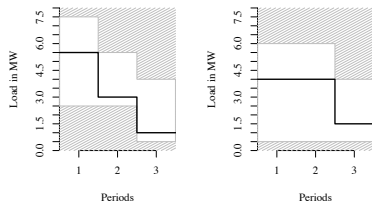
- ▶ overvoltage problem at *Bus 4*,
- ▶ congestion problem on the *MV/HV* transformer.

Two flexible loads; only three market periods; possibility to curtail the two DG sources before every market period (at a cost).



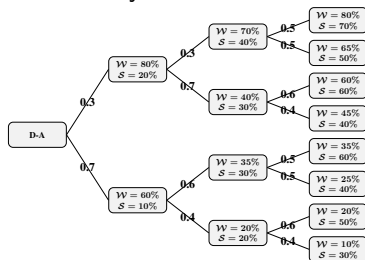
Information available to the DSO on the day-ahead

The flexible loads offer:



Residential aggregated (left) and industrial (right).

Scenario tree for representing uncertainty:



W = Wind; S = Sun.

Additional information: a load-flow model of the network; the price (per MWh) for curtailing generation.



Decisions output by o^*

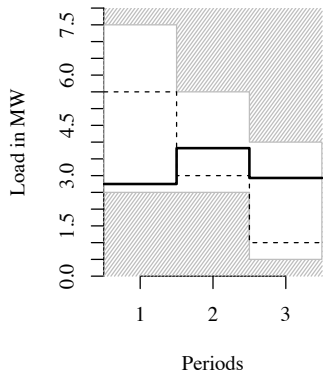
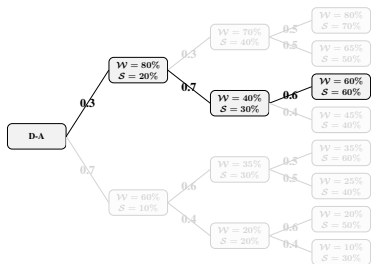
The day-ahead: To buy flexibility offer from the *residential aggregated load*.

Before every market period: We report results when generation follows this scenario.

Results:

Generation never curtailed.

Load modulated as follows:



On the importance of managing uncertainty well

	$E\{cost\}$	max_cost	min_cost	$std_dev.$
σ^*	46\$	379\$	30\$	72\$
MSA	73\$	770\$	0\$	174\$

where MSA stands for Mean Scenario Strategy.

Observations:

Managing uncertainty well leads to lower expected costs than working along a mean scenario.

More results in:

Q. Gemine, E. Karangelos, D. Ernst and B. Cornélusse. *“Active network management: planning under uncertainty for exploiting load modulation”*.



The optimal investment strategy

Remember that we had to choose between making investment A or not. Let AP be the recovery period and $cost_A$ the cost of investment A . The optimal investment strategy can be defined as follows:

1. Simulate using operational strategy o^* the distribution network with element A several times over a period of AP years. Extract from the simulations the expected cost of using o^* during AP years. Let $cost_o^*_with_A$ be this cost.
2. Simulate using operational strategy o^* the distribution network without element A several times over a period of AP years. Extract from the simulations the expected cost of using o^* during AP years. Let $cost_o^*_without_A$ be this cost.
3. If $cost_A + cost_o^*_with_A \leq cost_o^*_without_A$, do investment A . Otherwise, not.



Solving the GREDOR optimization problem

Solving the complete optimization problem

$$\arg \max_{(m,i,o,r) \in \mathcal{M} \times \mathcal{I} \times \mathcal{O} \times \mathcal{R}} \text{social_welfare}(m, i, o, r)$$

in a single step is too challenging. Therefore, the problem has been decomposed in 4 subproblems:

1. Finding m^* , the optimal interaction model,
2. Finding i^* , the optimal investment strategy,
3. Finding o^* , the optimal operation strategy,
4. Finding r^* , the optimal real-time control strategy.



Finding m^*

The set \mathcal{M} of interaction models is only limited by our imagination. In the GREDOR project, we have selected **four interaction models** to study in more detail.

These interaction models are defined by:

1. The type of access contract between the users of the grid and the DSO,
2. The financial compensation of flexibility services.

For simplicity, we focus only on the **access contract** feature of the interaction models in this presentation.

More information

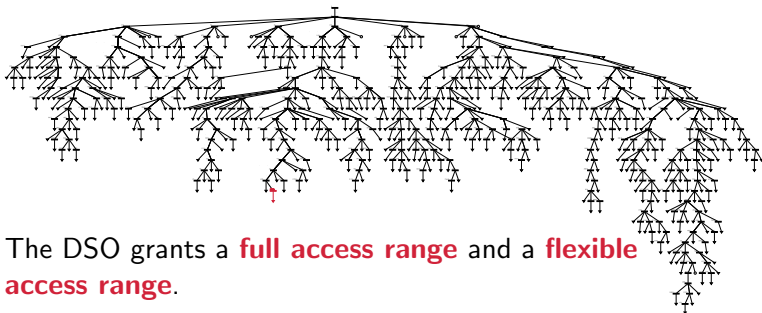
S. Mathieu, Q. Louveaux, D. Ernst, and B. Cornélusse, “*DSIMA: A testbed for the quantitative analysis of interaction models within distribution networks*”.



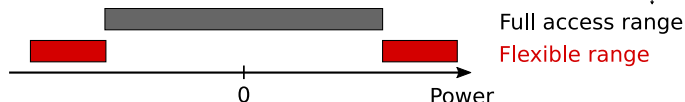
Access agreement

The interaction models are based on **access contracts**.

- ▶ The grid user **requests** access to a given bus.



- ▶ The DSO grants a **full access range** and a **flexible access range**.



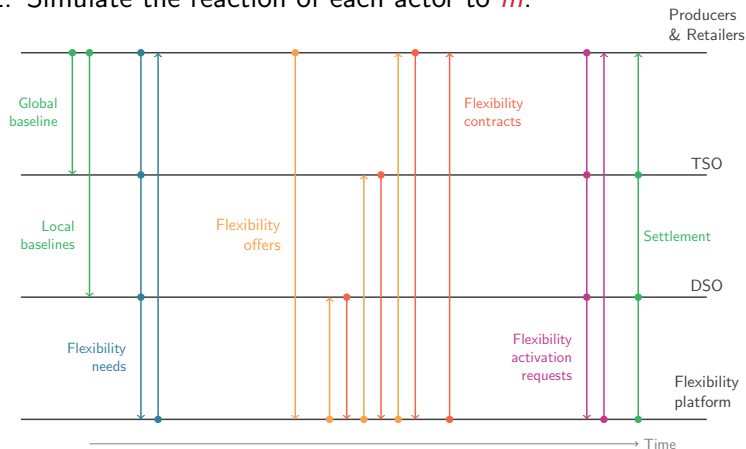
- ▶ The **width** of these ranges depends on the **interaction model**.



Flow of interactions

One method to obtain $social_welfare(m, i, o, r)$ is to simulate the distribution system with all its actors and compute the surpluses and costs of each of them. This simulation requires us to:

1. Define all decision stages as function of m ,
2. Simulate the reaction of each actor to m .



One day in the life of a producer selling flexibility services

A **producer** performs the following actions:

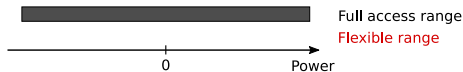
1. Sends its **baseline** to the **TSO** at the **high-voltage** level.
I will produce 15MWh in distribution network 42 between 8am and 9am.
2. Sends its **baseline** to the **DSO** at the **medium-voltage** level.
I will produce 5MWh in bus 20 between 8am and 9am.
3. Obtains **flexibility needs** of the flexibility services users.
The DSO needs 3MWh downward in bus 20 between 8am and 9am.
4. Proposes **flexibility offers**.
I can curtail my production by 2MWh in bus 20 between 8am and 9am.
5. Receives **activation requests** for the contracted services.
Curtail production by 1MWh in bus 20 between 8am and 9am.
6. Decides the final **realizations**.
Produce 4MWh, or 5MWh if more profitable, in bus 20 between 8am and 9am.



Parameters of the interaction models

The implementation of the models are based on 3 **access contracts**:

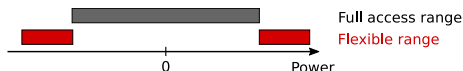
- ▶ **“Unrestricted” access**: Allow the grid users access to the network **without restriction**.



- ▶ **“Restricted” access**: **Restrict** the grid users so that no problems can occur.



- ▶ **“Flexible” access**: Allow the users to produce/consume as they wish but if they are **in the flexible range**, they are obliged to propose **flexibility services** to the DSO.



In this presentation, we assume that these flexibility services are paid by the **DSO** at a cost which **compensates** the **imbalance** created by the activation of the service.



Effects of the access range on the baseline of an actor

The access restriction of the DSO is shown by the red dotted line.

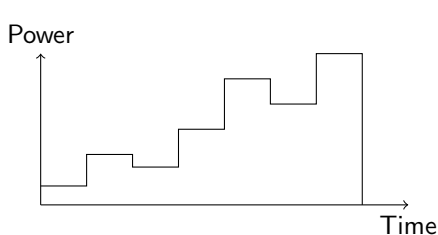


Figure : Unrestricted access

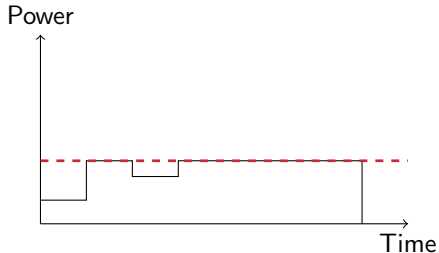


Figure : Restricted access

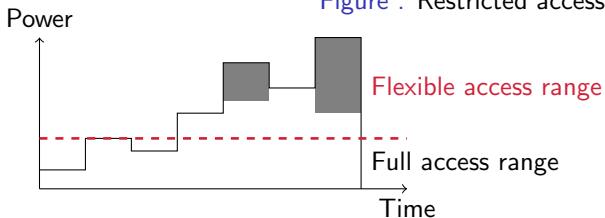


Figure : Flexible access - The filled areas represents the energy curtailed by the DSO by the activation of mandatory flexibility services.

Back to our optimization problem

These models are studied for a given investment, operation planning and real-time control strategy, i.e. **one strategy** (i, o, r) .

$$\arg \max_{(m,i,o,r) \in \mathcal{M} \times I \times \mathcal{O} \times \mathcal{R}} \text{social_welfare}(m, i, o, r)$$

Consider the simplified subset of interaction models

$\mathcal{M} = \{ \text{"unrestricted"}, \text{"restricted"}, \text{"flexible"} \}$.

$\text{social_welfare}(m, i, o, r)$: the sum of the surpluses minus the costs of all actors and a cost given by the protection scheme of the real-time control strategy.

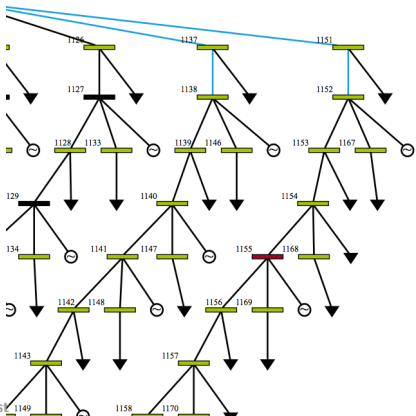


Open-source testbed

The testbed evaluating interaction models is available as an open source code at the address

<http://www.montefiore.ulg.ac.be/~dsima/>.

It is based on an agent-based model where every agent solves an optimization problem for each decision stage.

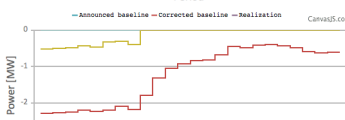
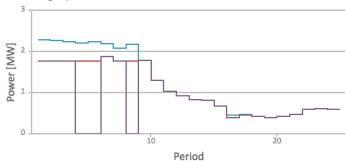


Bus 56

Data

Shed	in period(s) 4, 5, 8
Flexibility used	in period(s) 1, 2, 3, 4, 5, 6, 7, 8
Downward access request bound	0.00
Upward access request bound	2.71
Safe downward access bound	0.00
Safe upward access bound	1.77

Time graphs



Comparison of the interaction models

Simulation of a **75 bus** system in an **expected 2025 year** with **3 producers and 3 retailers** owning assets connected to the DN.

Interaction model	Unrestricted	Restricted	Flexible	
Welfare	29077	27411	39868	€
Protections cost	12071	0	914	€
TSO surplus	2878	2879	2873	€
DSO costs	0	0	444	€
Producers surplus	37743	24005	37825	€
Retailers surplus	527	527	528	€

Table : Mean daily welfare and its distribution between the actors.

Key messages

Unrestricted: Too much renewable production leading to high protections cost. Who would pay this cost?

Restricted: Little allowed renewable generation but a secure network.

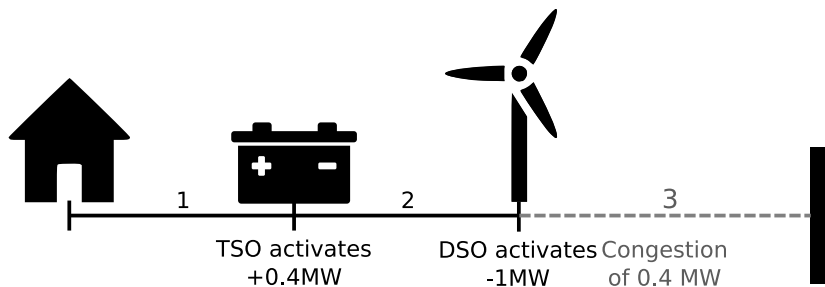
Flexible: Large amount of renewable generation but still requiring a few sheddings due to coordination problems.



Coordination problem

The model “flexible” suffers from the **lack of coordination** between the **DSO** and the **TSO**.

Assume that the flow exceeds the capacity of line 3 by 1MW. To solve this issue, the **DSO curtails** a windmill by 1MW. In the same time, assume that the **TSO asks** a storage unit to **inject** 0.4MW. These activations leads to a remaining congestion of 0.4MW.



Finding i^*

The investment strategy i^* is divided in two parts:

1. Announcing the capacity of renewables that may be connected to the network: **Global Capacity ANnouncement**.
2. Determining the target optimal network: **Investment planning tool**.



GCAN: Global Capacity ANnouncement

GCAN is a tool that determines the maximum hosting capacity of a medium voltage distribution network.

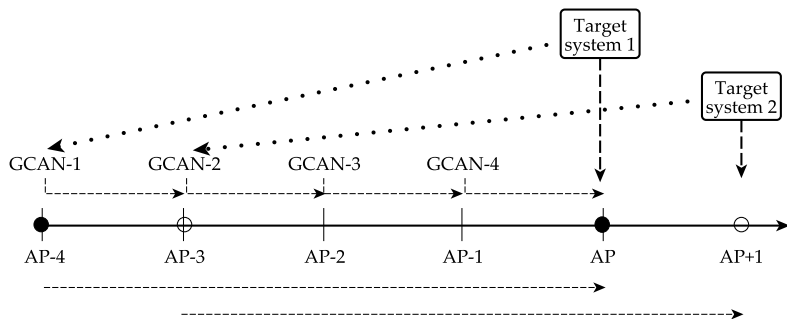
Features of GCAN:

- ▶ Determines the capacity of each bus.
- ▶ Accounts for the future of the system.
- ▶ Relies on the tools that are routinely used by DSOs (repeated power flows).
- ▶ Results may be published in appropriate form (tabular, map, through the regulator, etc.).

GCAN is not meant to be a replacement for more detailed computations for generation connection projects.



GCAN procedure



The procedure is implemented in a **rolling horizon** manner.
The results are refreshed at each step of the planning horizon.

More information:

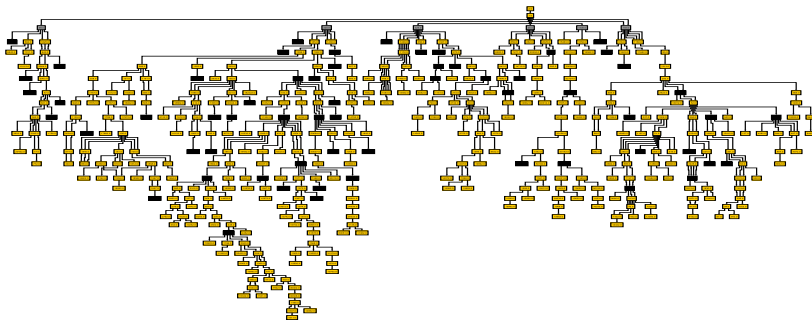
B. Cornélusse, D. Vangulick, M. Glavic, D. Ernst: *“Global capacity announcement of electrical distribution systems: A pragmatic approach”*.



GCAN results

Subst. name	Feeder name	Voltage (kV)	Gener. (MW)	Gener. type
99	FN1	10.0	0.75	PV
2064	FN1	10.0	0.30	PV
...

Black squares in one-line diagram indicate generation substations.



Investment planning tool

Main software tools

Smart Sizing – determines the main features of the ideal network.

Rating of cables, number of substations, etc.

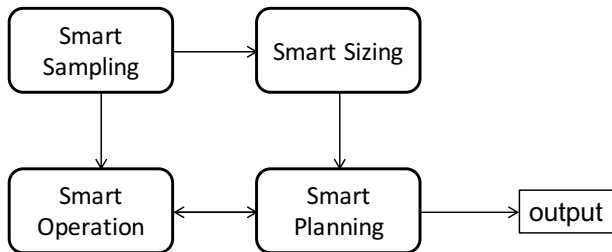
Smart Planning – development of grid expansion plans.

Change cable between bus 16 and 17 in 2020.

Supporting software tools

Smart Operation – mimics the grid operation. Proxy of o^* .

Smart Sampling – provides exogenous data such as load profiles.



Smart sampling

Smart Sampling creates calibrated **time series models** able to generate **synthetic load and generation profiles** mimicking the statistical properties of real measurements.

Advantages

- ▶ **Compactness:** as they are represented by mathematical formula with a few parameters.
- ▶ **Information reduction:** computational burden can be reduced by working on a reduced statistically relevant data set.

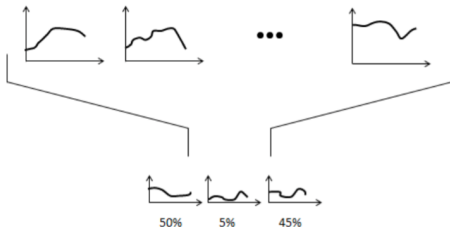
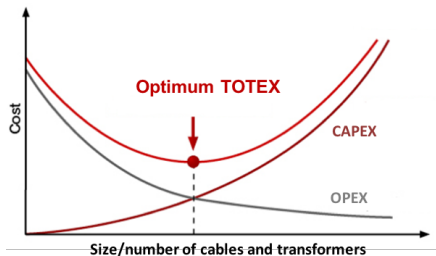


Figure : A large set of profiles is reduced to 3 profiles.

Smart Sizing

A tool for long-term planning to find **“least cost features of the distribution network”**, taking into account CAPEX/OPEX while meeting voltage constraint given **targets of load and DG penetration**.



Smart sizing evaluates the **“traditional aspects”** just like any traditional planning tool (number of transformer, infrastructure cost, cost due to losses, etc.), the **benefits of flexibility** and the impact of **distributed generation** on grid costs.



Smart Planning

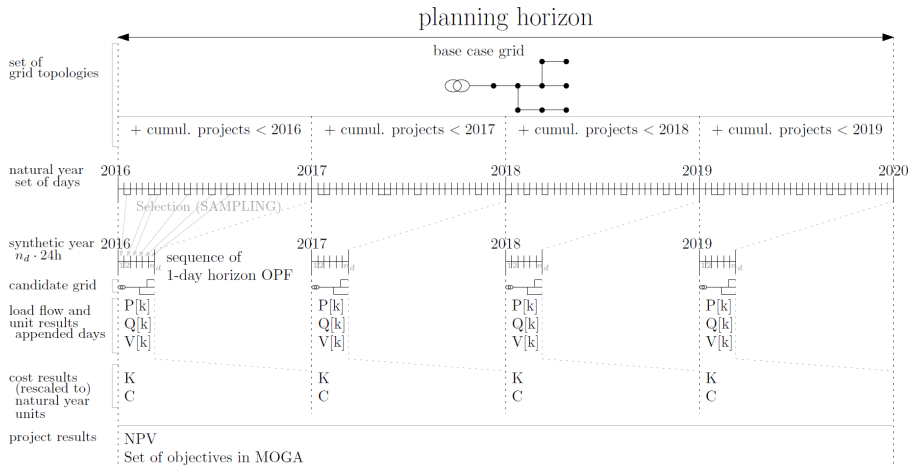
The multistage investment planning problem is hard to tackle as planning decisions are subject to **uncertainty**.

The smart planning tool **schedules optimal investment plans** from today to target architecture (with smart planning) integrating the optimal future system operation (with smart operation). It decides:

- ▶ The type of grid investment and optimal year of investment,
Install a cable between node A and B in 2016.
- ▶ The optimal use of available flexibility,
Load shifting, PV curtailment.
- ▶ Reactive power support.
From PV/storage.



Smart Planning - Overview



Finding o^* - Goal

Given an electrical distribution system, described by:

- ▶ \mathcal{N} and \mathcal{L} , the network infrastructure;
- ▶ \mathcal{D} , the electrical devices connected to the network;
- ▶ \mathcal{C} , a set of operational limits;
- ▶ \mathcal{T} , the set of time periods in the planning horizon.

We want the best strategy o^* which defines the set of **power injections** of the devices

$$\{(P_d, Q_d) \mid d \in \mathcal{D}\}$$

to be such that the **operational constraints**

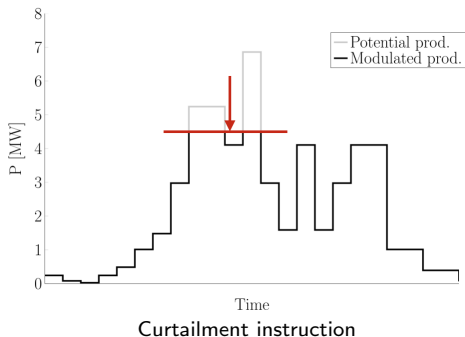
$$\{g_c(\cdot) \geq 0 \mid c \in \mathcal{C}\}$$

are respected for all $t \in \mathcal{T}$.



Control actions - curtailment

A **curtailment instruction**, i.e. an upper limit on the production level of a generator, can be imposed for some distributed generators.

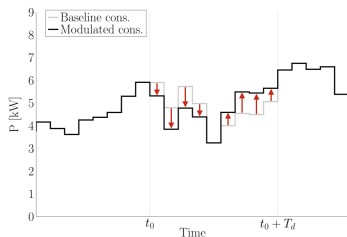


The DSO has to **compensate for the energy that could not be produced** because of its curtailment instructions, at a price that is proportional to the amount of curtailed energy.

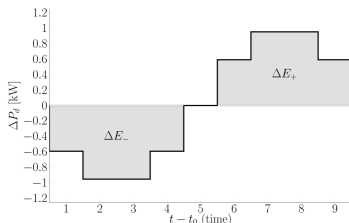


Control actions - load modulation

The **consumption** of the flexible loads can be **modulated**, as described by a modulation signal over a certain time period.



Load modulation instruction



Load modulation signal

The **activation** of a flexible load is acquired **in exchange for a fee** that is defined by the flexibility provider.



Decisional Framework

We rely on a **Markov Decision Process** framework for modeling and decision-making purposes. At each time-step t , the system is described by its state \mathbf{s}_t and the control decisions of the DSO are gathered in \mathbf{a}_t .

The evolution of the system is governed by:

$$\mathbf{s}_{t+1} \sim p(\cdot | \mathbf{s}_t, \mathbf{a}_t),$$

which models that the next state of the system follows a probability distribution that is conditional on the current state and on the actions taken at the corresponding time step.



Decisional Framework

A **cost function** evaluates the efficiency of control actions for a given transition of the system:

$$\begin{aligned} \text{cost}(\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{t+1}) = & \text{curtailment costs} + \\ & \text{flex. activation costs} + \\ & \text{penalties for violated op. constraints.} \end{aligned}$$

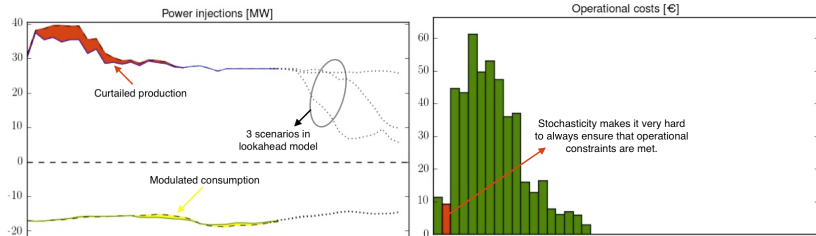
Finally, we associate the operational planning problem with the minimization of the **expected sum** of the **costs** that are accumulated over a T -long trajectory of the system:

$$\min_{\mathbf{a}_1, \dots, \mathbf{a}_T} \mathbb{E}_{\mathbf{s}_1, \dots, \mathbf{s}_T} \left(\sum_{t=1}^{T-1} \text{cost}(\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{t+1}) \right)$$



Computational Challenge

Finding an **optimal sequence** of control actions is **challenging** because of many computational obstacles. The figures illustrate a simple lookahead policy on an ANM simulator.



This **simulator** and a 77-buses test system are available at

<http://www.montefiore.ulg.ac.be/~anm/>.

More information

Q. Gemine, D. Ernst, B. Cornélusse. "Active network management for electrical distribution systems: problem formulation, benchmark, and approximate solution".

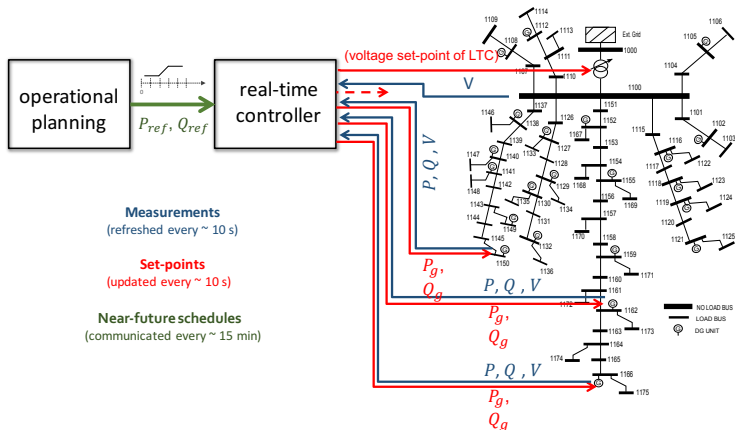


Centralized real-time controller

The **role** of the real-time controller is to **handle limit violations** observed or predicted close to real-time.

Over/under-voltage, thermal overload.

To bring the system to a **safe state**, the controller controls the **DG units outputs** and adjusts the **transformers' tap positions**.



Multistep optimization problem

Consider a set of **control horizon** periods \mathcal{T} . For each time step k we solve the following problem:

$$\min_{P_g, Q_g} \sum_{i \in \mathcal{T}} \pi^P \|P_g(k+i) - P_{ref}(k+i)\|^2 + \sum_{i \in \mathcal{T}} \pi^C \|Q_g(k+i) - Q_{ref}(k+i)\|^2$$

where π^P and π^C are coefficients prioritizing active over reactive control.

Linearized system evolution

For all $i \in \mathcal{T}$,

$$V(k+i | k) = V(k+i-1 | k) + S_V [u(k+i-1) - u(k+i-2)]$$

$$I(k+i | k) = I(k+i-1 | k) + S_I [u(k+i-1) - u(k+i-2)]$$

where S_V and S_I are sensitivities matrices of voltages and currents with respect to control changes.

Operational constraints

For all $i \in \mathcal{T}$,

$$V^{low}(k+i) \leq V(k+i | k) \leq V^{up}(k+i)$$

$$I(k+i | k) \leq I^{up}(k+i)$$

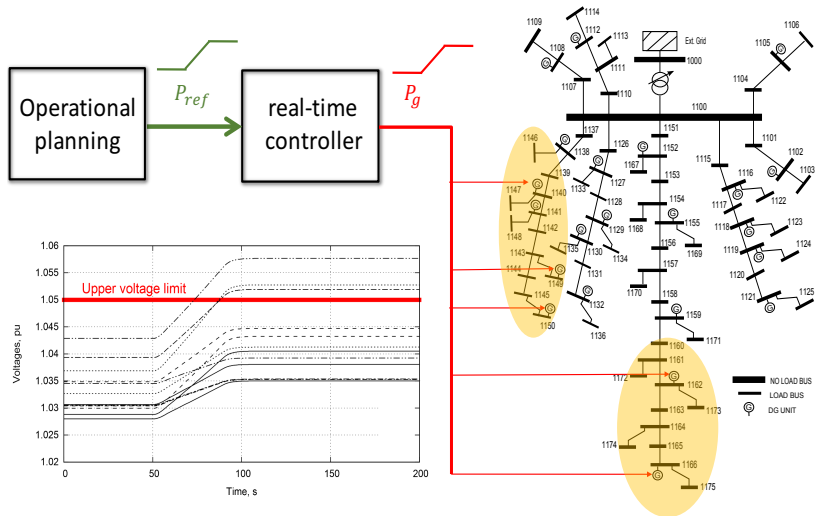
For all $i \in \mathcal{T}$,

$$u^{min} \leq u(k+i | k) \leq u^{max}$$

$$\Delta u^{min} \leq u(k+i | k) - u(k+i-1 | k) \leq \Delta u^{max}$$



Network behavior without real-time corrective control



Network behaviour with real-time corrective control

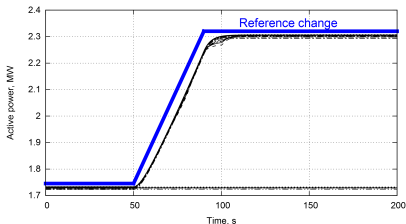


Figure : Active power

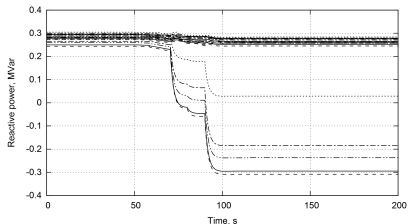


Figure : Reactive power

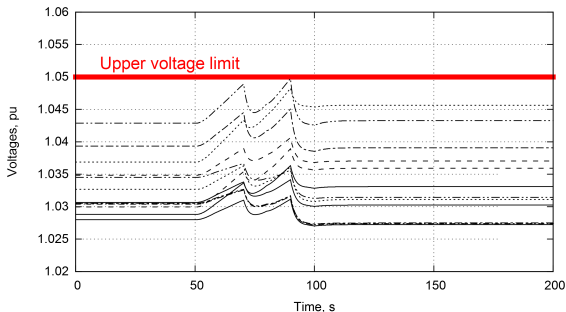


Figure : Voltages

Four main challenges of the GREDOR project

Data:

Difficulties for DSOs to gather the right data for building the decision models (especially for real-time control).

Computational challenges:

Many of the optimization problems in GREDOR are out of reach of state-of-the-art techniques.

Definition of *social_welfare*($\cdot, \cdot, \cdot, \cdot$) function:

Difficulties to reach a consensus on what is social welfare, especially given that actors in the electrical sector have conflicting interests.

Human factor:

Engineers from distribution companies have to break away from their traditional practices. They need incentives to change their working habits.



Acknowledgements

1. To all the partners of the GREDOR project:



2. To the Public Service of Wallonia - Department of Energy and Sustainable Building for funding this research.



GREATOR project website

More information, as well as the list of all our **published scientific papers** are available at the address:

<https://www.gredor.be>

The screenshot shows the GREATOR project website. At the top, there is a navigation menu with links for Home, Work packages, Partners, Publications, and Links. Below the menu is a large QR code. To the left of the QR code, there is a text snippet: "Gest... RE... is... in... 'ables'". Below the QR code, there is a banner image showing wind turbines and solar panels. Below the banner, there is a section titled "Communication day" with the text: "The event was held in Molin de Beuson Wednesday April 29, 2015 with 15 attendees. For those interested, presentations can be found [here](#)." and a social media link: "https://www.facebook.com/GredorProject".



Outline

Active network management

Rethinking the whole decision chain - the GREDOR project

GREDOR as an optimization problem

Finding m^* , the optimal interaction model

Finding i^* , the optimal investment strategy

Finding o^* , the optimal operation strategy

Finding r^* , the optimal real-time control strategy

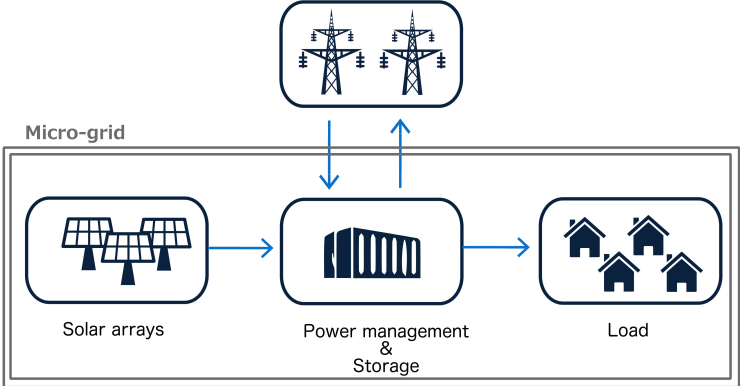
Conclusion

Microgrid: an essential element for integrating renewable energy



Microgrid

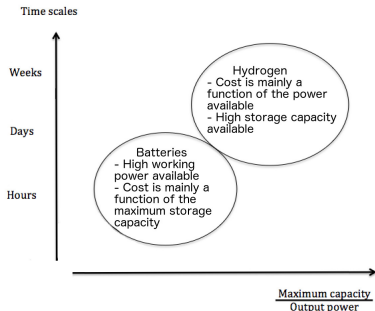
A microgrid is an electrical system that includes multiple loads and distributed energy resources that can be operated in parallel with the broader utility grid or as an electrical island. **Essential objects** for integrating large amount of renewable energy into distribution networks.



Microgrids and storage

Many authors claim that microgrids should come with two types of storage device:

- ▶ A short-term storage capacity (typically batteries),
- ▶ A long-term storage capacity (e.g., hydrogen).



Here we study the sizing and the operation of a microgrid powered by PV panels and having batteries and a long-term storage device working with hydrogen.



Formalization and problem statement: exogenous variables

$$E_t = (c_t, i_t, \mu_t, e_t^{PV}, e_t^B, e_t^{H_2}) \in \mathcal{E}, \forall t \in \mathcal{T}$$

and with $\mathcal{E} = \mathbb{R}^{+2} \times \mathcal{I} \times \mathcal{E}^{PV} \times \mathcal{E}^B \times \mathcal{E}^{H_2}$,

where:

- ▶ $c_t [W] \in \mathbb{R}^+$ is the electricity demand within the microgrid;
- ▶ $i_t [W/m \text{ or } W/W_p] \in \mathbb{R}^+$ denotes the solar irradiance incident to the PV panels;
- ▶ $\mu_t \in \mathcal{I}$ represents the model of interaction;
- ▶ $e_t^{PV} \in \mathcal{E}^{PV}$ models the photovoltaic technology;
- ▶ $e_t^B \in \mathcal{E}^B$ models the battery technology;
- ▶ $e_t^{H_2} \in \mathcal{E}^{H_2}$ models the hydrogen storage technology;
- ▶ $\mathcal{T} = \{1, 2, \dots, T\}$ represents the discrete time steps.



Formalization and problem statement: state space

Let $s_t \in \mathcal{S}$ denotes a time varying vector characterizing the microgrid's state at time $t \in \mathcal{T}$:

$$s_t = (s_t^{(i)}, s_t^{(o)}) \in \mathcal{S}, \forall t \in \mathcal{T} \text{ and with } \mathcal{S} = \mathcal{S}^{(i)} \times \mathcal{S}^{(o)},$$

where $s_t^{(i)} \in \mathcal{S}^{(i)}$ and $s_t^{(o)} \in \mathcal{S}^{(o)}$ represent the state information related to the infrastructure and to the operation of the microgrid, respectively.

$$s_t^{(i)} = (x_t^{PV}, x_t^B, x_t^{H_2}, L_t^{PV}, L_t^B, L_t^{H_2}, D_t^B, P_t^B, R_t^{H_2}, \eta_t^{PV}, \eta_t^B, \eta_t^{H_2}, \zeta_t^B, \zeta_t^{H_2}, r_t^B, r_t^{H_2}) \in \mathcal{S}^{(i)} \forall t \in \mathcal{T} \text{ and with } \mathcal{S}^{(i)} = \mathbb{R}^{+9} \times]0, 1]^7,$$

$$s_t^{(o)} = (s_t^B, s_t^{H_2}) \in \mathcal{S}^{(o)}, \forall t \in \mathcal{T} \text{ and with } \mathcal{S}^{(o)} = \mathbb{R}^{+2}$$



Formalization and problem statement: action space

As for the state space, each component of the action vector $a_t \in \mathcal{A}$ can be related to either notion of the sizing or control, the former affecting the infrastructure of the microgrid, while the latter affects its operation. We define the action vector as:

$$a_t = (a_t^{(i)}, a_t^{(o)}) \in \mathcal{A}_t, \forall t \in \mathcal{T} \text{ and with } \mathcal{A}_t = \mathcal{A}^{(i)} \times \mathcal{A}_t^{(o)},$$

where $a_t^{(i)} \in \mathcal{A}^{(i)}$ relates to sizing actions and $a_t^{(o)} \in \mathcal{A}_t^{(o)}$ to control actions.



A microgrid featuring PV, battery and storage using H_2 has two control variables that correspond to the power exchanges between the battery, the hydrogen storage, and the rest of the system:

$$a_t^{(o)} = (p_t^B, p_t^{H_2}) \in \mathcal{A}_t^{(o)}, \forall t \in \mathcal{T},$$

where p_t^B [W] is the power provided to the battery and with $p_t^{H_2}$ [W] the power provided to the hydrogen storage device. We have, $\forall t \in \mathcal{T}$:

$$\mathcal{A}_t^{(o)} = \left([-\zeta_t^B s_t^B, \frac{x_t^B - s_t^B}{\eta_t^B}] \cap [-P_t^B, P_t^B] \right) \times \left([-\zeta_t^{H_2} s_t^{H_2}, \frac{R_t^{H_2} - s_t^{H_2}}{\eta_t^{H_2}}] \cap [-x_t^{H_2}, x_t^{H_2}] \right),$$

which expresses that the bounds on the power flows of the storing devices are, at each time step $t \in \mathcal{T}$, the most constraining among the ones induced by the charge levels and the power limits.



Robust sizing of a microgrid

Let C be a function defined over the triplet $(state, action, environment)$ such that $C(s_t, a_t, E_t)$ is the sum of investment costs and operating costs related to the microgrid over the period t till $t + 1$.

Let

$$\mathbf{E} = \{(E_t^1)_{t=1\dots T}, \dots, (E_t^N)_{t=1\dots T}\}$$

with $E_t^i \in \mathcal{E}, \forall t \in \mathcal{T}, i \in \{1, \dots, N\}$ be a set of plausible scenarios for the exogeneous variables.

We define the *robust optimization of the sizing of a microgrid where investments can only be made at $t = 1$* by:

$$\begin{aligned} \max_{i \in \{1, \dots, N\}} \min_{\substack{a_{i,t} \in \mathcal{A}_{i,t}, s_{i,t} \in \mathcal{S}, \\ \forall t \in \mathcal{T}}} & \sum_{t \in \mathcal{T}} C(s_{i,t}, a_{i,t}, E_t^i) \\ \text{s.t.} & s_{i,t} = f(s_{i,t-1}, a_{i,t-1}), \quad \forall t \in \mathcal{T} \setminus \{1\} \\ \text{s.t.} & a_{i,t}^{(i)} = 0, \quad \forall t \in \mathcal{T} \setminus \{1\} \\ \text{s.t.} & a_{j,1}^{(i)} = a_{k,1}^{(i)}, \quad \forall j, k \in \{1, \dots, N\}, s_{i,1}^{(o)} = 0 \end{aligned}$$

Levelized Energy Cost (LEC)

Given a microgrid trajectory $(s_t, a_t, s_{t+1})_{t \in \mathcal{T}}$ and an environment trajectory $(E_t)_{t \in \mathcal{T}}$, the LEC_r is computed as follows:

$$LEC_r = \frac{\sum_{y=1}^n \frac{I_y - M_y}{(1+r)^y} + I_0}{\sum_{y=1}^n \frac{\epsilon_y}{(1+r)^y}}$$

where

- ▶ n = Life of the system (years)
- ▶ I_y = Investment expenditures in the year y
- ▶ M_y = Operational revenues in the year y
- ▶ ϵ_y = Electricity consumption in the year y
- ▶ r = Discount rate which may refer to the interest rate or discounted cash flow

The LEC_r represents the price at which electricity must be generated to break even over the lifetime of the project.



Investment costs

The overall investment cost I_y can be written as the sum of the investments in the PV panels, the battery and the hydrogen:

$$I_y = I_y^{PV} + I_y^B + I_y^{H_2}$$



Operational costs

We will now associate to each time step a reward function ρ_t that is a function of the net demand for electricity and the actions:

$$\rho_t : (a_t, d_t) \rightarrow \mathbb{R}$$

From the reward function ρ_t , we obtain the operational revenues over year y defined as:

$$M_y = \sum_{t \in \tau_y} \rho_t$$

where τ_y is the set of time steps belonging to year y . We now introduce two variables:

- ▶ $\phi_t [W] \in \mathbb{R}^+$ as the local production of electricity that refers to the photovoltaic production given by:

$$\phi_t = x^{PV} i_t$$

- ▶ $d_t [W] \in \mathbb{R}$ as the net demand for electricity that is the difference between the consumption and the production:

$$d_t = c_t - \phi_t$$



Operational costs

In the case where the microgrid is fully off-grid, we consider that the microgrid has no possibility to generate any income. The reward function is therefore equal to the penalty induced by the energy that was not supplied to follow the demand:

$$\rho_t = \begin{cases} k E_t^I, & E_t^I < 0 \\ 0, & \text{otherwise} \end{cases}$$

where $E_t^I < 0$ is the quantity of energy not supplied at time t and k is the cost endured per kWh. The quantity of energy that the microgrid alone lacks to cover the consumption is given by:

$$E_t^I = - \sum_{R \in \{B, H_2\}} p_t^R - d_t, \quad \forall t \in \mathcal{T}$$



Linear programming

In the fully off-grid case, the overall optimization problem can be written as:

$$\text{Minimize } LEC = \frac{\sum_{t=0}^{T-1} \frac{-k F_t}{(1+r)^t} + I_0}{\sum_{y=1}^n \frac{e^y}{(1+r)^y}} \text{ with } y = \text{ceil}\left(\frac{t}{365}\right)$$

$$\text{With } \begin{aligned} 0 \leq s_t^B \leq x^B, & \quad \forall t \in [0, T] \\ 0 \leq p_t^{B,+} \leq P^B, & \quad \forall t \in [0, T-1] \\ -P_t^B \leq p_t^{B,-} \leq 0, & \quad \forall t \in [0, T-1] \\ 0 \leq s_t^{H_2} \leq R^{H_2}, & \quad \forall t \in [0, T] \\ 0 \leq p_t^{H_2,+} \leq x^{H_2}, & \quad \forall t \in [0, T-1] \\ -x^{H_2} \leq p_t^{H_2,-} \leq 0, & \quad \forall t \in [0, T-1] \\ s_t^B = s_{t-1}^B + \eta_t^B p_{t-1}^{B,+} + \frac{p_{t-1}^{B,-}}{\zeta_{t-1}^B}, & \quad \forall t \in [1, T] \\ s_t^{H_2} = s_{t-1}^{H_2} + \eta_t^B p_{t-1}^{H_2,+} + \frac{p_{t-1}^{H_2,-}}{\zeta_{t-1}^{H_2}}, & \quad \forall t \in [1, T] \\ F_t \leq -d_t - p_t^{B,+} - p_t^{B,-} - p_t^{H_2,+} - p_t^{H_2,-}, & \quad \forall t \in [1, T] \\ F_t \leq 0, & \quad \forall t \in [1, T] \end{aligned}$$



Results - Belgium

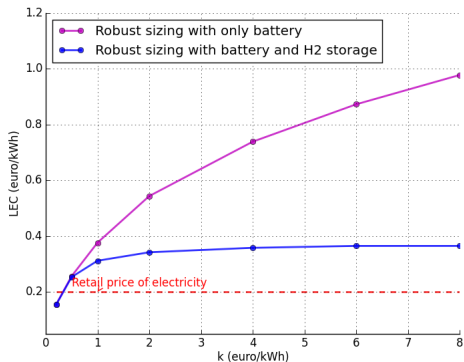


Figure : LEC in Belgium over 20 years for different investment strategies as a function of the cost endured per kWh.



Results - Belgium

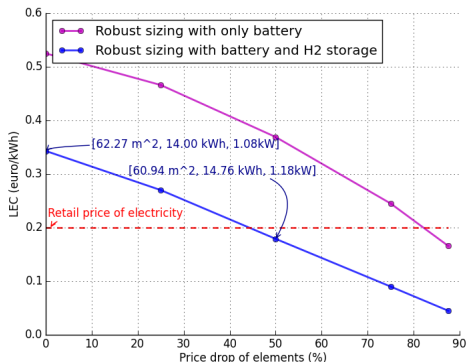


Figure : LEC in Belgium over 20 years for a value of loss load of 2€/kWh as a function of a unique price drop for all the constitutive elements of the microgrid.



Results - Spain

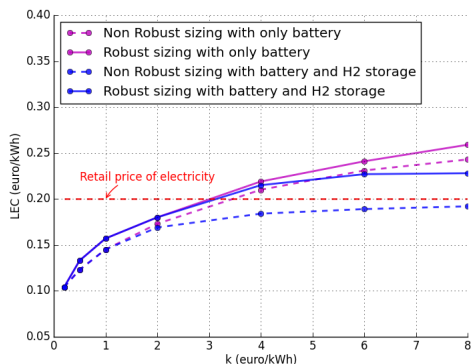


Figure : LEC ($r = 2\%$) in Spain over 20 years for different investment strategies as a function of the cost endured per kWh not supplied within the microgrid.



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