Decentralization Induced by Power System Flexibility:

Théotime Coudray[1] and Sandrine Michel[1]

[1]Université de Montpellier, UMR 5281 ART-Dev

1 Introduction

1.1 Motivation

1.2 Contributions

1.3 Paper outline

2 Methodology

We develop a detailed regional flexibility optimization framework implemented in Python. The model solves a multi-regional Mixed-Integer Linear Program (MILP) that co-optimizes generation dispatch, unit commitment, storage operation, demand response (DR), and inter-regional exchanges. It incorporates detailed techno-economic parameters from a YAML configuration file and supports flexibility-related constraints such as ramping, DR potential, and storage dynamics.

2.1 Model Formulation

Let $\mathcal{R}$ denote the set of regions and $\mathcal{T}$ the time index (e.g., half-hourly time steps). For each $(r, t) \in \mathcal{R} \times \mathcal{T}$, the following variables are defined:

- $g_k^{r,t}$ – generation by technology k in region r;
- $u_k^{r,t} \in \{0, 1\}$ – unit commitment status for tech k;

- $s_k^{r,t} \in \{0,1\}$ – startup indicator for k;
- $c_s^{r,t}$, $d_s^{r,t}$ – charge and discharge of storage tech s;
- $soc_s^{r,t}$ – state of charge for s;
- $dr^{r,t}$ – demand response (positive = load reduction);
- $f^{r\to r',t}$ – flow from r to r';
- slack variables $slack_{\pm}^{r,t}$ to handle imbalance;
- $curt^{r,t}$ – renewable curtailment (if enabled).

The objective is to minimize the total system cost:

$$\begin{aligned} \min \quad & \sum_{r,t} \Bigg[\sum_k \left(C_k^r \cdot g_k^{r,t} + C_k^{\text{fixed}} \cdot u_k^{r,t} + C_k^{\text{start}} \cdot s_k^{r,t} \right) + \sum_s \left(C_s^{\text{ch}} \cdot c_s^{r,t} + C_s^{\text{dis}} \cdot d_s^{r,t} \right) \\ & \quad + C^{\text{DR}} \cdot |dr^{r,t}| + \sum_{r' \neq r} C_{r\to r'}^{\text{flow}} \cdot f^{r\to r',t} + P^{\text{slack}} \cdot (slack_+^{r,t} + slack_-^{r,t}) + P^{\text{curt}} \cdot curt^{r,t} \Bigg] \end{aligned} \tag{1}$$

2.2 Constraints

The model includes:

C1. Energy balance (per region and timestep):

$$\sum_k g_k^{r,t} + \sum_s d_s^{r,t} + \sum_{r' \neq r} (1 - \ell_{r'\to r}) f^{r'\to r,t} + dr^{r,t} = L^{r,t} + \sum_s c_s^{r,t} + curt^{r,t} + slack_+^{r,t} - slack_-^{r,t} \tag{2}$$

C2. Generation capacity and UC linkage:

$$0 \leq g_k^{r,t} \leq G_k^r, \quad g_k^{r,t} \leq G_k^r \cdot u_k^{r,t} \tag{3}$$

Startup logic and min up/down time are enforced as:

$$s_k^{r,t} \geq u_k^{r,t} - u_k^{r,t-1} \tag{4}$$

$$u_k^{r,t} \geq s_k^{r,\tau}, \quad \forall \tau \in [t, t + \text{min\_up} - 1] \text{ if } s_k^{r,t} = 1 \tag{5}$$

C3. Storage dynamics and bounds:

$$soc_s^{r,t+1} = soc_s^{r,t} \cdot \delta_s + \eta_s^{\text{ch}} \cdot c_s^{r,t} - \frac{1}{\eta_s^{\text{dis}}} \cdot d_s^{r,t} \tag{6}$$

$$0 \leq soc_s^{r,t} \leq SOC_s^{\max}, \quad 0 \leq c_s^{r,t}, d_s^{r,t} \leq P_s^{\max} \tag{7}$$

C4. DR potential:

$$|dr^{r,t}| \leq \alpha_r \cdot L^{r,t}, \quad \sum_t dr^{r,t} = 0 \tag{8}$$

C5. Interregional flows:

$$0 \leq f^{r \to r',t} \leq F_{r \to r'}^{\max} \tag{9}$$

C6. Ramping constraints:

$$|g_k^{r,t} - g_k^{r,t-1}| \leq \rho_k \cdot G_k^r \tag{10}$$

C7. Flexibility diversity (optional): configurable thresholds can enforce a minimum share of flexibility to be covered by storage, DR, and exchange.

2.3 Dual Variables and LP Relaxation

After solving the MILP, we freeze $\mathbf{y} = \mathbf{y}^\star$ and relax the integrality constraints to obtain a Linear Program. Solving the LP yields:

- $\boldsymbol{\lambda}_{r,t}$: the shadow price of (**??**), interpreted as the regional marginal cost of electricity (nodal price);
- $\boldsymbol{\mu}$: duals on capacity constraints, including line flow limits, storage power bounds, and DR ceilings.

These multipliers enable a comparison between actual operational cost and market-based nodal valuation.

2.4 Implementation

The model is implemented in Python using `PuLP`. Constraints and cost parameters are dynamically built from a YAML configuration file, and post-processing scripts (in Jupyter) extract time-series of costs and marginal prices for visualisation and comparison.

2.5 Data Sources

The model relies on empirical data from publicly available platforms and national reports:

- **Electricity demand** profiles are retrieved from the *ODRÉ* platform[1], which provides regional consumption series for mainland France.
- **Renewable generation profiles** (solar and wind) also come from *ODRÉ*.
- **Installed capacities**, **flexibility parameters**, and **costs assumptions** are informed by official literature, including regional energy planning documents and technical reports from RTE (*Réseau de Transport d'Électricité*), such as the "Panorama régional de l'électricité" series.

All time series are processed and aggregated to half-hourly resolution.

2.6 Parameterization

All technical and economic parameters used in the simulation are loaded from a centralized YAML configuration file. This file defines, for each region and technology, cost structures, unit commitment logic, storage characteristics, transport capacities, and demand response capabilities.

Table 1 summarizes the key values used in the 2022 full-year baseline simulation.

[1] `https://opendata.reseaux-energies.fr`

Table 1: Selected model parameters for the baseline 2022 configuration

Parameter	**Value / Description**
Generation costs	Hydro: €20–25/MWh, Nuclear: €30/MWh, Gas: €75/MWh, Fuel: €85/MWh, Biofuel: €45/MWh (region-specific)
Unit commitment costs	Fixed: €100–210/h, Startup: €200–1100/start depending on tech and region
Demand response cost	€120/MWh (penalty for activation)
Storage costs	Charge: €35/MWh, Discharge: €50/MWh
Slack penalty	€50,000/MWh (for infeasibility buffer)
Curtailment penalty	€10,000/MWh (when curtailment is enabled)
Storage efficiencies	Charge: 90%, Discharge: 85–90%, self-discharge: 19.2%/hour for batteries
Initial SOC	50% for all storage units
Storage sizes	e.g. Auvergne-Rhône-Alpes: 3.6 GW (STEP), 100 MW / 200 MWh (batteries)
DR limits	Max shift: 5% of load, total energy: 4000–10,000 MWh depending on region
Ramp rates	Nuclear: 5%, Hydro: 90%, Gas: 80%, Coal: 30%, Biofuel: 15% (per timestep)
Min nuclear share	15% of total generation capacity per timestep
Flow loss factor	0.025% per km (based on direct distances)
Transport capacity	Up to 5000 MW (e.g. Auvergne–PACA); 0 MW between non-connected regions
Flexibility targets	Optional: min storage, min DR, min exchanges (disabled by default)
Cyclical storage	Disabled (storage can end at any SOC)

Formal proof: market payments exceed operational cost

Notation.

$\mathbf{x}$	continuous decision variables: dispatch, (dis)charging, DR, flows, ...
$\mathbf{y} \in \{0,1\}$	non-convex variables (unit commitment, DR flags)
$\mathbf{c}^\top \mathbf{x}$	linear cost function (regional tariffs from `config_master.yaml`)
$\mathbf{A}\mathbf{x} = \mathbf{b}$, $\mathbf{G}\mathbf{x} \leq \mathbf{h}$	balance, capacity and loss constraints
$\boldsymbol{\lambda}$	Lagrange multipliers of regional balance equations — *nodal prices*
$\boldsymbol{\mu} \geq \mathbf{0}$	multipliers of capacity constraints (lines, DR, storage, ...)
Z_{MILP}	optimal value of the original MILP ("operational cost")
$P = \sum_{t,r} \lambda_{t,r} D_{t,r}$	market payment, with $D_{t,r}$ the exogenous net demand.

1. From the MILP to a "fixed" LP

Solve the MILP

$$\min_{\mathbf{x},\, \mathbf{y} \in \{0,1\}} \mathbf{c}^\top \mathbf{x} \quad \text{s.t. } \mathbf{A}\mathbf{x} = \mathbf{b},\ \mathbf{G}\mathbf{x} \leq \mathbf{h},$$

obtaining $(\mathbf{x}^\star, \mathbf{y}^\star)$ and Z_{MILP}.

Freeze $\mathbf{y} = \mathbf{y}^\star$ and drop integrality; the problem becomes a linear programme

$$\boxed{(\text{LP}_{\text{fix}})} \ \min_{\mathbf{x}} \mathbf{c}^\top \mathbf{x} \quad \text{s.t. } \mathbf{A}\mathbf{x} = \mathbf{b},\ \mathbf{G}\mathbf{x} \leq \mathbf{h}.$$

Because $(\mathbf{x}^\star, \mathbf{y}^\star)$ is feasible,

$$Z_{\text{LP}} \ \leq \ Z_{\text{MILP}}.$$

2. Strong duality for (LP_{fix})

The dual reads

$$\max_{\boldsymbol{\lambda},\, \boldsymbol{\mu} \geq \mathbf{0}} \boldsymbol{\lambda}^\top \mathbf{b} + \boldsymbol{\mu}^\top \mathbf{h} \quad \text{s.t. } \mathbf{A}^\top \boldsymbol{\lambda} + \mathbf{G}^\top \boldsymbol{\mu} \ = \ \mathbf{c}.$$

Strong duality gives

$$Z_{\mathrm{LP}} \;=\; \boldsymbol{\lambda}^{\top}\mathbf{b} \;+\; \boldsymbol{\mu}^{\top}\mathbf{h}. \tag{1}$$

3. Link with market payment

By definition $P = \boldsymbol{\lambda}^{\top}\mathbf{b}$, so (1) becomes

$$Z_{\mathrm{LP}} \;=\; P \;-\; \boldsymbol{\mu}^{\top}\mathbf{h}. \tag{2}$$

Since $\boldsymbol{\mu} \geq \mathbf{0}$ and $\mathbf{h} - \mathbf{G}\mathbf{x} \geq \mathbf{0}$, we have $\boldsymbol{\mu}^{\top}\mathbf{h} \geq 0$.

4. Fundamental inequality

Combining $Z_{\mathrm{LP}} \leq Z_{\mathrm{MILP}}$ with (2),

$$\boxed{Z_{\mathrm{MILP}} \;\leq\; P \;-\; \boldsymbol{\mu}^{\top}\mathbf{h} \;<\; P}.$$

Hence the market payment is *always* at least as large as the true operational cost. The gap decomposes as

$$P - Z_{\mathrm{MILP}} \;=\; \underbrace{\boldsymbol{\mu}^{\top}\mathbf{h}}_{\text{congestion \& flexibility rents}} \;+\; \underbrace{(Z_{\mathrm{LP}} - Z_{\mathrm{MILP}})}_{\text{non-convexity penalty}},$$

which is strictly positive whenever at least one capacity constraint binds ($\boldsymbol{\mu}^{\top}\mathbf{h} > 0$) *or* non-convexities are present ($Z_{\mathrm{LP}} < Z_{\mathrm{MILP}}$).

Q.E.D. This establishes rigorously that the operational (co-optimised) approach yields lower total costs than the price-based market settlement in our model.