The evolution of European balancing energy markets in Europe and the activation process of Transmission System Operators

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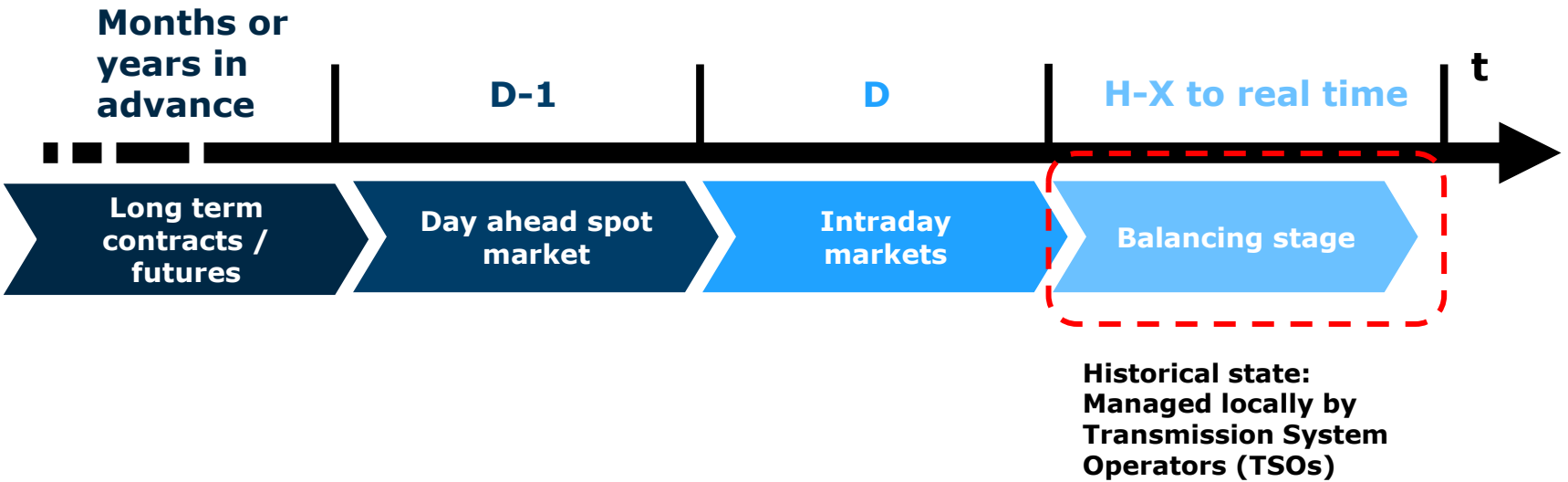
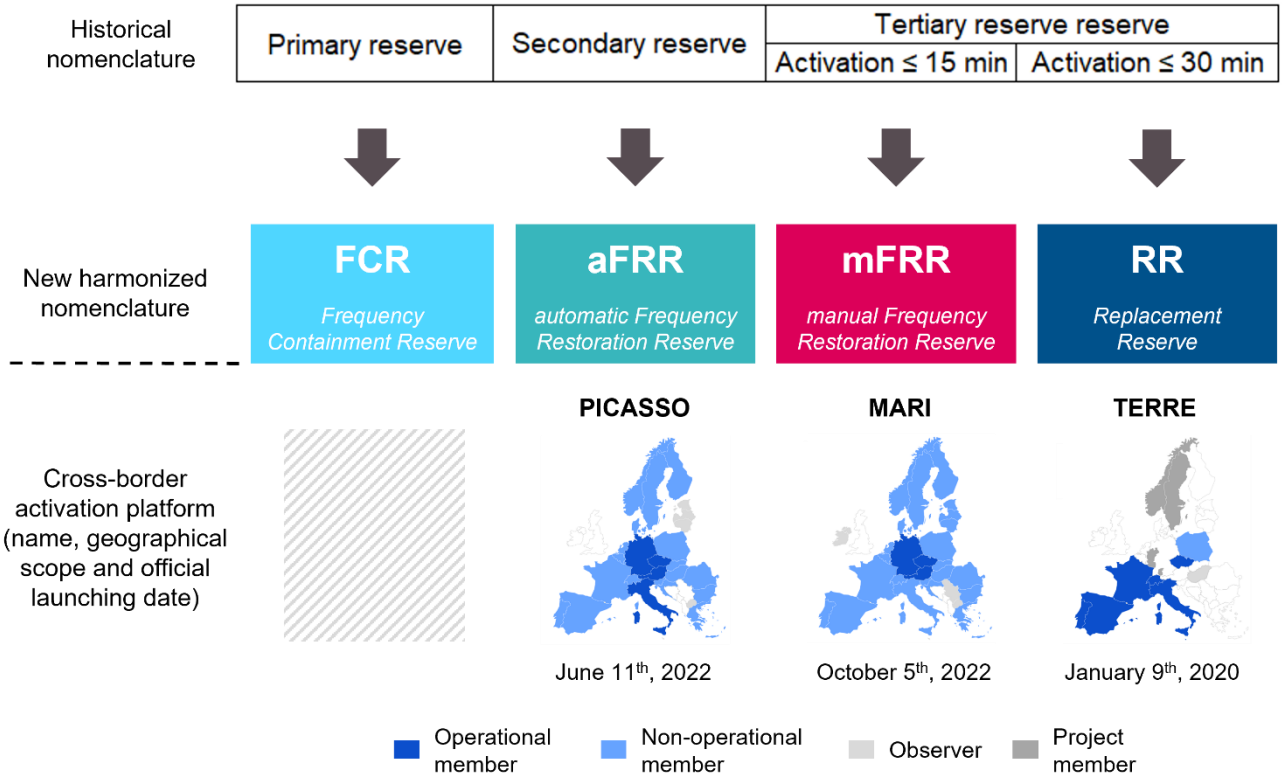
General context: Transition from local processses to European common balancing energy markets

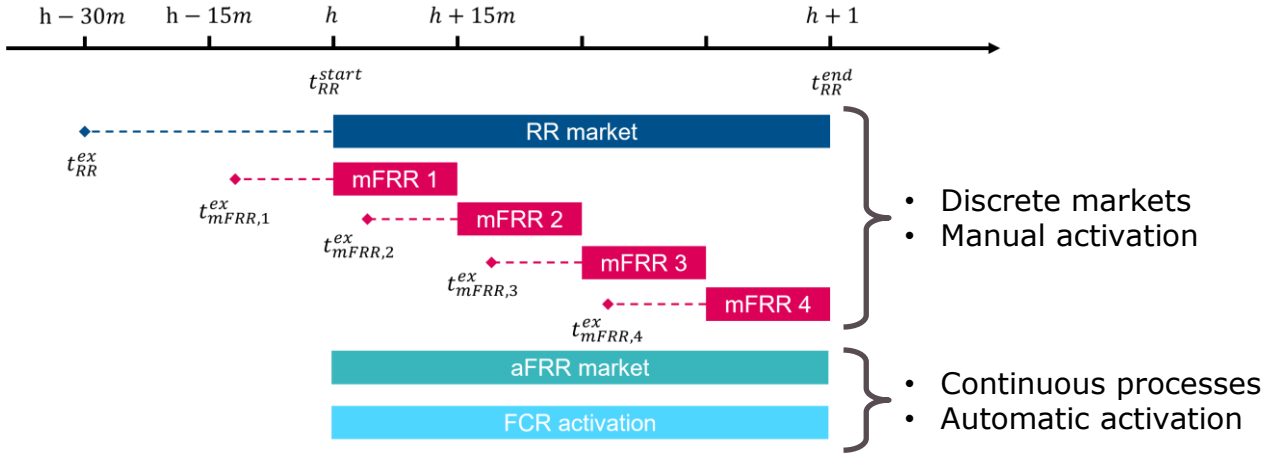


Historical state: Managed locally by Transmission System Operators (TSOs)

General context: Transition from local processses to European common balancing energy markets



General context: Specifities of new common balancing energy markets



A distinctive feature of common balancing energy markets: specific actors

Balancing Services Providers

Offer upward and downward reserves

Transmission System Operators

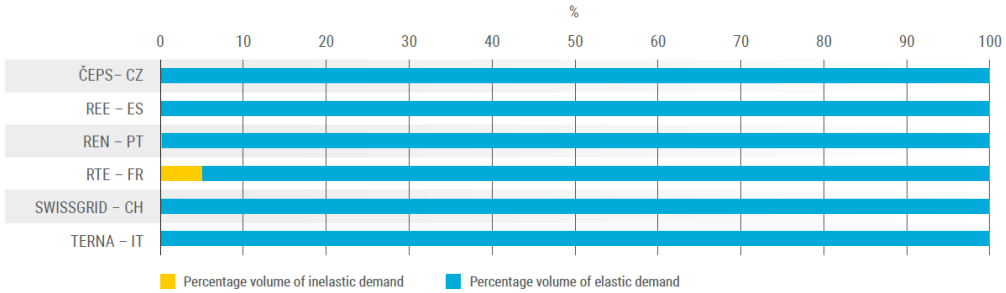
Create balancing demands on their area

Bidding strategies of TSOs on balancing energy markets: a gap in the literature

- **Various studies look at the bidding strategies of BSPs**: for instance (Just & Weber, 2015), (Pei et al., 2016), (Ocker and Ehrhart, 2017), (Poplavskaya, Lago & De Vries, 2019), (Guo et al., 2022), or (Silva et al., 2022).
- To our knowledge, **a single article focuses on TSO bidding strategies**: (Haberg & Doorman, 2017). Proposes a first high-level approach for formulating RR orders based on arbitrage with the mFRR market.
  This article has not been further extended, and TSO demand has been modeled as **price-inelastic** since then.

1) In light of recent market implementations, is it relevant to represent TSOs as price-elastic?

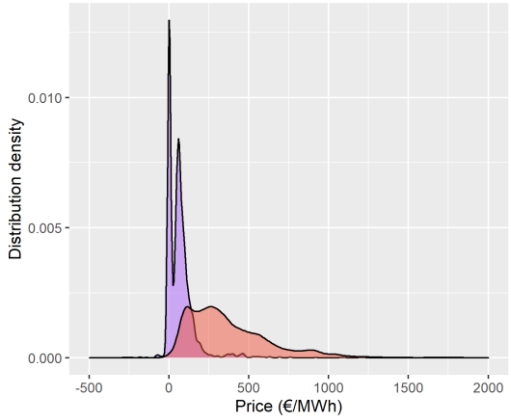
- Recent market reports by ENTSO-E on the actual RR markets (over 2021 and 2022) suggests so.



Highlighting the price-elasticity of TSOs with a empirical analysis of the RR market

Empirical analysis of RR orders formulated by the French TSO RTE over 2021 and 2022.
Conducted using open access data published by RTE and ENTSO-E Transparency.

Distribution of RTE's RR orders prices



RR orders prices spread between 0 and 1000 €/MWh for both directions

➡ Confirming a price-elastic behavior

Examples of demand curves formulated and statistics

Order position	Submitted orders	Acceptance ratio
First	20584	71%
Second	3400	49%
Third	1282	39%
Fourth	416	35%
Fifth	68	28%

➡ Demand curves are already been formulated in practice and have an impact on accepted volumes

Contributions to TSO bidding strategies

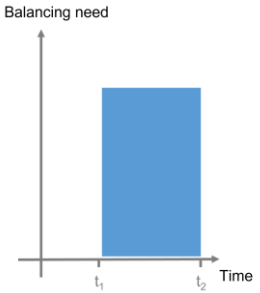
(Haberg & Doorman, 2017) identifies several « complicating issues » to be adressed, notably:

- ❑ The existence of several categories of alternatives to the RR market
- ❑ The uncertainty of the volume of TSO balancing needs
- ❑ The intricacy of estimating the opportunity costs of the alternative

In addition, the article does not provide any application in a case study, to evaluate the impact of bidding strategies.

2) How can their bidding strategies be improved by building on (Haberg & Doorman, 2017), and what are their impacts in terms of balancing costs and balancing market outcomes?

Overview of the proposed bidding framework for the RR market



Input:
Balancing needs B_t

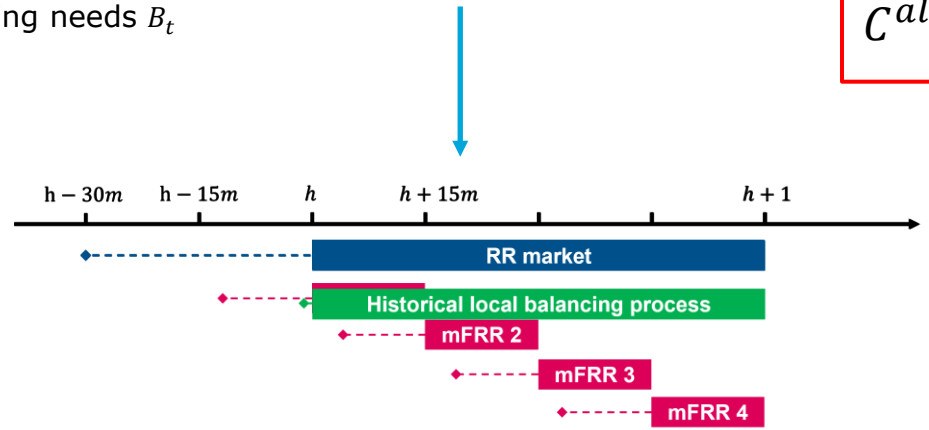
Selection of an alternative alt to the RR market

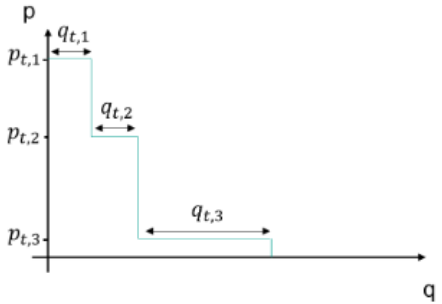
Estimation of opportunity costs C^{alt}

Creation of demand orders

$C^{alt}(B_t)$

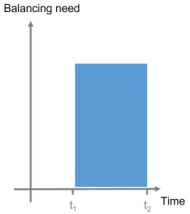
$(q_{t,i}, p_{t,i}) = f(C^{alt}(B_t))$





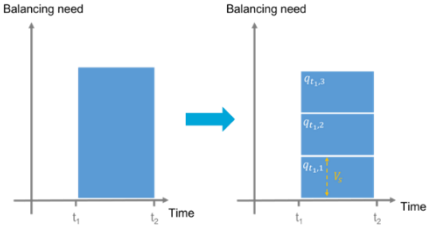
Proposed bidding methods for the RR market

1) Usual price-inelastic (benchmark)



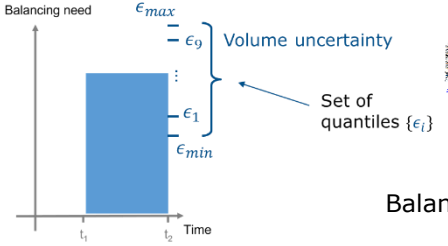
$$f\left(C^{alt}(B_t)\right) = \begin{cases} q_t = |B_t| \\ p_t = \sigma_{B_t} * 10{,}000 \end{cases}$$

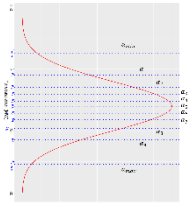
2) Basic price-elastic (similar to (Haberg & Doorman, 2017))



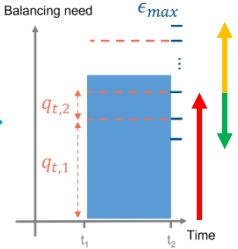
$$f\left(C^{alt}(B_t)\right) = \begin{cases} q_{t,i} = V_s \\ p_{t,i} = \sigma_{B_t} * \dfrac{C^{alt}(\sum_{1\le j\le i} q_{t,j})}{\sum_{1\le j\le i} q_{t,j}} \end{cases}$$

3) Price-elastic with volume uncertainty





Balancing needs forecast error function



$$f\left(C^{alt}(B_t)\right) = \begin{cases} q_{t,i} = \epsilon_i - \epsilon_{i-1} \\ p_{t,i} = \dfrac{1}{\sum_{1\le j\le i} q_{t,j}} * \left[C^{alt}\left(\sum_{1\le j\le i} q_{t,j}\right) + \right. \\ \qquad \sum_{min\le j<i} (\alpha_{j+1} - \alpha_j) * C^{alt,opp}(\epsilon_j - \epsilon_{j+1}) + \\ \qquad \left. \sum_{i<j\le max} (\alpha_j - \alpha_{j-1}) * C^{alt}(\epsilon_j - \epsilon_{j-1}) \right] \end{cases}$$

The size of each slice is the difference between consecutive quantiles

Basic cost

Over-estimation costs

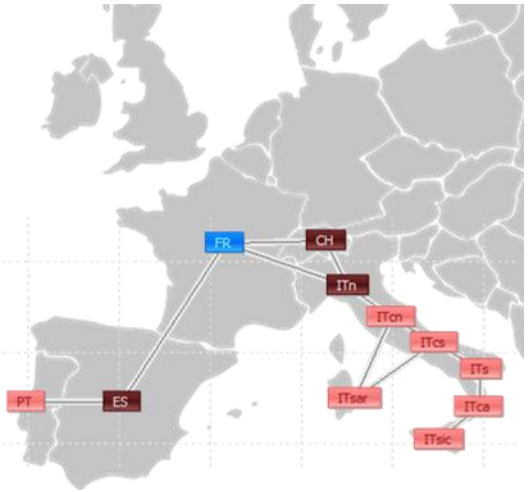
Under-estimation costs

Case study: methodology and scenarios

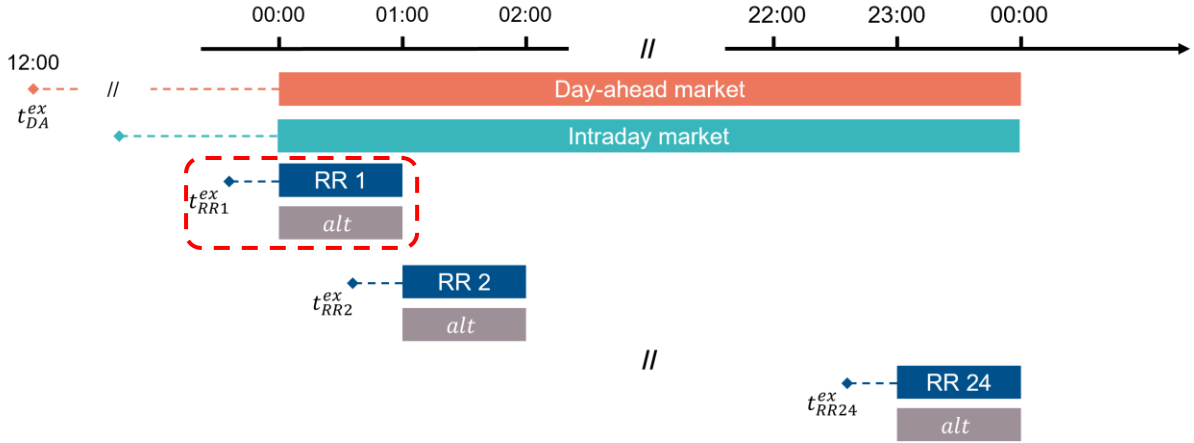
1 day of electricity markets simulated with the electricity market model ATLAS:

Input dataset

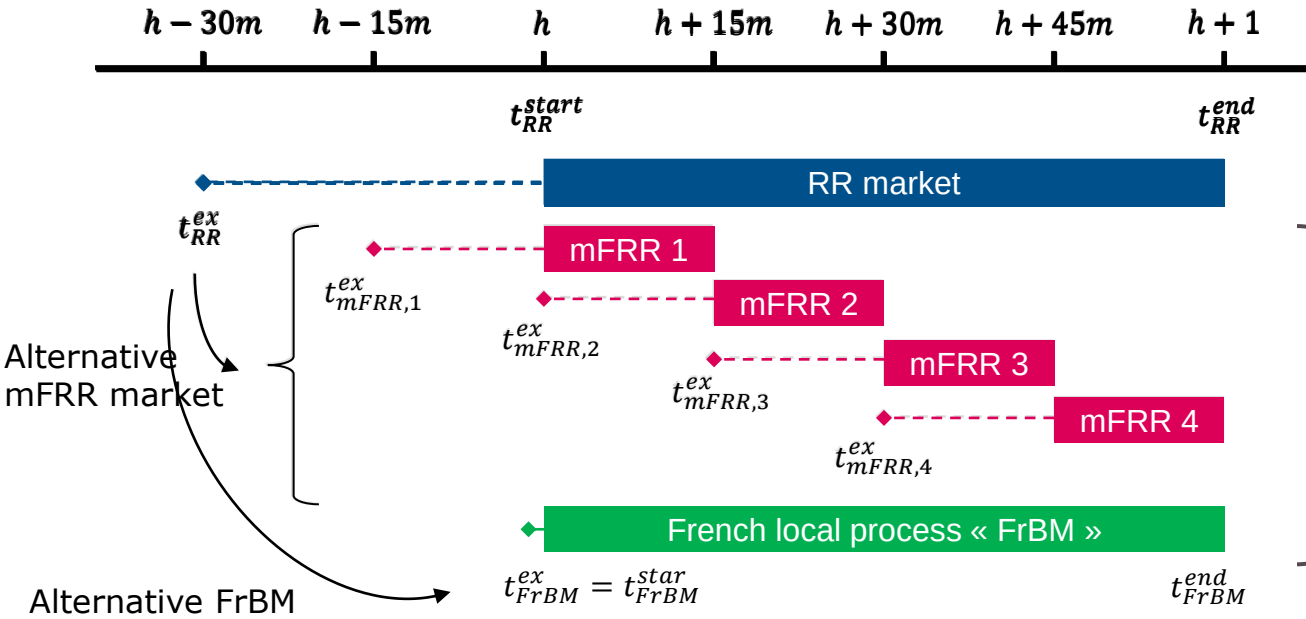
Representative 2030 European power system, based on *Energy Pathways to 2050* (RTE, 2022)



Simulation framework



Case study: methodology and scenarios



Opportunity costs function:

$$C^{mFRR}(B_t) = \tilde{\lambda}^{mFRR} * B_t$$

The 3 bidding methods are compared for both alternatives

Exogenous historical prices

Opportunity costs function:

$$C^{FrBM}(B_t) = FrBM(B_t)$$

Endogenous simulations of the local process

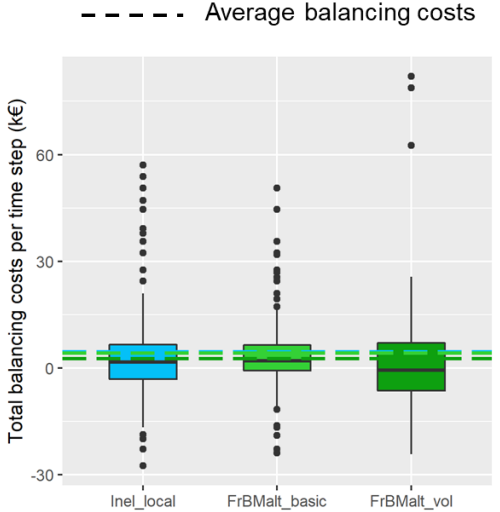
Case study: main results (FrBM alternative)

Balancing costs computation:

$$\forall alt \in \{FrBM, mFRR\}, \quad C^{TSO,alt} = \sum_t C_t^{RR} + C_t^{alt}$$

Scenario	RR market costs	FrBM costs	Total costs
Inel_local	331.2	105.4	436.6
FrBMalt_basic	305.9	100.8	406.7
FrBMalt_vol	54.4	203.2	257.6

Daily TSO balancing costs (k€)



TSO balancing costs boxplot

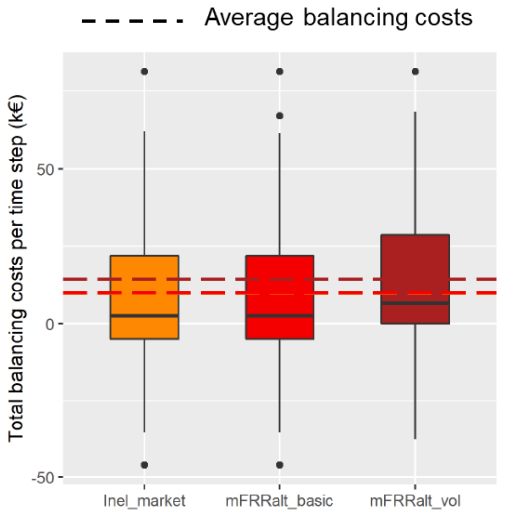
→ **Price-elastic bidding methods perform better than the price-inelastic formulation**, albeit slightly for the basic price-elastic method.

→ The **volume uncertainty bidding method displays significant balancing costs reduction (-40% compared to the inelastic method).** Notably, RR market costs are substantially reduced while FrBM costs are increased: this stragegy correctly identifies when the FrBM becomes a better option than the RR market.

Case study: main results (mFRR alternative)

Scenario	RR market costs	mFRR market costs	Total costs
Inel_market	331.2	-349.8	-18.6
mFRRalt_basic	329.8	-349.1	-19.1
mFRRalt_vol	550.6	-423.5	127.1

Daily TSO balancing costs (k€)



TSO balancing costs boxplot (upward needs)

→ The volume uncertainty method has worse performance than the others.

→ Linked with the **inaccuracy of the cost estimation function** for upward needs / upward mFRR prices

Estimated $\tilde{\lambda}_{up}^{mFRR}$ average	Estimated $\tilde{\lambda}_{up}^{mFRR}$ range	Simulated λ_{up}^{mFRR} average	Simulated λ_{up}^{mFRR} range
62.16	[42.41 - 82.72]	43	[41.22 - 52.39]

Table 5.12: Accuracy of the mFRR price estimation function

Conclusion and key takeaways

1) **TSOs are price-elastic on actual balancing energy markets**, and their bidding strategies should be further studied.

2) **Several types of alternatives** to a given balancing product exists, based on which arbitrages can be computed.

3) Including **uncertainty on the volume of TSO balancing needs** in the bidding formulation **can yield balancing costs reductions**, translating into an increase of social welfare.

4) An **inacurrate opportunity cost estimation function can lead to worse performances**, and it should be properly calibrated.

Future research avenues

- **Improvements of TSO bidding methods:**
  - Using advanced price estimation methods in the opportunity cost computation.
  - Inclusion of risk aversion associated with volume uncertainty.
  - Combination of several simultaneous alternatives (e.g. mFRR market + local balancing process, or mFRR market + aFRR market).
- **Improved assesment of potential effects of TSO bidding strategies and regulatory implications:**
  - Impact on BSP bidding behavior and potential feedback loops.
  - Regulatory framework to avoid potential market distorsions (e.g. caused by an inaccurate TSO bidding strategy) and define strategies that reflect the balancing costs of TSOs.

Thank you for your attention