How to design economic mechanisms for efficient operation of low-inertia power grids

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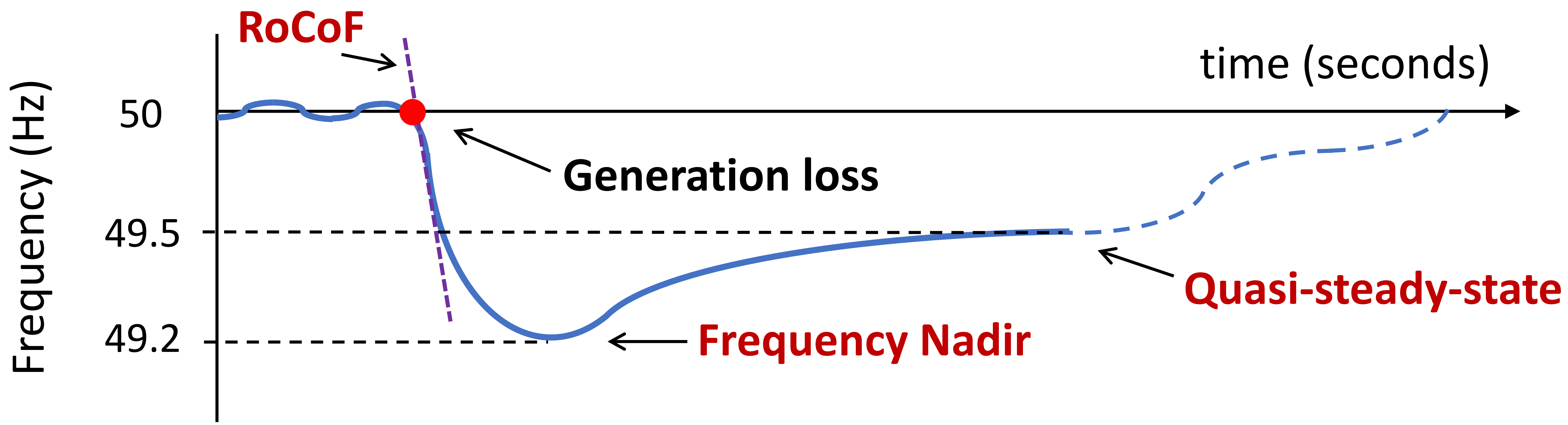
3 topics covered

1. **Unlocking the support from DER** via risk-constrained optimization
2. From **low-level control** instructions to **system-level optimization** via data-driven methods
3. **Who should pay** for frequency-containment services?

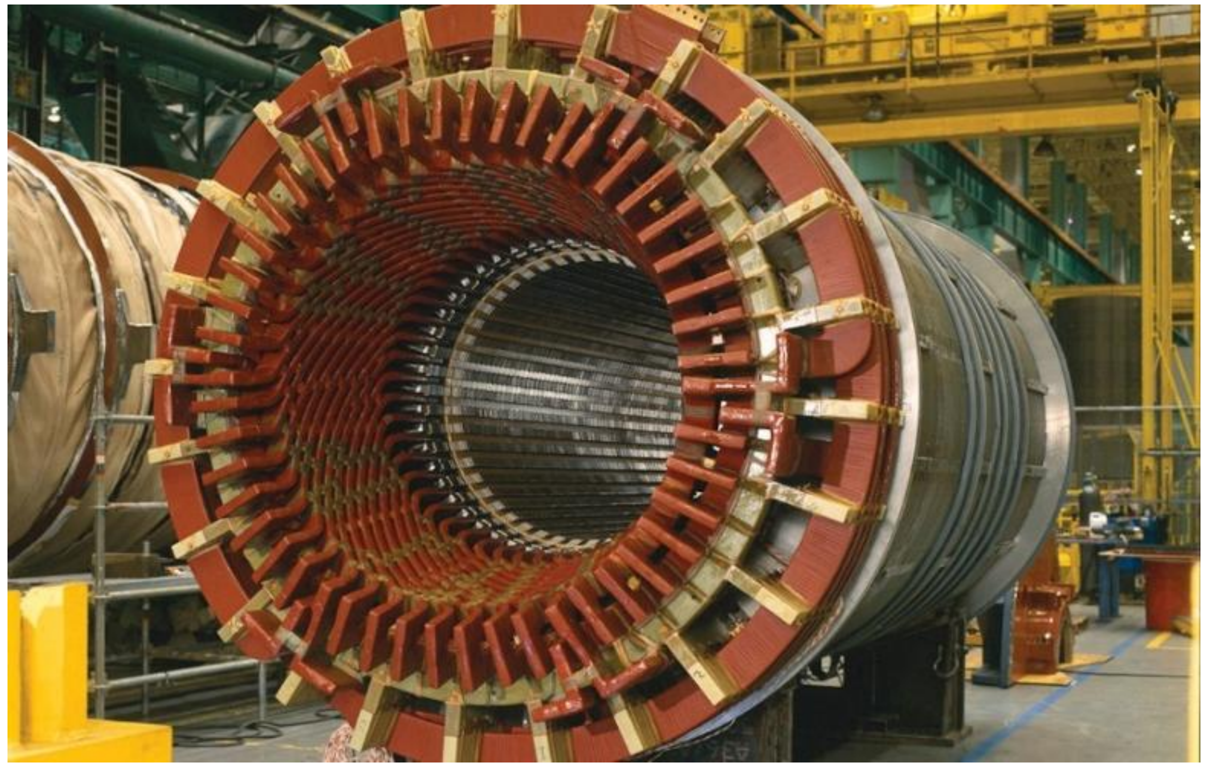
Frequency stability



Key to keep frequency within safe limits to
avoid demand disconnection!

Lower inertia on the road to lower emissions

Thermal generators
(nuclear, gas, coal…)



Decarbonization

Most **renewables**:
no inertia

The **risk of instability has increased!**

Inertia <u>stores kinetic energy</u>:
this energy gave us time to contain a sudden generation-demand imbalance

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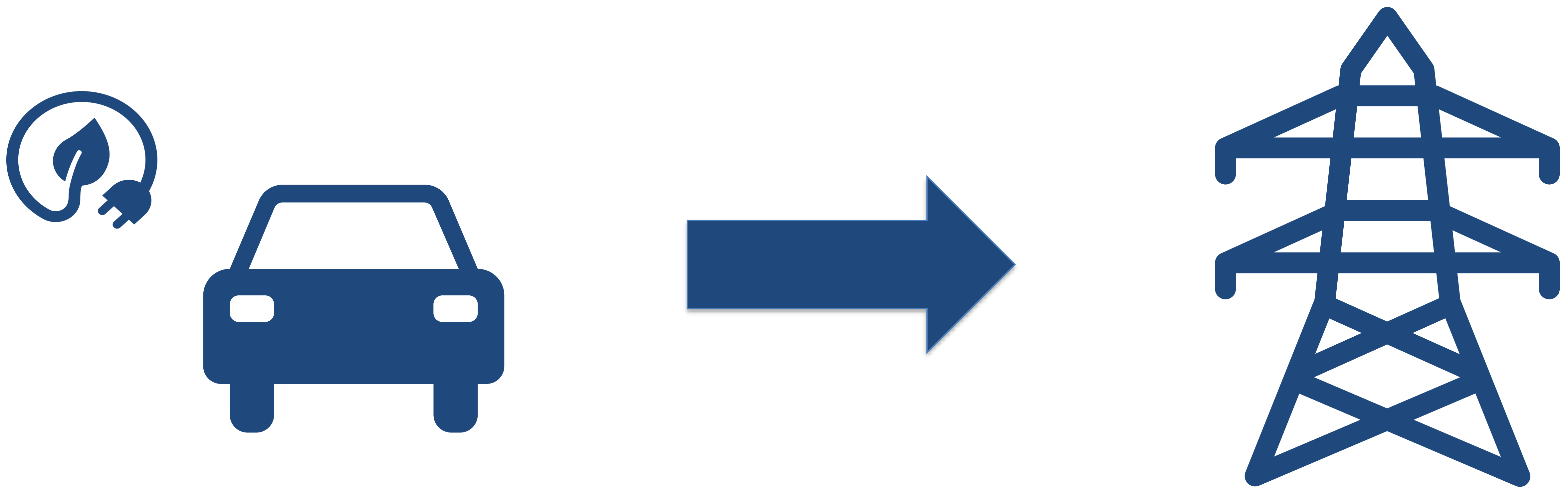
Paper:

C. O’Malley, L. Badesa et al., “Frequency Response from Aggregated V2G Chargers With Uncertain EV Connections,” ***IEEE Trans. on Power Systems***, 2023

Unlocking support from Distributed Energy Resources

- **DER could be very valuable** to support system stability, but they are **inherently uncertain**

- We focus on **Vehicle-to-Grid (V2G)**: the system operator cannot control when the EV owners plug in their vehicles



Why is this important?

Now	→	Future
Stability through **gas plants**		Stability services from **DER**
• **Pros**: certain + reliable		• **Pros**: abundant + **cheap**
• **Cons**: expensive + polluting		• **Cons**: uncertain

Stability conditions for optimization

What is the **value of V2G** as a countermeasure to low inertia?

Described by ***differential equations***

(timescale of sub-seconds)

Based on ***algebraic equations***

(timescale of min/hours)

Uncertainty within the stability conditions

We propose the use of **chance constraints**:

Probability of complying with **stability limit** $\geq$ 1 - **ϵ**

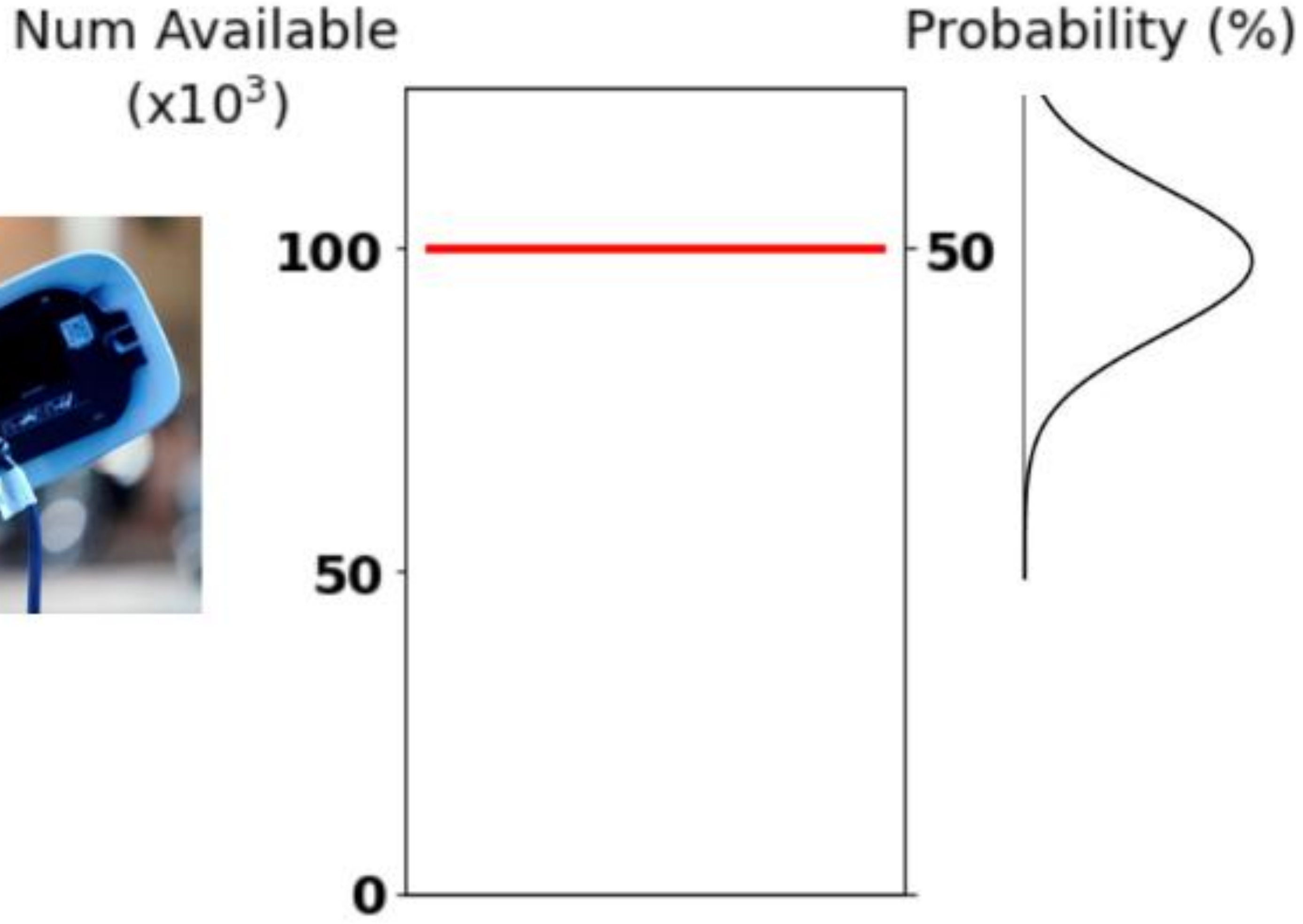
Uncertainty in
EV plug-in times

Risk appetite
(*e.g.*, 1% chance of
under-delivery)

What do we mean by risk?

Probabilistic forecast

for EV connections



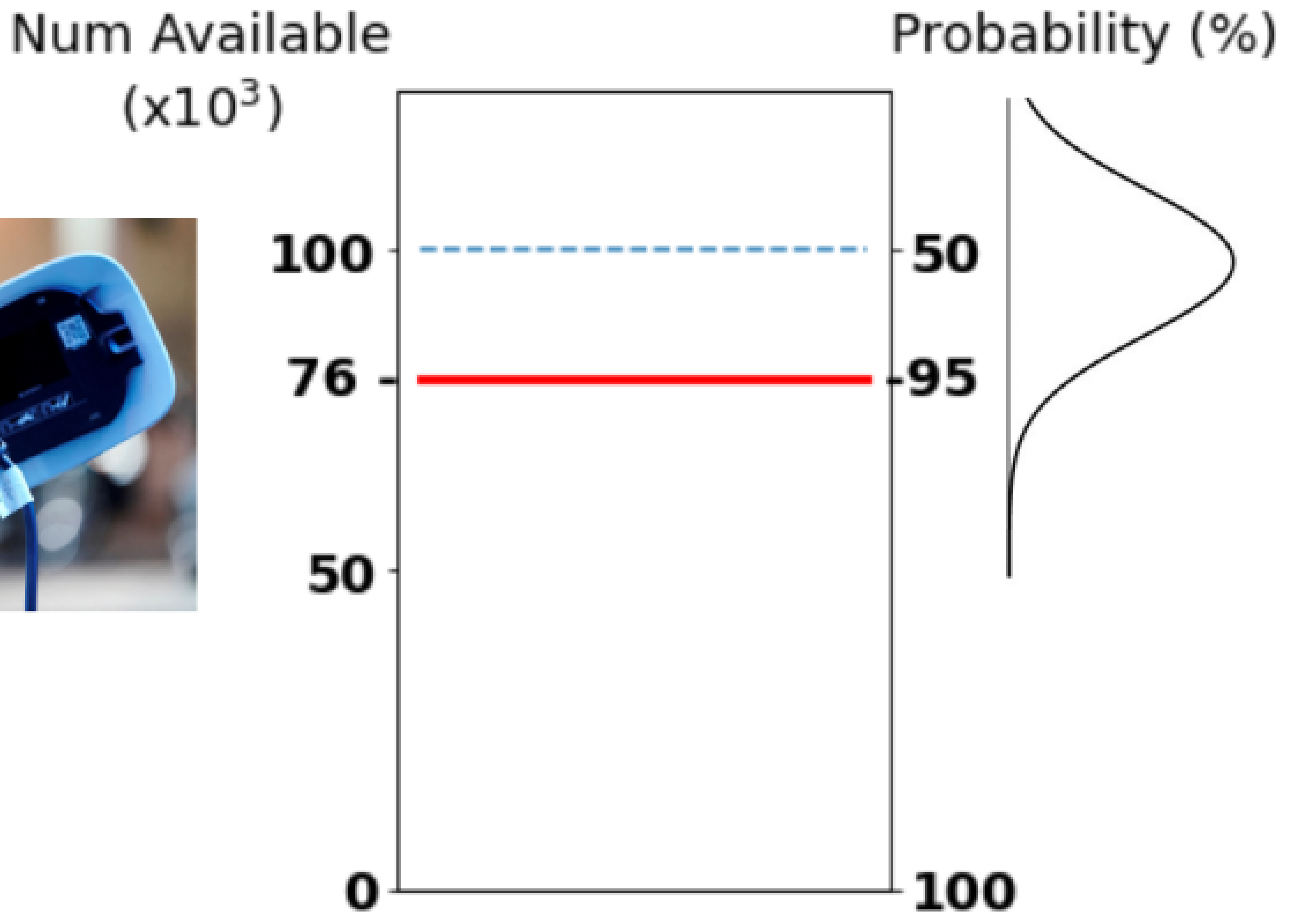
Naïve scheduling:

- Use **deterministic forecast** (mean)
- Count on 100k EVs
- 50% chance of having less than expected

Risky!

What do we mean by risk?

Probabilistic forecast
for EV connections

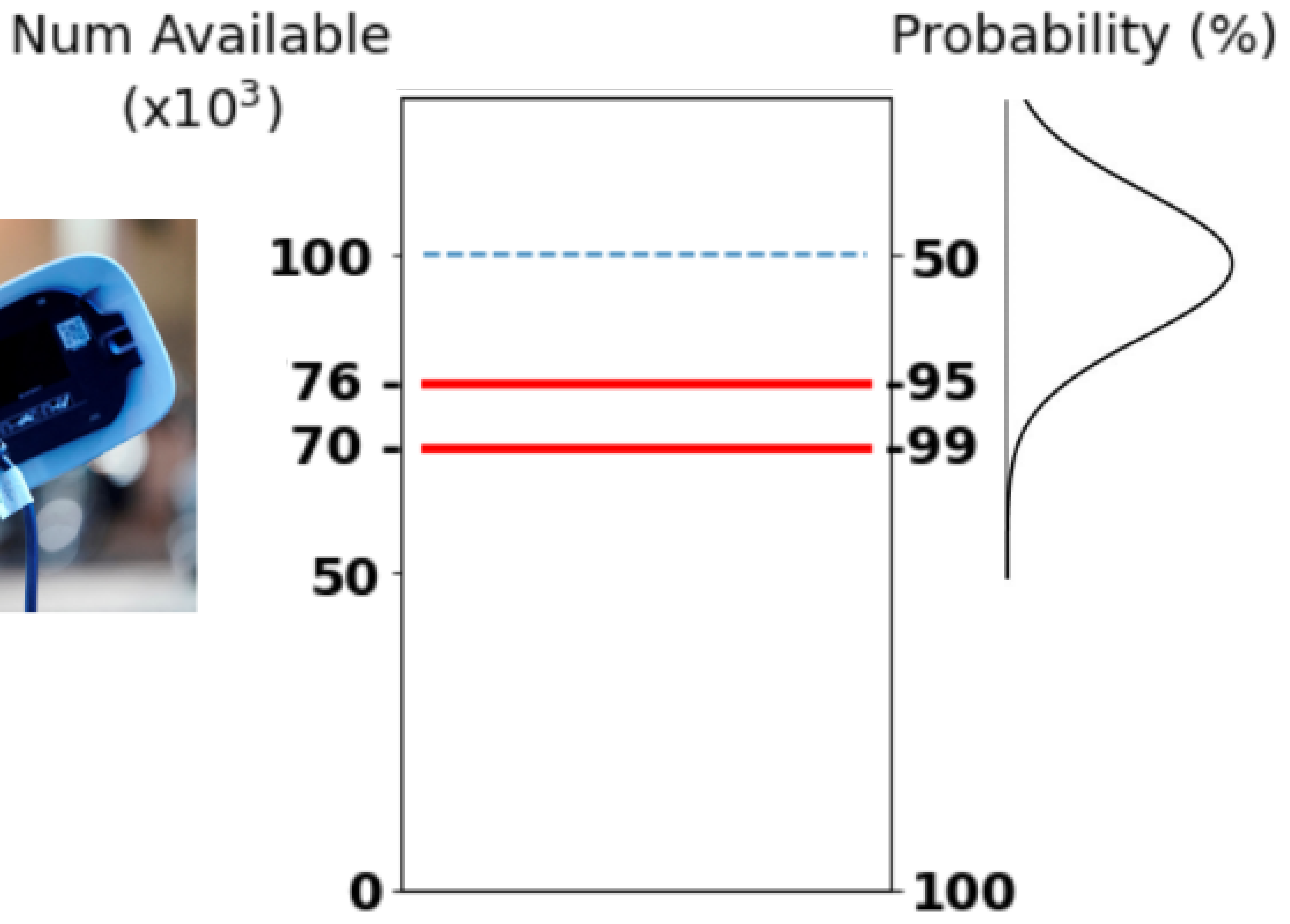


Risk-limited scheduling:

- Specify **risk tolerance** (*e.g.*, 5%)
- Count on **76k** EVs

What do we mean by risk?

Probabilistic forecast
for EV connections



Risk-limited scheduling:

- Specify **risk tolerance** (*e.g.*, **1%**)
- Count on **70k** EVs

Lower risk implies
less support from EVs
considered

Steps for deducing chance constraints

1. Model system frequency via **single-machine swing equation**:

$$\frac{2H}{f_0}\frac{d\Delta f}{dt} = R^{EV}(t) + R^{ND}(t) + R^{G}(t) - PL_{max}$$

2. **Solve swing equation** to obtain RoCoF and nadir **constraints**:

$$\mathbb{P}\left[\left(\frac{H}{f_0} - \frac{(R^{ND} + R^{EV})\cdot T_1}{4\Delta f_{max}}\right)\frac{R^G}{T_2} \geq \left(\frac{PL_{max} - (R^{ND} + R^{EV})}{2\sqrt{\Delta f_{max}}}\right)^2\right] \geq 1 - \epsilon$$

3. Use a **convex reformulation** for the non-convex chance constraints

Convexification of chance constraint

Several options for the **convex reformulation**:

The **more information** available in the forecast,
the **less conservative** the reformulation:

- **Gaussian** uncertainty?
- **Unimodal** distribution? (single peak)
- Only mean and variance known?
  Distributionally-robust formulation (most conservative)

Results for Great Britain

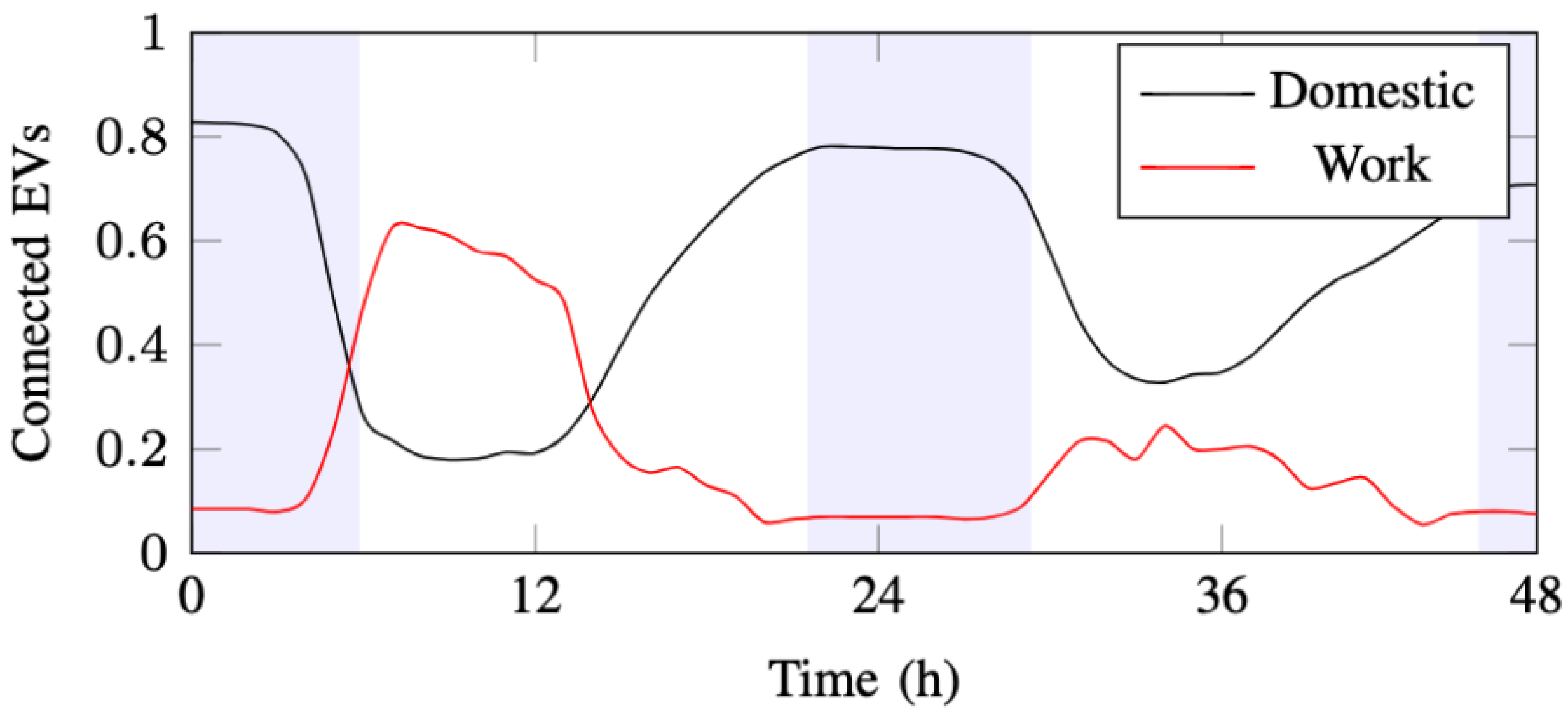
- **Frequency-secured UC** run for a full year in 2030

- Two **EV fleets** considered:
  - ‘**Domestic** V2G’: 85,000 units, 10 kW chargers
  - ‘**Work** V2G’: 15,000 units, 20 kW chargers

- **Risk** of under-delivery set at **1%**
  - Does **not mean** 1% risk of **violating security**: that risk is extremely small (largest *N*-1 contingency needs to happen too)

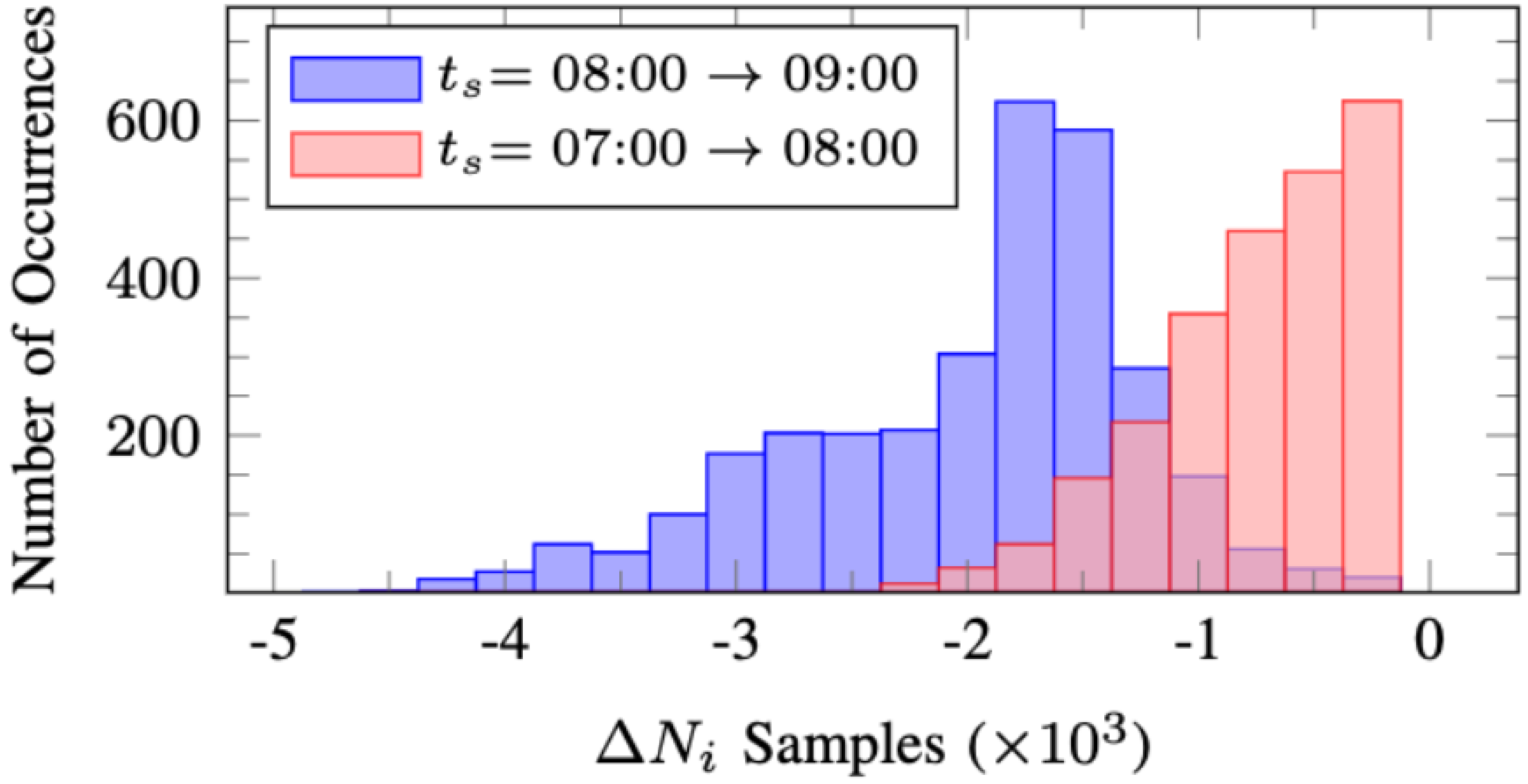
EV connectivity forecasting and data analysis

Data from UK Department of Transport, 2017



Test for ambiguity set

Domestic fleet disconnections
on weekday

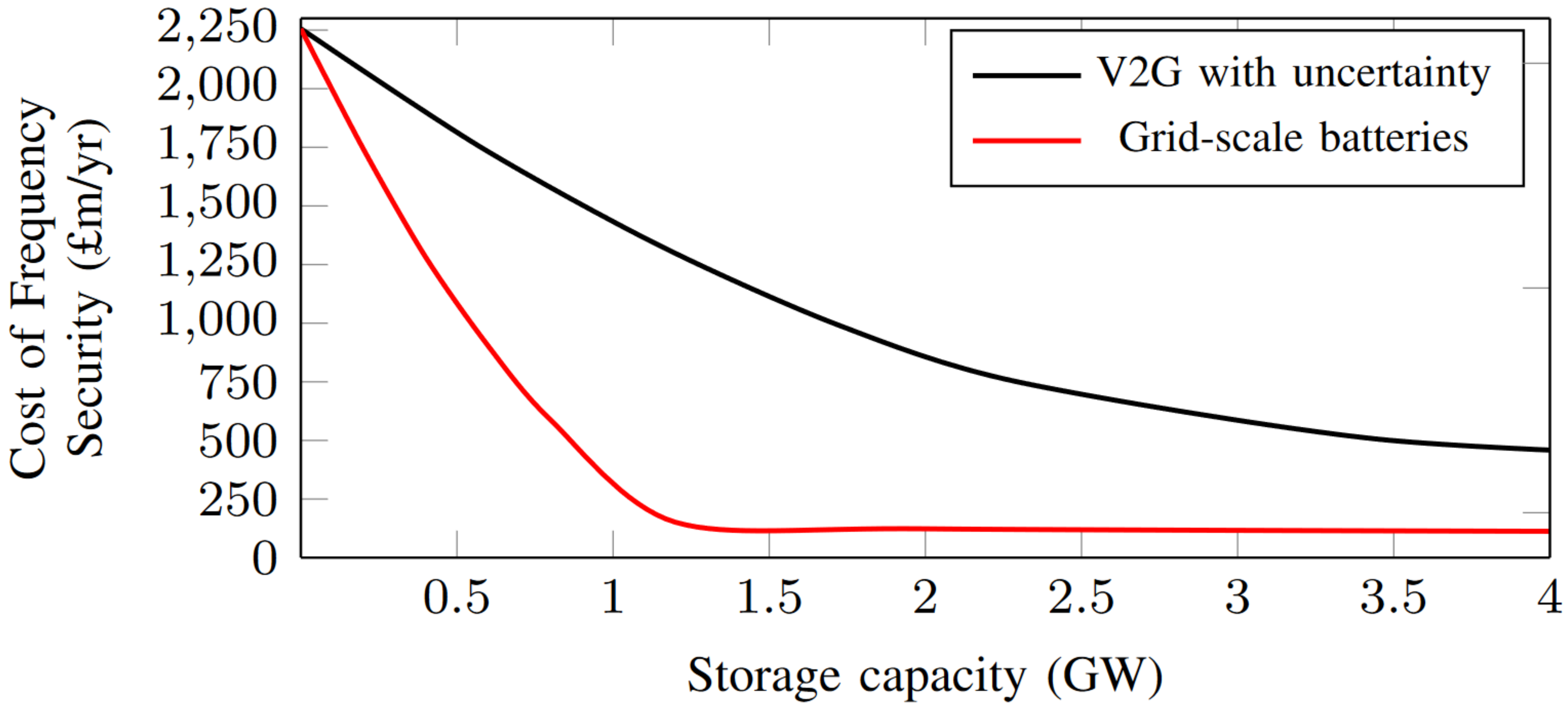


- **Not** Gaussian
- **Unimodal** with high confidence (from Shapiro-Wilk test)

Results: comparison of V2G to BESS

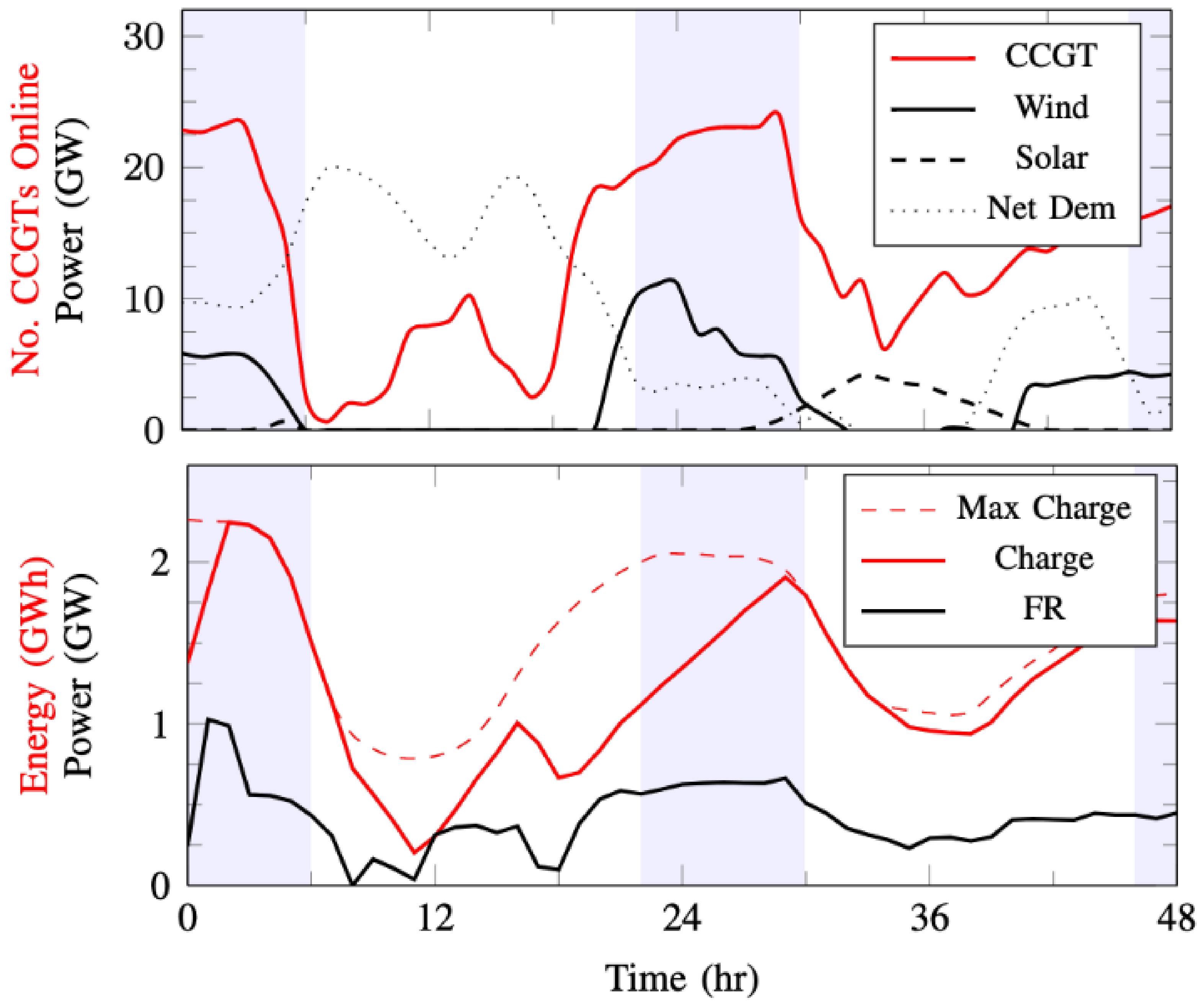
V2G capacity shown to be **one third as valuable** as stationary BESS

- EV chargers only have an **EV connected ~40% of the time**
- EV chargers are subject to **uncertainty**



But EVs have **no additional** investment cost!

Where does this value come from?



Fewer CCGTs are needed,

thanks to **frequency support** from **EVs**

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1. **Unlocking the support from DER** via risk-constrained optimization

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3. **Who should pay** for frequency-containment services?

Paper:

Q. Chen, L. Badesa et al., “Adaptive Droop Gain Control for Optimal Kinetic Energy Extraction From Wind Turbines to Support System Frequency,” ***IEEE Access***, 2024

Research question

How to **translate** the **system** optimal **dispatch**
into **specific control gains** for devices?

(not possible with fully analytical methods as the one shown earlier)

Goal:

Optimal kinetic energy extraction from wind turbines
depending on **overall system dispatch**

Approach we used

Data-driven methods allow to compute explicit control instructions

But, **how to choose the classifier?**

- We opt for an **Optimal Classification Tree** (OCT):
  simple structure and **tractable** for incorporating into optimization

Other options:

- Logistic regression and SVM: limited by hyperplane separation (although kernels could be used)
- Neural Networks: problems with tractability due to binary variables

Adaptive Droop Gain (ADG)

$$\mathrm{ADG}(\underbrace{v_w, \boldsymbol{P_G}, L_D, pl, \Delta P_L,}_{\text{System operating condition}} \omega_r) = \widetilde{K}_{\mathrm{sys}} \cdot \underbrace{(\omega_r{}^2 - \omega_{r,min}{}^2)}_{\text{deter over-deceleration}}$$

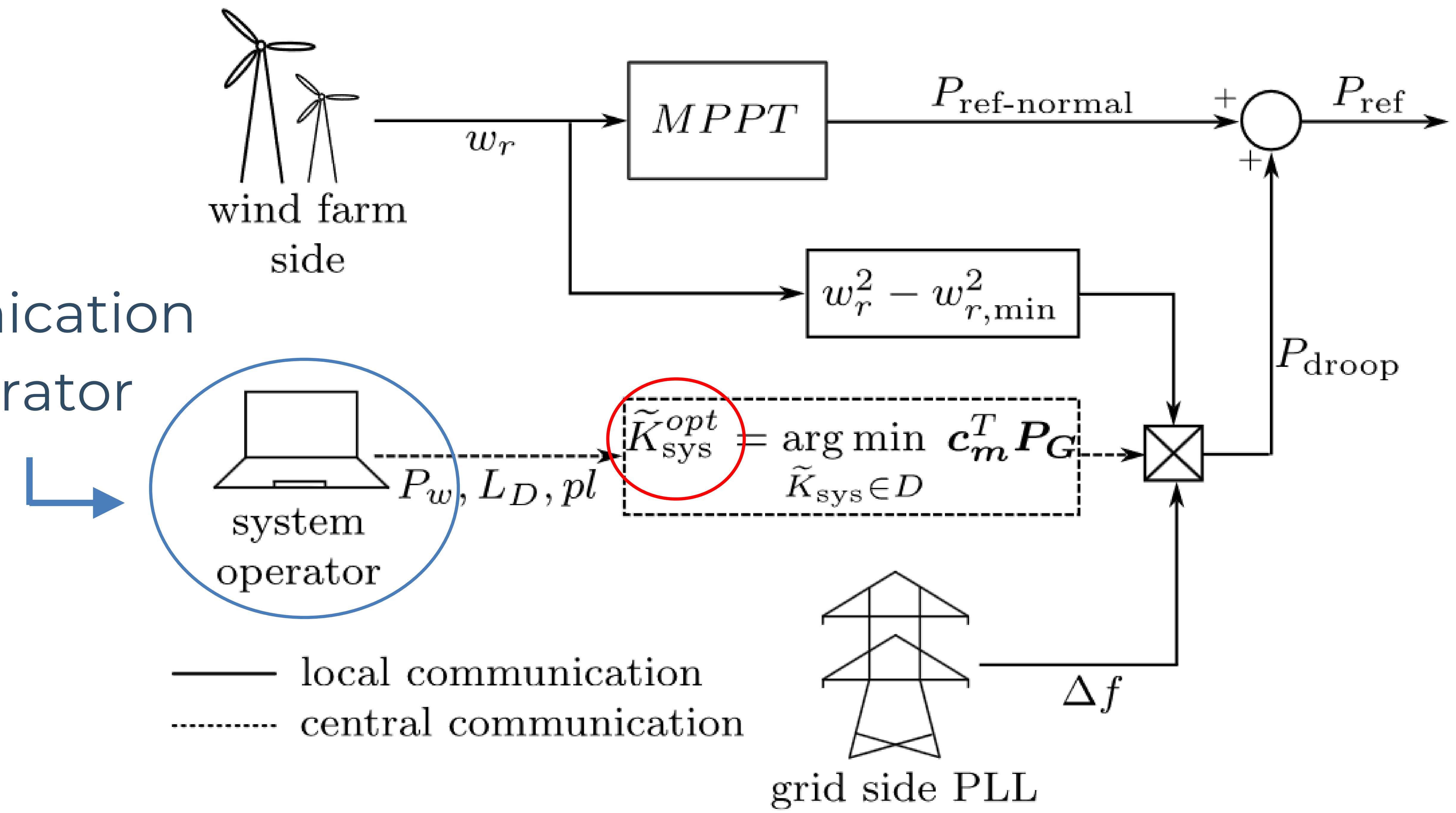
$$\widetilde{K}_{\mathrm{sys}} = f(v_w, \boldsymbol{P_G}, L_D, pl, \Delta P_L)$$

An **Optimal Classification Tree** (OCT) is used to encode frequency-stability conditions within a system-wide economic dispatch

- The **ADG** is **explicitly incorporated** into the OCT

Communication requirements

Hourly communication with system operator (rest is local)



Optimal Classification Tree

Offline training

(outside the Unit Commitment / OPF)

Minimize classification error

Penalize tree depth

$$\min \frac{1}{\hat{\mathcal{L}}} \sum_{t \in \underline{\Omega}^{\mathcal{T}}} l_t + \alpha \sum_{m \in \underline{\Omega}^{B}} d_m$$

$$\begin{aligned}
\text{s.t. } & l_t \geq \omega \cdot n_{0t} - \mathcal{M} \cdot (1 - c_t) \quad \forall t \in \underline{\Omega}^{\mathcal{T}} \\
& l_t \leq \omega \cdot n_{0t} + \mathcal{M} \cdot c_t \quad \forall t \in \underline{\Omega}^{\mathcal{T}} \\
& l_t \geq n_{1t} - \mathcal{M} \cdot c_t \quad \forall t \in \underline{\Omega}^{\mathcal{T}} \\
& l_t \leq n_{1t} + \mathcal{M} \cdot (1 - c_t) \quad \forall t \in \underline{\Omega}^{\mathcal{T}}
\end{aligned}$$

Classification boundaries (linearized via big-M)

Penalize ‘false safe’ predictions (adjustable parameter)

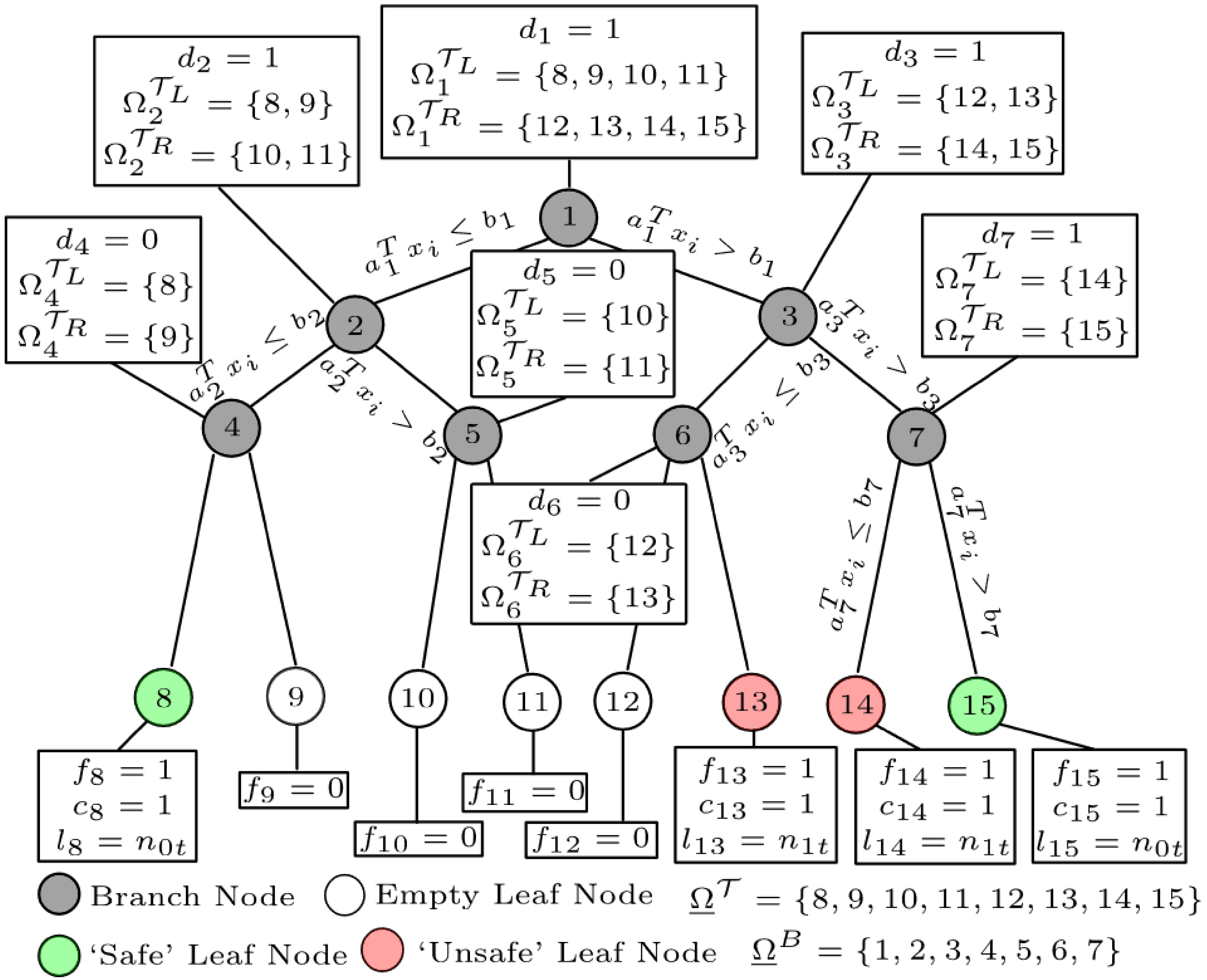
$$n_{1t} = \sum_{i \in \Omega^{\mathcal{N}}} z_{it} \cdot Y_i \quad \forall t \in \underline{\Omega}^{\mathcal{T}}$$

‘Safe’ classifications

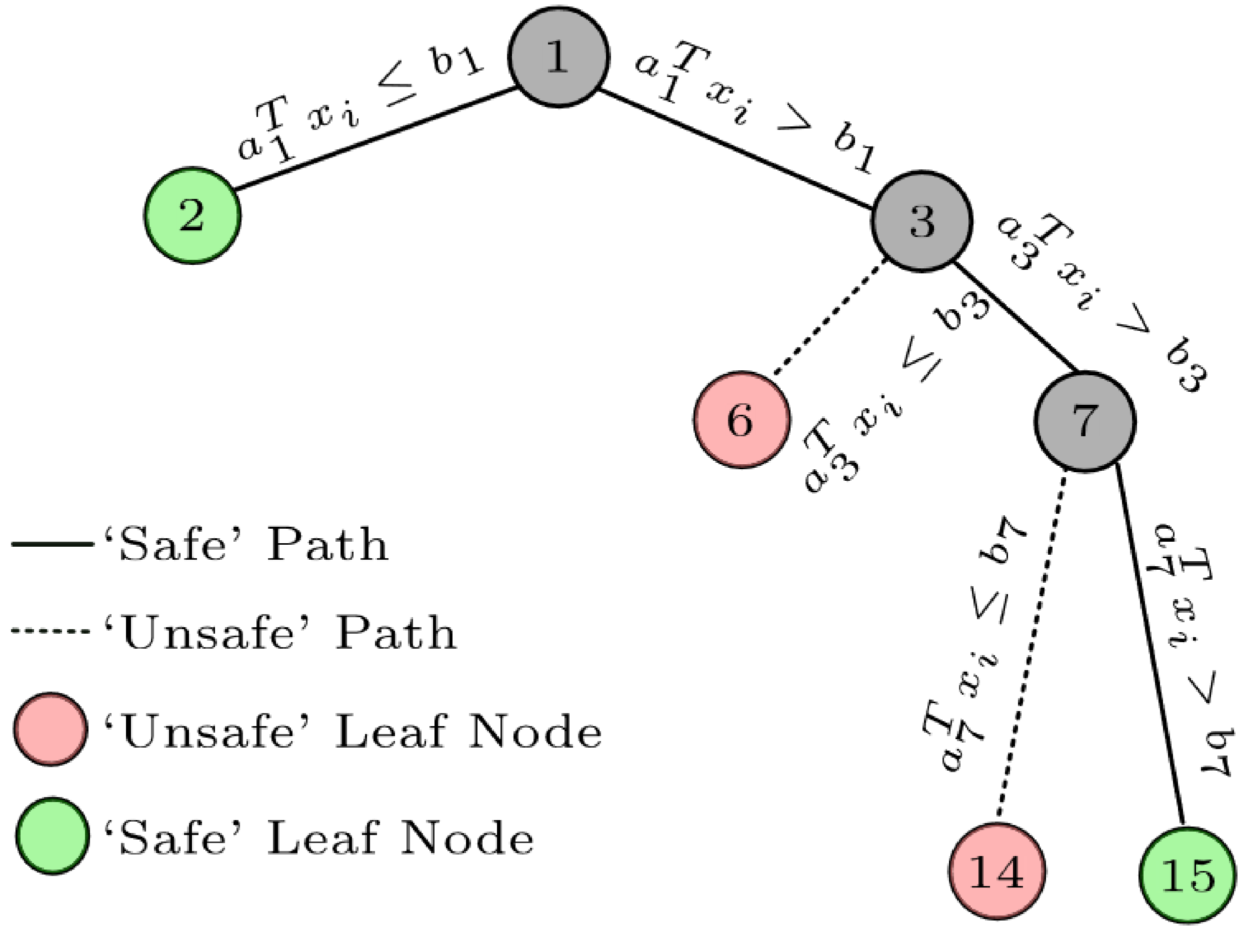
$$n_{0t} = \sum_{i \in \Omega^{\mathcal{N}}} z_{it} - n_{1t} \quad \forall t \in \underline{\Omega}^{\mathcal{T}}$$

‘Unsafe’ classifications

Optimal Classification Tree



Pruning redundancies



This OCT is **integrated into the OPF** as a set of constraints

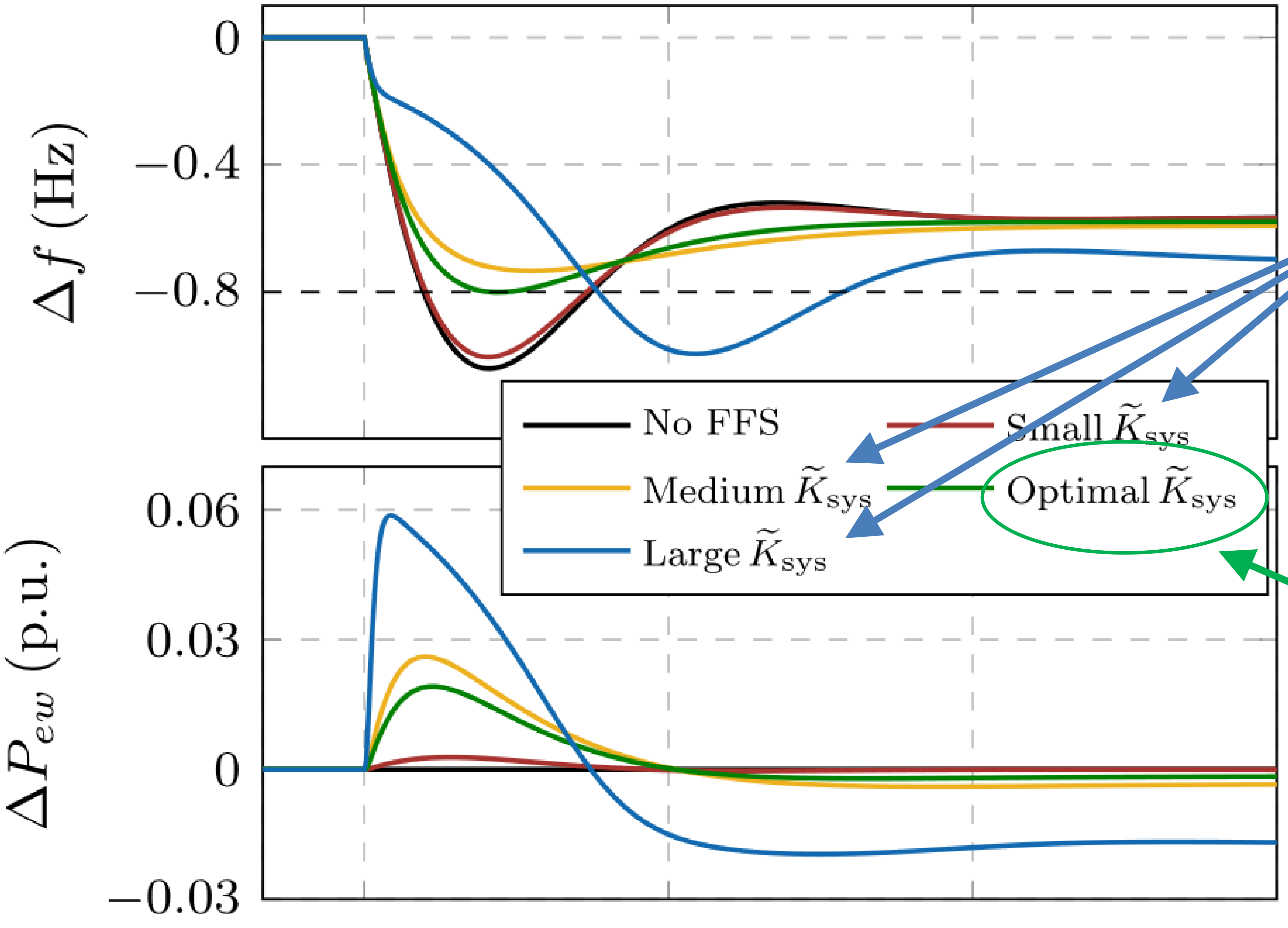
Case studies

- **Frequency-secured OPF** run for an IEEE 14-bus network

- 1,500 **labelled samples** from **dynamic simulations** in Simulink
  - ~2 days computing time (on standard laptop)
  - 70% for training, 20% for validation, 10% for testing

- **Training OCT** offline (solving MILP): ~30 min
  - Could be retrained, *e.g.*, daily, using new datasets with updated wind and load forecasts (reduces conservativeness)

Results



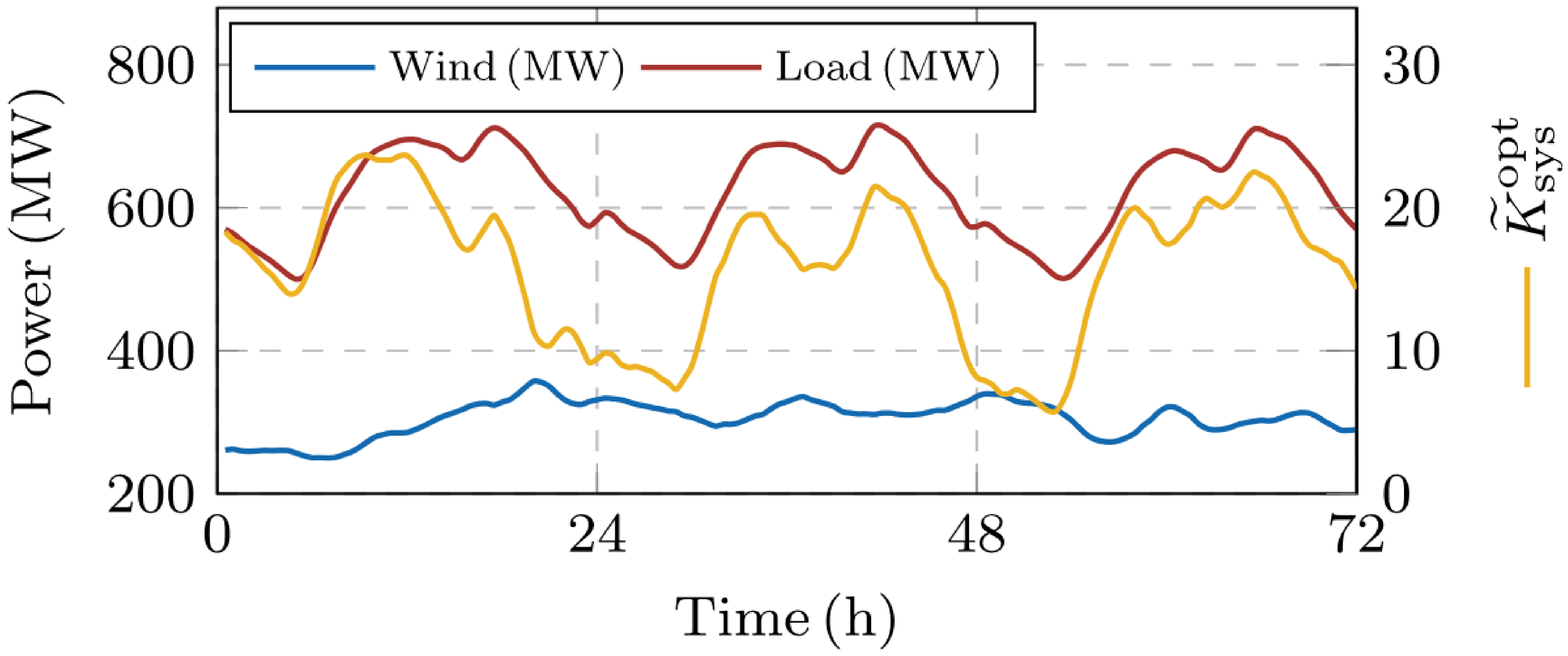
Fixed *a priori*

Optimized for current **operating condition** via the classification tree

Dispatch solutions

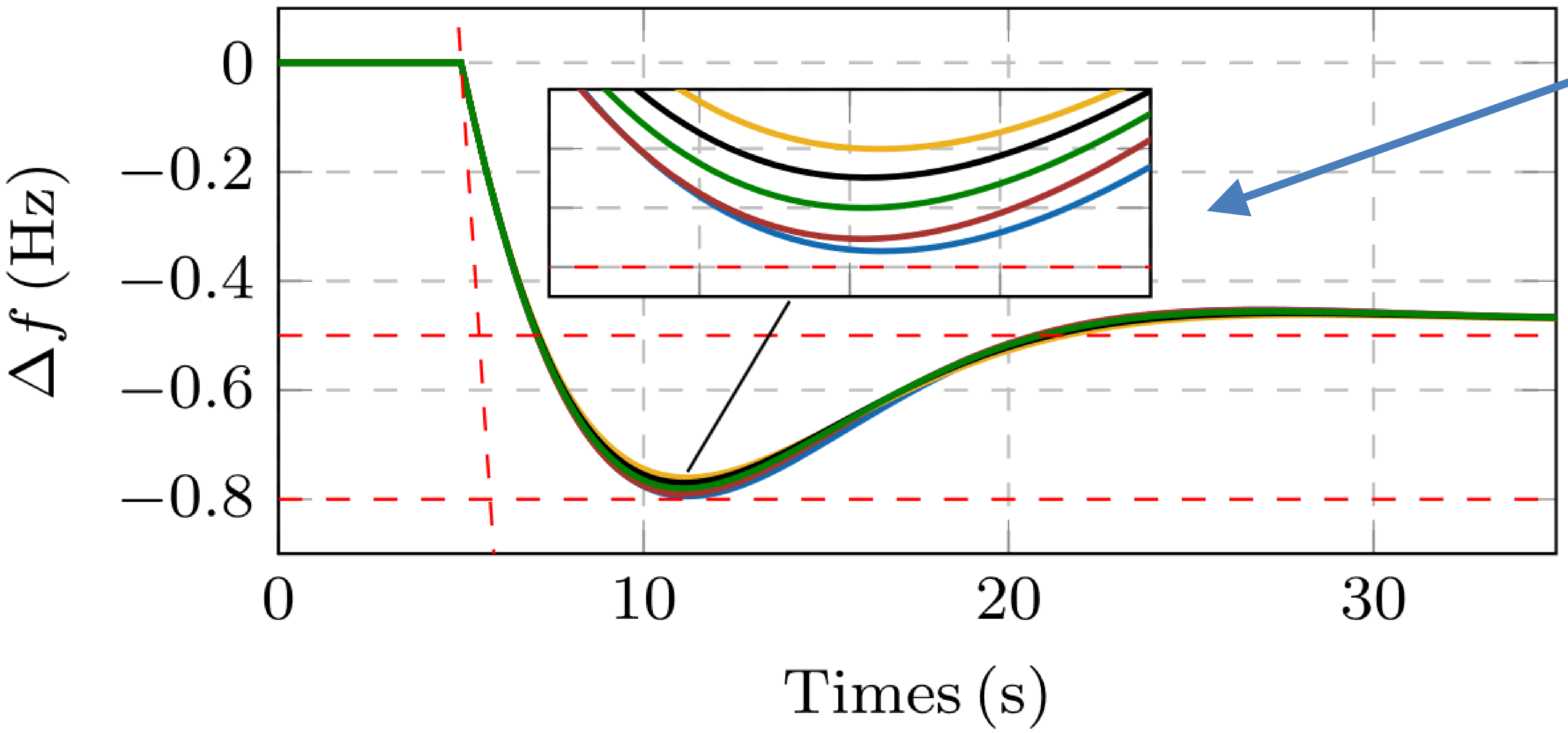
The **optimal** droop gain $\boldsymbol{K_{sys}}$ **fluctuates** with the system dispatch:

roughly inversely proportional to wind power



Security boundary

Slight underestimation of nadir due to **conservativeness** in **OCT**

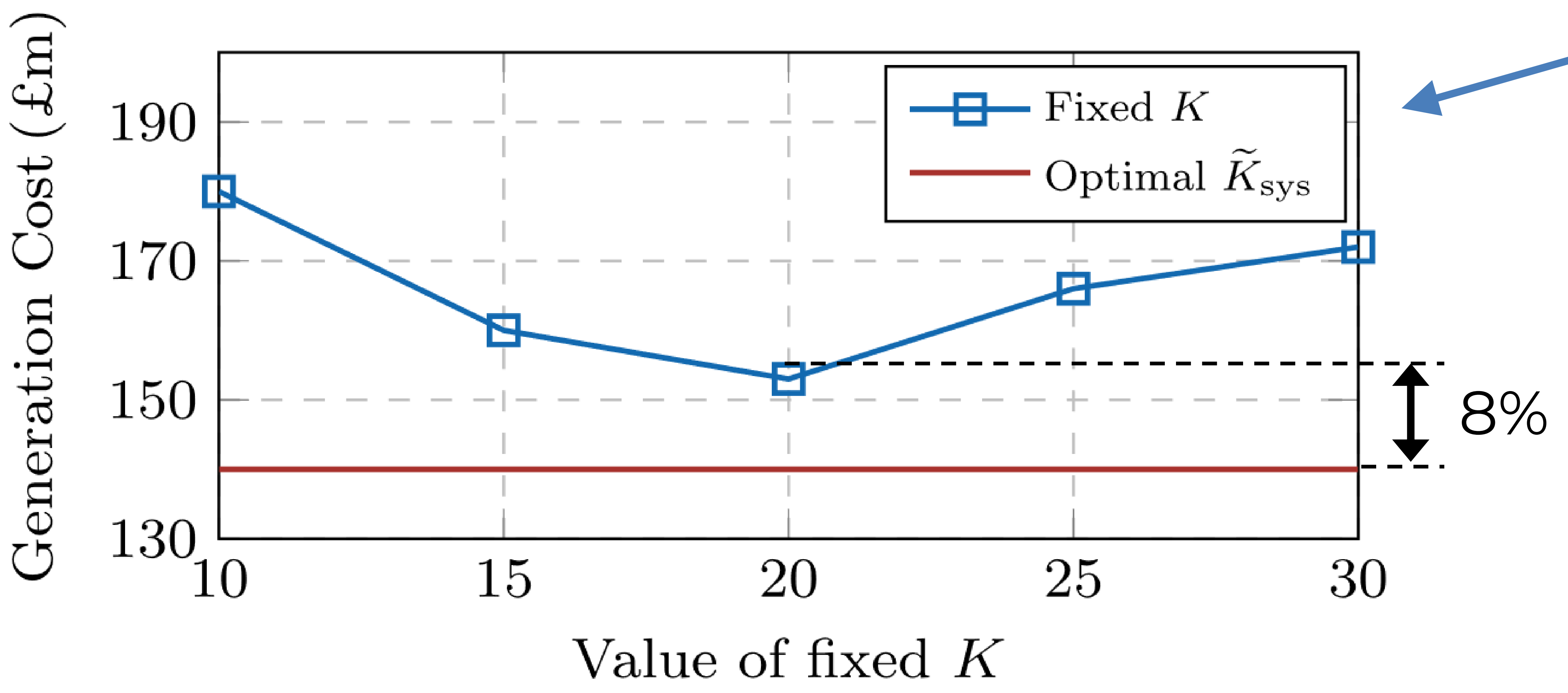


5 different
OPF solutions,
arbitrarily chosen

Cost savings

System **savings of** at least **8%** compared to system-unaware controller

Weekly costs for 50% wind penetration



Note that the optimal value of fixed gain (K = 20) can only be computed by system optimization (through the OCT)

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3. **Who should pay** for frequency-containment services?

Paper:
L. Badesa et al., "Who should pay for frequency-containment ancillary services? Making responsible units bear the cost to shape investment in generation and loads," ***Energy Policy***, 2025

Cost allocation for frequency services

We have focused on optimizing the total cost of frequency services, but…

1. **Who should cover this cost?**
   - Generators?
   - Consumers?
   - Only a subset of the former?

2. **How much should each market participant pay?**

First, why worry about who pays?

- Currently **costs are socialized** in most countries (except Australia)
- **Until recently**, irrelevant who paid (**costs were small** due to high inertia)

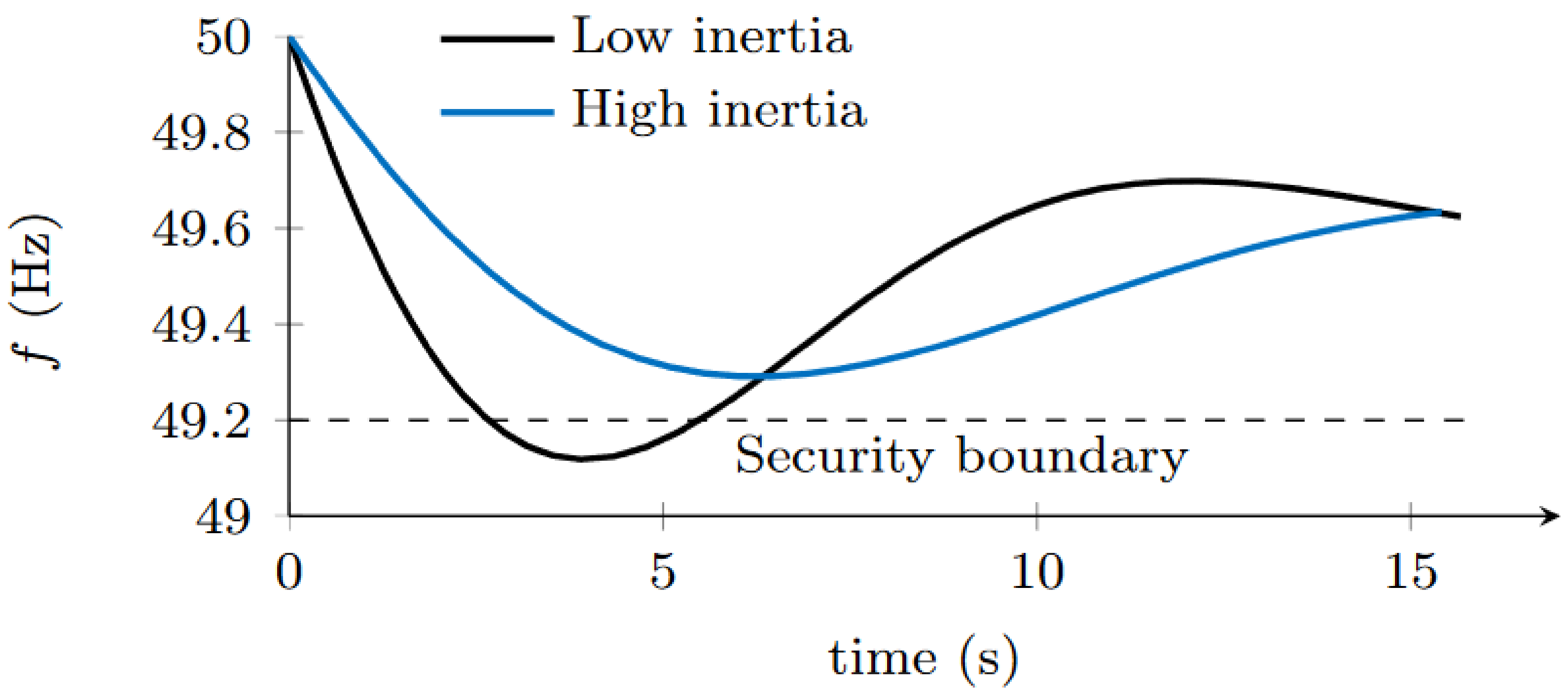
Goal of moving towards a **‘causer pays’ framework**:

To create **incentives** **to ‘do less harm’** to the grid

(in order to **reduce the cost** of frequency services for consumers)

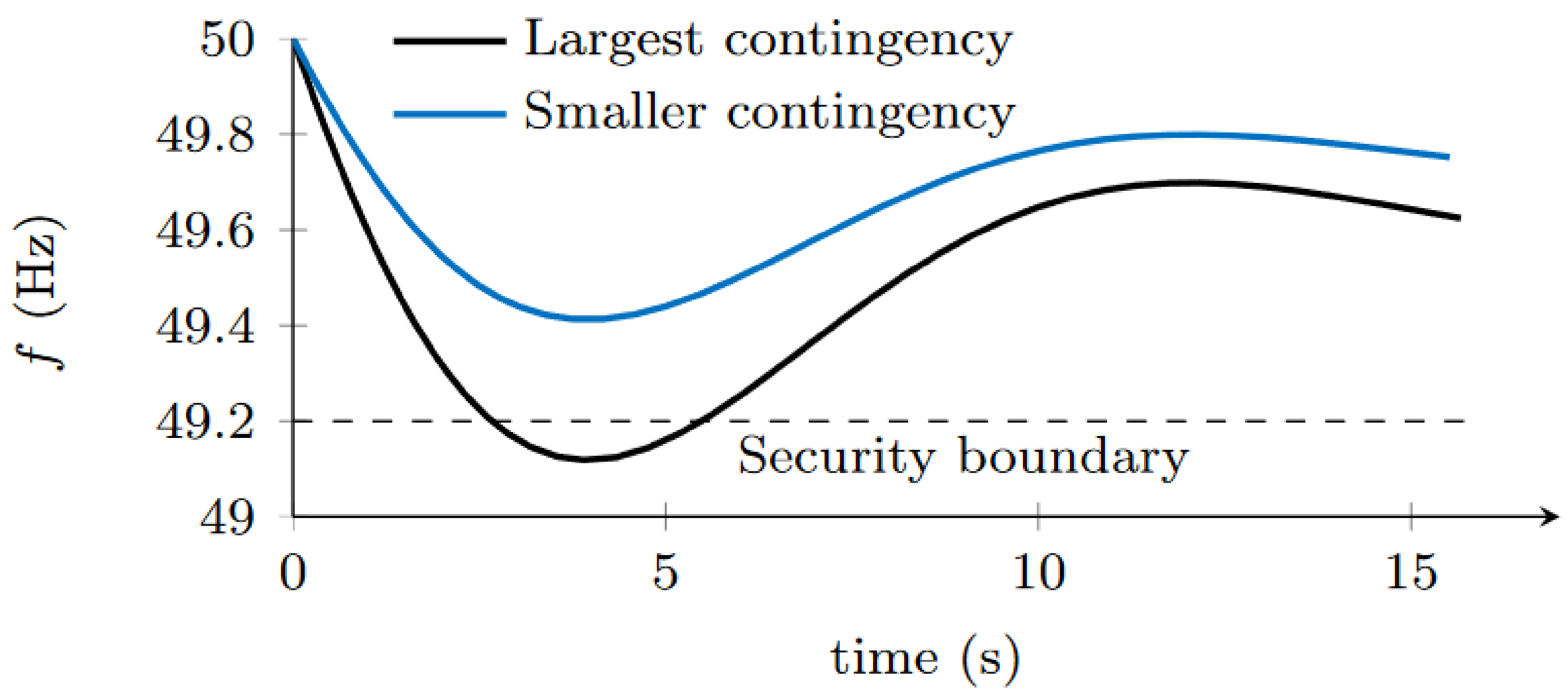
Who causes the need for frequency services?

Large units do: a low-inertia system would do fine if all units were small (there would be no large, sudden power imbalances)



Impact of inertia

under a large contingency



Impact of contingency size

in a low-inertia system

Who causes the need for frequency services?

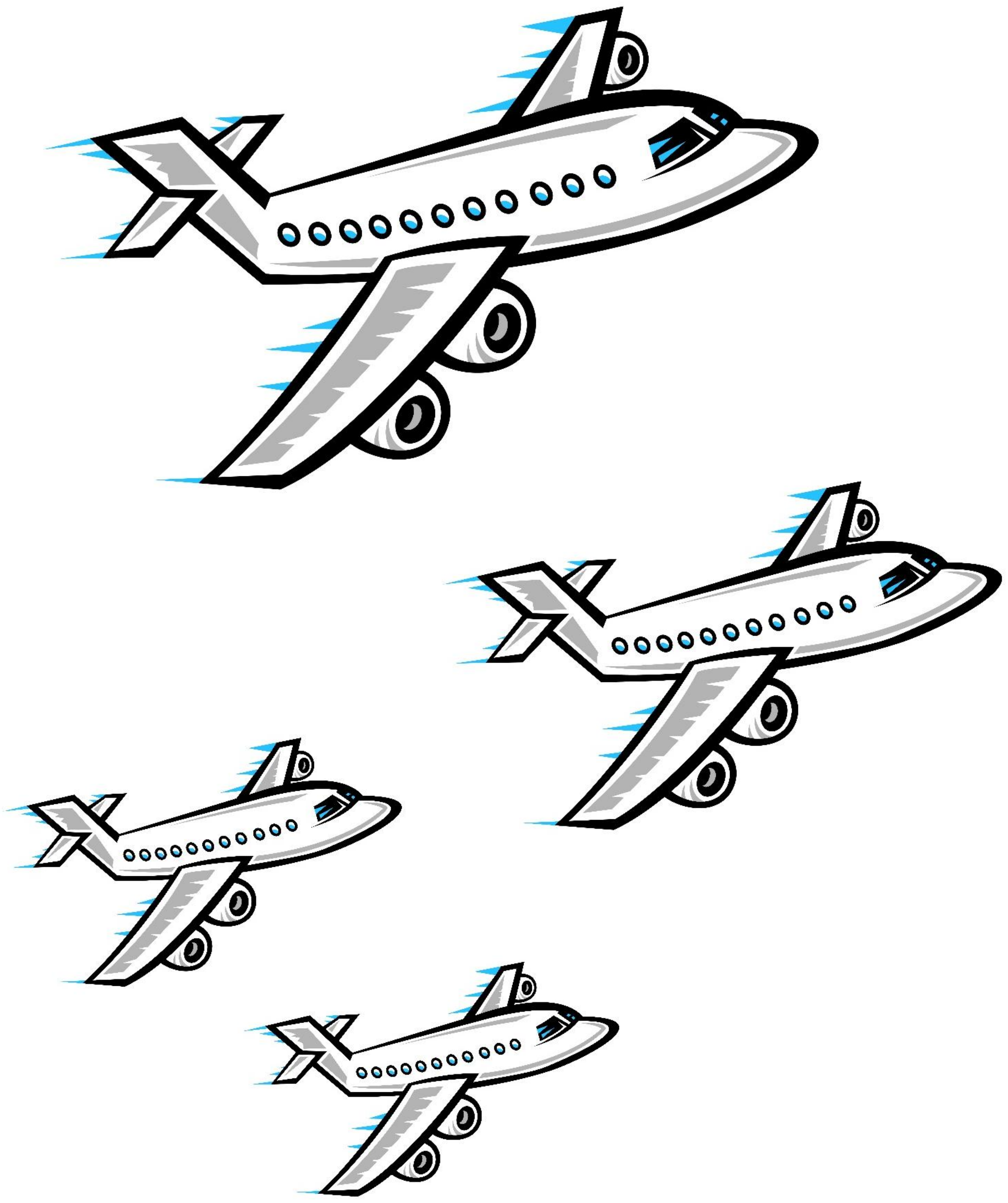
Large units do: a low-inertia system would do fine if all units were small (there would be no large, sudden power imbalances)

We **rule out penalizing** the **lack of inertia**

- Inertia is a service, it should be remunerated appropriately
- But lack of inertia is not a problem by itself

How to split the cost?

‘Airport problem’



How to split the cost?

Option 1: **proportional cost allocation**

- ✓ Easy to design: **each unit pays in proportion to its size**
- ✓ Creates **incentive** for large units **to 'do less harm'**
- **Problem**: it **maintains cross-subsidies**

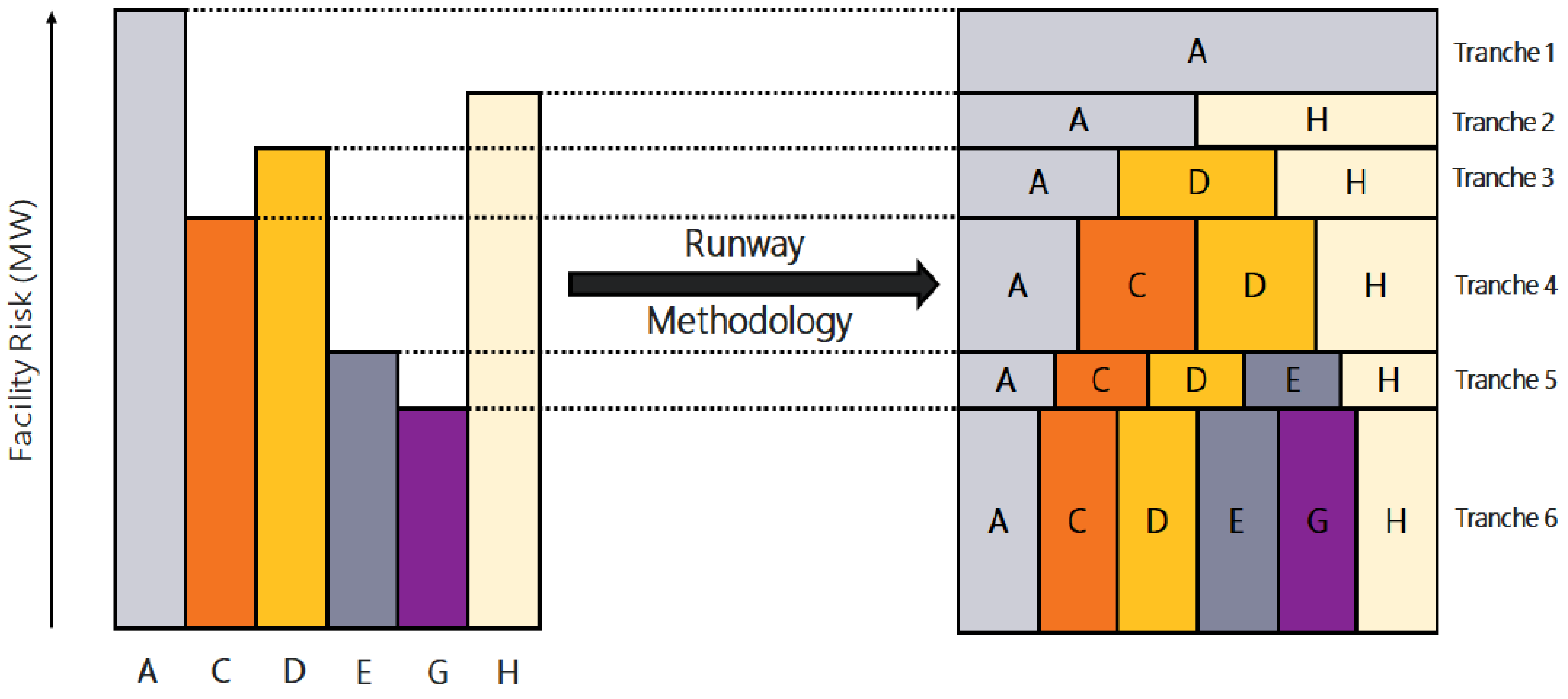
(small units still subsidize large ones)

Option 2: **sequential cost allocation** (coming next)

- ✓ Advantage: no cross-subsidies

Sequential cost allocation (Shapley value)

Each unit pays for the **additional cost** that it creates

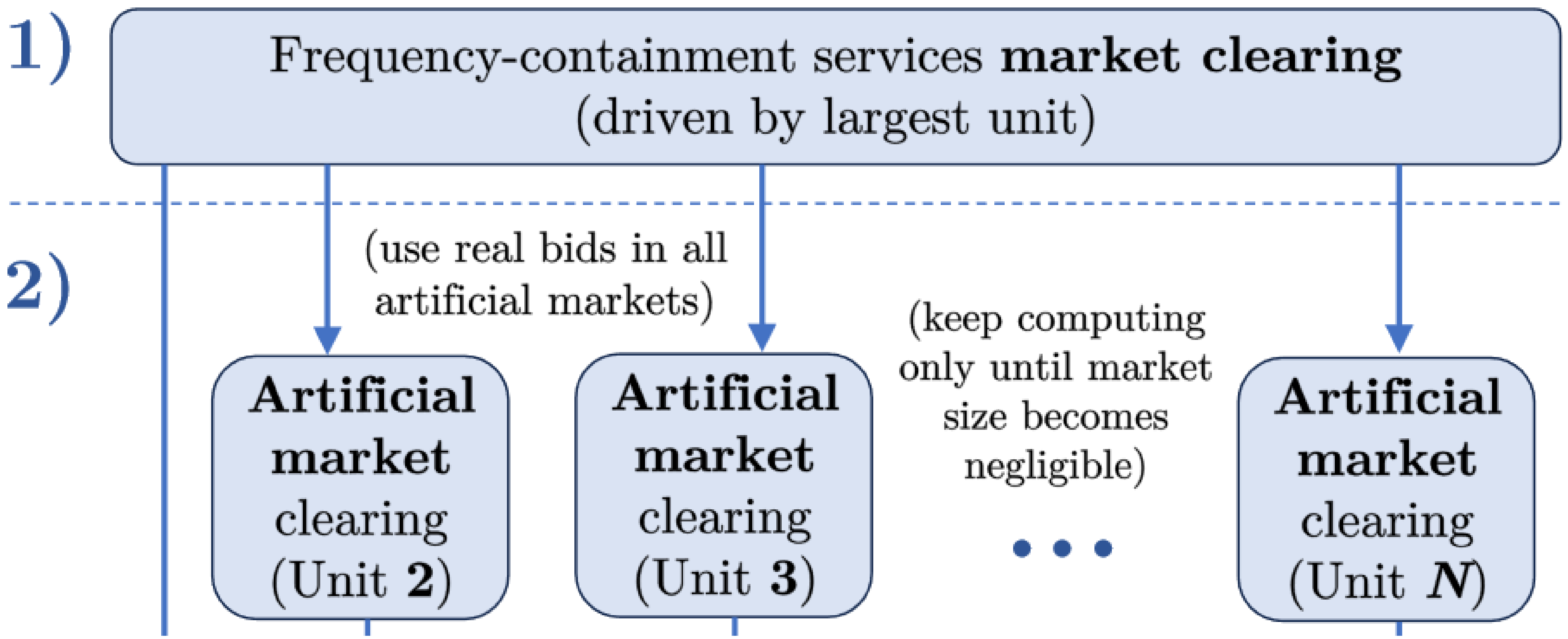


Reference: "A report describing the Wholesale Electricity Market in the South West Interconnected System", Australian Energy Market Operator, September 2023

Steps

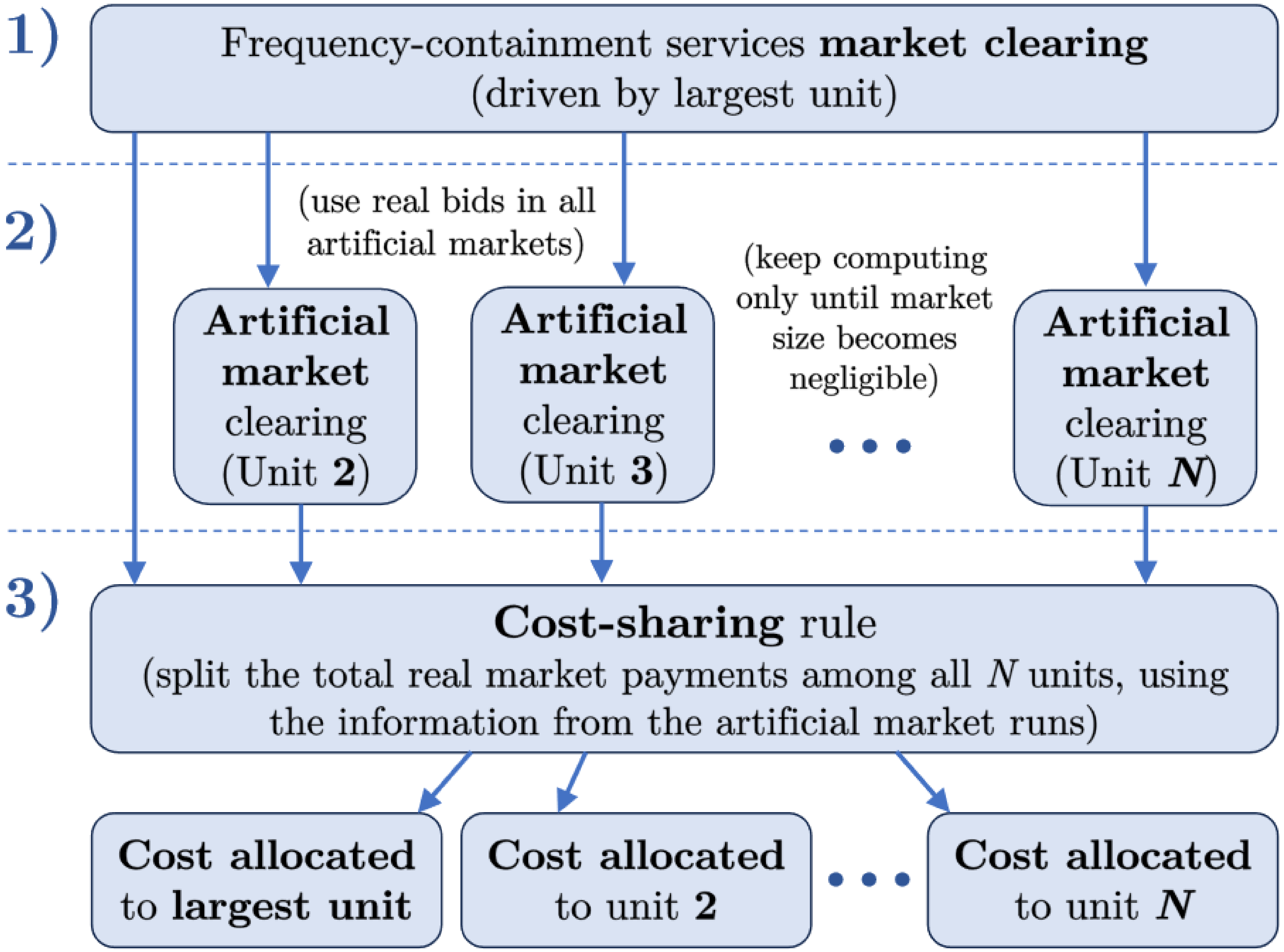
1) Frequency-containment services **market clearing** (driven by largest unit)

Steps



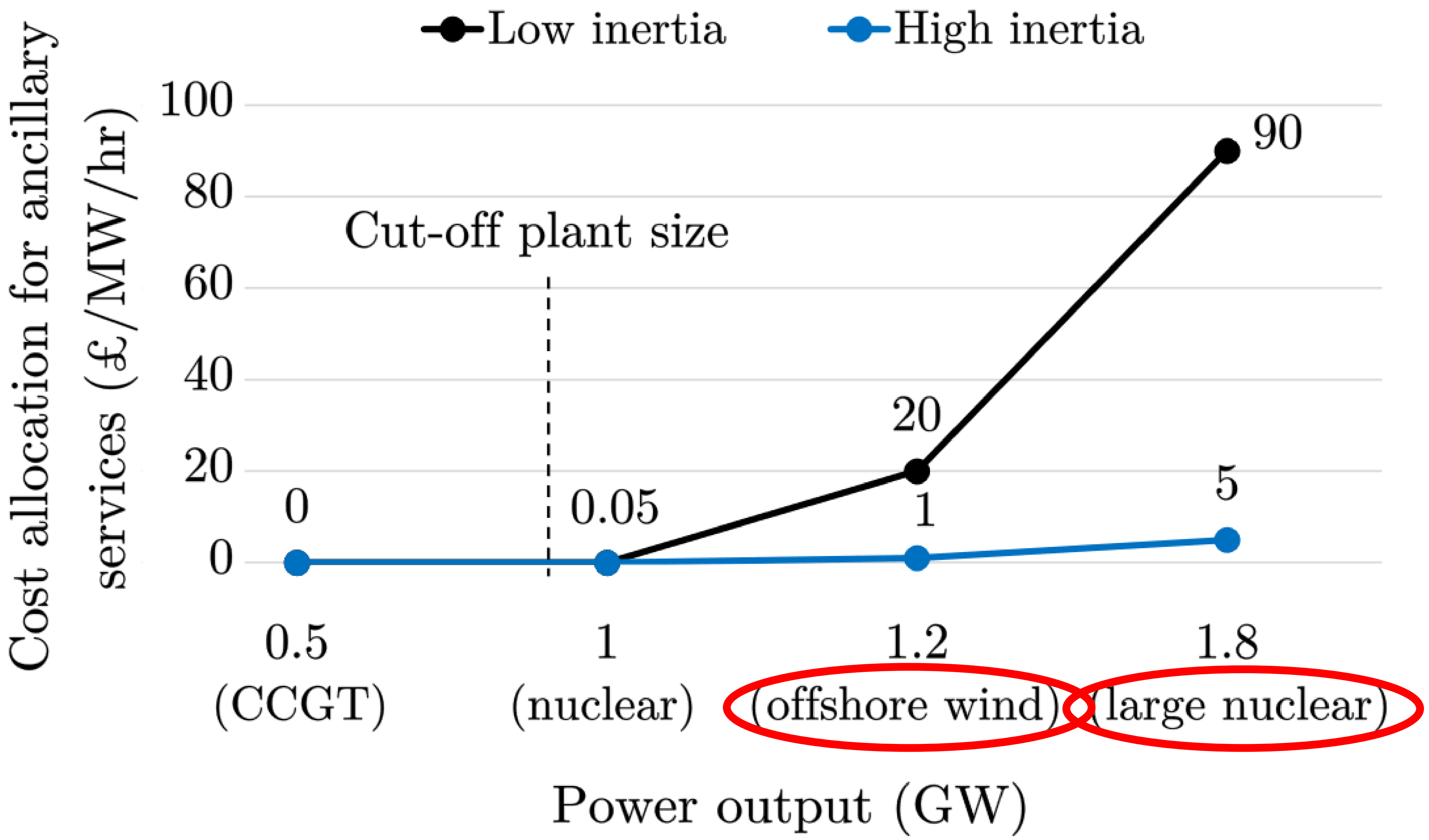
1)
Frequency-containment services **market clearing**
(driven by largest unit)
2)
(use real bids in all artificial markets)
Artificial market clearing (Unit **2**)
Artificial market clearing (Unit **3**)
(keep computing only until market size becomes negligible)
Artificial market clearing (Unit ***N***)

Steps



1)
Frequency-containment services **market clearing**
(driven by largest unit)
2)
(use real bids in all artificial markets)
Artificial market clearing (Unit **2**)
Artificial market clearing (Unit **3**)
(keep computing only until market size becomes negligible)
...
Artificial market clearing (Unit ***N***)
3)
Cost-sharing rule
(split the total real market payments among all N units, using the information from the artificial market runs)
Cost allocated to **largest unit**
Cost allocated to unit **2**
...
Cost allocated to unit ***N***

Analysis for Great Britain



Benefits of the cost allocation

- To create **investment signals**

  - Large units would **internalize their system-integration cost** (*e.g.*, nuclear, offshore wind, HVDC)

  - **Costs** would still **trickle down to consumers**, but appropriate economic signals for generation would be in place

- To **incentivize flexibility**

  - Large units can reduce the cost they are allocated by **reducing power output/demand**

Thank you for your attention!

All papers and some related code on my website:

https://badber.github.io/

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